Abundant information resources online, equalized development? Using the internet for learning and the mitigation of unequal occupational mobilities

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Chong Zhang

Abstract

This study explores the possibility that using the internet for learning mitigates the inequality of occupational mobility between rural migrant workers, a disadvantaged group in cities, and their advantaged counterparts, urban resident workers, in urban China. To investigate the mitigation of unequal occupational mobilities, this study examines, a) the extent to which using the internet for learning offers greater labour market benefits for the disadvantaged – rural migrant workers, and b) the extent to which rural migrant and urban resident workers have equal use of the internet for learning. This study uses quantitative and qualitative data in a complementary manner, with the quantitative analysis (data from China Family Panel Studies) being used to offer more rigorous results of comparison and the qualitative findings (data from 24 additional semi-structured interviews) being used to enrich explanations to interpret the observed comparative results. The results show a 'negative selection' phenomenon in using the internet for learning. That is, while rural migrant workers seem to be able to get more labour market benefits from learning online, they are actually less likely to use the internet for learning in the first place. As such, the results do not show that using the internet for learning mitigates the inequality of occupational mobility between the two groups. Structural inequalities cause rural migrant workers more excluded from using the internet for learning in the first place. The stronger 'learning-mobility' relationship for rural migrant workers merely reflects their deprivation of skill- and non-skill-related resources for occupational attainment in the urban labour market. The 'negative selection' phenomenon in using the internet for learning demonstrates the way that pre-existing structural inequalities are constantly being reproduced with new manifestations in an ever-changing world.

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Submitted for the degree of Doctor of Philosophy

Department of Sociology

Durham University

2020

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List of abbreviations

p.14	RMW	Rural migrant worker
p.14	URW	Urban resident worker
p.14	UIL	Using the internet for learning
p.20	CFPS	China Family Panel Studies
p.23	ICT	Information and communications technology
p.25	CCP	Chinese Communist Party
p.35	ISEI	International Socio-Economic Index of Occupational Status
p.39	ARPANET	Advanced Research Projects Agency Network
p.39	WWW	World Wide Web
p.39	CERN	European Organization for Nuclear Research
p.39	HTTP	Hypertext Transfer Protocol
p.39	URI	Uniform Resource Identifier
p.40	UNESCO	United Nations Educational, Scientific and Cultural Organization
p.64	EGP	Erikson-Goldthorpe-Potocarero class scheme
p.85	MOOC	Massive Online Open Course
p.87	OED	'Social Origin – Education – Destination' relationship
p.112	CNNIC	China Internet Network Information Center
p.237	OECD	Organization for Economic Co-operation and Development
p.238	IALS	International Adult Literacy Survey
p.238	ALLS	Adult Literacy and Life skills Survey

Declaration

I confirm that no part of the material presented in this thesis has been previously submitted by me or any other person for a degree in this or any other university. In all cases, where it is relevant, material from the work of others has been acknowledged. Based on some of the work within this thesis, the following publication has been submitted for consideration:

Chapter Four

Zhang, C. (2020). 'Unequal Occupational Mobilities Between Rural Migrant and Urban Resident Workers in Urban China'. *Frontiers in sociology* 5: 55. DOI: 10.3389/fsoc.2020.00055

Statement of Copyright

Acknowledgements

The successful completion of this thesis owes a huge thanks to many people.

Firstly, a massive thanks to my supervisors Dr. Matthew David and Dr. Keming Yang for their continuous support throughout my PhD journey. Their intellectual guidance, immense knowledge, patience, and kindness helped me in all the time of research and writing of this thesis. Thank you very much indeed! In addition, I would like to thank all the academic and non-academic staffs in the Department of Sociology, for the support and help they have given. In particular, special thanks to Professor Vikki Boliver and Dr. William Craige, for your kindness and the support you have given.

Secondly, I would like to thank all of my lovely PhD colleague friends within the Department of Sociology and the Department of Sport and Exercise Sciences. In particular, those with whom I have spent days in Room 101. All of you are lovely fellows. And I am going to miss you all when not seeing you guys in my future office.

Thirdly, I would like to thank my parents and my partner Sheryl. Thank you so much for allowing and supporting me to pursue my intellectual goal.

Fourthly, I would like to thank my participants. Thank you so much for letting me know something about your lives.

Lastly, I would like to thank the Great Britain-China Centre and Hatfield College for providing some financial support to my PhD project.

Chapter One: Introduction

'*The Web evolved into a powerful, ubiquitous tool because it was built on egalitarian principles […]'* (Berners-Lee, 2010)

The urban-biased *hukou* (household registration) system leads to an outcome of economic inequality between **rural migrant workers (RMWs)** and **urban resident workers (URWs)** in China's urban areas (Chan, 2010a). In contemporary China, people are encouraged to improve their economic well-being through career progression (Li, 2019a). However, in terms of occupational mobility, RMWs are at a notable disadvantage compared to URWs (e.g. Li, 1999, 2004). Skill-deficiency is pointed out to be a major cause of poor occupational attainment for RMWs, and therefore RMWs are encouraged to engage in continual learning and skill-development to improve their occupational mobility and economic well-being (Han, 2006; Li, 2019a). Whilst the internet has been portrayed as a powerful tool for learning and challenging inaccessibility to knowledge, we still know very little about whether and to what extent **using the internet for learning (UIL)** can help people from disadvantaged backgrounds improve their skill-development and occupational mobility. Thus, this study sets out to investigate the extent to which ***UIL mitigates the unequal occupational mobilities between RMWs and URWs in urban China***.

1.1. A disadvantaged group in the urban labour market

RMWs are a large group[1] of economically disadvantaged populations in urban China. Introduced in 1958, China's urban-biased *hukou* (household registration) system divides citizens into two types: the agricultural and non-agricultural. The so-called RMWs are those who have migrated to cities as non-agricultural workers but still retain an agricultural *hukou* status (Chan, 1996). The *hukou* system was originally implemented to speed up

[1] There are 290 million RMWs in China's urban areas in 2019 (National Bureau of Statistics, 2020)

industrialisation in China's urban areas, resulting in rural-urban disparity in China (Chan, 2009). When free migration between rural and urban areas was permitted at the beginning of economic reform at the end of the 1970s, a massive rural-to-urban migration occurred. Rural origin individuals moved to cities for job opportunities and better economic life chances. Under China's strict *hukou* regulations, most of the rural migrants were not permitted to change their *hukou* status to the non-agricultural type, even after moving to cities, and are still classified as 'temporary' or *de facto* residents in cities (Chan, 1996). As *de facto* residents in cities, RMWs are not entitled to the state-supplied urban welfare benefits, making them more reliant on work and employment to secure economic well-being (Chan, 1996, 1999). However, RMWs are also more disadvantaged in the urban labour market compared to URWs. For example, in the urban labour market, RMWs are more likely to take over low-paid and unskilled '3-D' (dangerous, dirty, and demeaning) jobs, whereas the jobs of URWs, who have a non-agricultural *hukou* status and are the *de jure* citizens in urban China, are more likely to be skilled and exhibit good economic remuneration (e.g. Chan, 1996, 2009; Li, 1999, 2004; Li, 2008; Démurger et al., 2009).

In most industrialised countries, political regimes purport to address the issue of economic injustice by promoting equal opportunities for the so-called 'meritocratic' social mobility. (Brown, 2013; Littler, 2017). In contemporary China, where efficiency for continuous economic growth is identified as the key goal, economic inequality is tolerated in order to stimulate competition and continuous growth in productivity, after the market-oriented economic reform was initiated (Harvey, 2005, pp. 120-151; Whyte, 2012). In such a context, individuals are expected to cope on their own to secure their economic well-being rather than rely on redistributive welfare policies. Individuals are encouraged to improve their economic life chances through career advancement and entrepreneurial success through fierce competitions (Li, 2012). Social mobility attained through individuals' hard-work and engagement in fierce competitions is praised as '*the important passcode for China's prosperous development*' (Li, 2019a). Nevertheless, the conditions for equal opportunities for mobility are far from being reached. Even though individuals nowadays have the freedom to migrate and change jobs to improve their economic situations, RMWs are nevertheless found to be disadvantaged when it comes to occupational mobility (i.e. poor job security and low upward mobility rate) (e.g. Li, 1999, 2004).

1.2. Accessing learning opportunities on the Internet?

To reduce disadvantages in occupational mobility, RMWs are often encouraged to engage in continual learning and skill-development, since 'skill-deficiency' is considered to be the main cause of their poor performance in occupational attainment and economic achievement in cities (Han, 2006; Tian et al., 2013; Li, 2019a). However, traditional forms of adult learning opportunities (e.g., employer-provided training, vocational training programs, government-supported schemes) are found to be difficult to access for RMWs. Training opportunities provided by employers often do not favour those from rural areas, who are not considered to have certainty of settlement in city and lack good literacy skills in order to make use of these training opportunities (Zhu, 2004; Xu, 2014). Further, because RMWs lack sufficient economic resources, they are less likely to purchase training courses and self-learning materials from private providers (Lei, 2004; Zhu, 2004; Xu and Liu, 2005; Xu, 2014). With a large number of RMWs in cities and a limited funding, government-supported training schemes are simply not sufficient to meet the demand (Xu, 2013).

Among technological optimists, the internet is considered to be a flexible and affordable means for widening learning opportunities (e.g. Selwyn et al., 2001; Gulati, 2008). Since the beginning of the 21st century, when the internet had just become popular, a narrative has been emerging whereby the 'transformative effect' of the internet will challenge inaccessibility to knowledge in the new information age (Selwyn et al., 2001; Gorard and Selwyn, 2005). Regardless of how uncritical those technological optimists are, the internet does provide people with a new means to learn, with some desirable effects like information resource abundance. Since information has no natural scarcity, the reproduction and dissemination of digital forms of information resources incur at almost no cost (e.g. David, 2010, p. 45). Furthermore, global connectivity via the internet enables a full exchange of information resources (van Dijk, 2012). Whilst the internet has been portrayed as the largest library for learning in human history (Ibid.), the potential for UIL to help disadvantaged populations' learning, skill-development, and occupational mobility remains unknown. *Thus, to fill this gap, this research sets out to investigate the potential of UIL for reducing the disparity in occupational mobility for RMWs in China's urban areas*.

1.3. Research questions

Thus, this research sets out to answer this central question:

> ***To what extent does UIL mitigate the unequal occupational mobilities between RMWs and URWs in China's urban labour market?***

To evaluate the role of UIL in mitigating the issue of unequal occupational mobilities, two aspects of the effect of UIL are considered simultaneously: *the compensatory effect of UIL* for the disadvantaged group (i.e. the extent to which RMWs enjoy more labour market returns to UIL) and *the inclusivity of UIL participation* (i.e., the extent to which RMWs and URWs have equal participation in UIL). This evaluation framework owes a debt to Bukodi's (2017) work on evaluating the role of further education on promoting equalised social mobility in Britain. According to Bukodi (2017), to sufficiently claim that a kind of new learning opportunity is really beneficial for disadvantaged-background individuals' social mobility, ideally, a) the new learning opportunity should bring more labour market returns to the disadvantaged-background individuals as a 'compensatory' second chance to upgrade their skills, and b) the disadvantaged-background individuals should not be excluded from accessing the learning opportunity. Following the evaluation framework, *three specific research questions are then proposed*.

First, before setting out to directly evaluate the role of UIL in mitigating the issue of unequal occupational mobilities, I need to answer the following question first in order to *make a clear sense* of the relationship between *UIL and occupational mobility* in the contemporary labour market:

1) To what extent is UIL related to occupational mobility in general?

The analysis then goes into the two key aspects (i.e., *the compensatory effect of UIL for the disadvantaged group* and *the inclusivity of UIL participation*) of the evaluation of the role of UIL in mitigating unequal occupational mobilities between RMWs and URWs. The following two research questions are then proposed:

2) Given the same participation in UIL, is there a stronger UIL-mobility association for RMWs?

3) Do RMWs and URWs have similar participation in UIL?

After answering each research question respectively, a combined discussion is given to evaluate UIL's potential for mitigating inequality of occupational mobility between RMWs and URWs. The evaluation of the mitigation effect mainly draws upon the findings from the second and the third research questions, since they are directly addressing the two key aspects of the effect of UIL. Table 1.1. shows nine possible combinations of the results for the second and the third research questions, as well as the interpretations for each combination of the findings, in relation to the implication of UIL's effect on the equality of occupational mobility between RMWs and URWs. As shown, three desirable outcomes are highlighted in green, indicating that UIL does play a role in mitigating inequality of mobility under such conditions. Those three ideal outcomes are: whilst RMWs and URWs have equal participation in UIL, UIL is more beneficial for occupational mobility for RMWs; whilst the effect of UIL for occupational mobility are similar for RMWs and URWs, RMWs are more active in UIL; whilst RMWs enjoy more labour market benefits from UIL, they are also more active in UIL. A more detailed discussion of these scenarios is given in Chapter Eight.

Table 1.1. Possible outcomes and the interpretations

Participation in UIL	Effectiveness on occupational mobility	Interpretation
URW>RMW	URW>RMW	Unequal mobility chances deepened
URW>RMW	URW=RMW	Unequal mobility chances deepened
URW>RMW	URW<RMW	Unequal mobility chances remained
URW=RMW	URW>RMW	Unequal mobility chances deepened
URW=RMW	URW=RMW	Unequal mobility chances remained
URW=RMW	URW<RMW	Unequal mobility chances mitigated
URW<RMW	URW>RMW	Unequal mobility chances remained
URW<RMW	URW=RMW	Unequal mobility chances mitigated
URW<RMW	URW<RMW	Unequal mobility chances mitigated

The changes of occupational mobilities: Mitigation No changes or unclear Deepening

To clarify, *UIL* is defined in a broad sense to include *all kinds of work-relevant learning activities assisted by the use of the internet*. RMWs are defined as those who hold an agricultural *hukou* type, have a non-agricultural job in an urban workplace, and reside in an urban area. URWs are those who hold a non-agricultural *hukou* type, have a non-agricultural job, and reside in an urban area. In using the term occupational mobility, this study mainly concerns itself with those 'vertical mobilities' (i.e., upward and downward mobility) that are more directly related to changes in individuals' economic life chances.

1.4. A mixed-methods approach

This study adopts a mixed-methods approach by analysing both quantitative and qualitative data to answer each research question. The way of mixing methods is *complementarity*, meaning that two different methods are used to address different parts or aspects of the inquiry for each research question, since quantitative and qualitative methods have their distinctive merits (Hammersley, 2002). Before analysing empirical data, for each research question, building on previous empirical and theoretical works, *a preliminary theory* (the *temporarily scarce skills theory* for the first research question, the *diligence dependence theory* for the second research question, and the *practical action theory of UIL* for the third research question) is constructed to *predict the hypothetical phenomena* for verification and to *offer a provisional explanation* to make sense of the mechanisms behind the observed patterns. Quantitative methods, given their merits of providing robust results of comparisons and describing general patterns and regularities, are used to carry out comparisons and to describe general patterns with high a level of accuracy. For the quantitative analysis, data from a large-scale social survey, the China Family Panel Studies (CFPS), are used. In most cases, the quantitative analysis is done by running mixed-effects models in *Stata* and *R* environments. Qualitative methods, given their merits of providing additional detail and depth to understand social phenomena and creating openness for exploration, are used to refine the interpretation of the mechanisms behind the observed patterns. The qualitative analysis draws on data from 24 semi-structured interviews conducted in Guangzhou, China, from 2018 to 2019. The qualitative data is analysed by a narrative analytical approach. More details of research design, data and methods can be found in Chapter 3.

1.5. An overview of the thesis

After giving a general introduction of the thesis in this chapter, the next chapter, *Chapter Two: Background*, introduces three key themes of the background knowledge of this study. First, Chapter Two introduces the origin of China's urban-biased *hukou* system, and the system's 'legacies' of rural-urban disparity in China, massive rural-to-urban migration, and the economic disadvantage of RMWs in urban China. Second, the chapter introduces the current situation of occupational mobility being promoted as a practical pathway to improve individuals' economic well-being whereas inequality of mobility between RMWs and URWs still exists. Third, the chapter introduces the potential of the internet for widening access to knowledge and learning opportunities, especially given the abundance of information resources online.

The next chapter (*Chapter Three: Research design*) introduces the research focus and methodology of this study. First, the chapter introduces the central question, the evaluation framework, three derived research questions, and the key concepts of this study. The second section then introduces the complementary mixed-methods approach, and the ways of combining quantitative and qualitative data to answer each research question.

The fourth chapter (*Chapter Four: An overview of the unequal mobility*) investigates the overall inequality of occupational mobility between RMWs and URWs, by presenting three sets of bivariate analyses (i.e., the outflow table comparison, the comparison of the numeric scores of mobility, and the comparison of mobility types). The results confirm the issue of inequality of occupational mobility, that overall URWs have an advantage in occupational mobility in the urban labour market. Regardless of their original occupations, RMWs have a higher chance of becoming manual or agricultural worker whereas URWs have a higher chance of becoming white-collar workers. Whilst the advantage in upward mobility among URWs is marginal, they generally have a significantly lower risk of downward mobility.

The fifth chapter (*Chapter Five: Learning and moving*) sets out to investigate the extent to which UIL is related to occupational mobility in the contemporary labour market, the first research question. A preliminary theory, *the temporarily scarce skills theory*, is proposed. The theory predicts a positive relationship between UIL and occupational mobility. It argues that whilst wage workers' skills' scarce-level helps them secure their economic remuneration, the level of the scarcity of skills is not constant and so continual learning with the use of the internet might have become a measure to help one develop and reproduce scarce work skills in an ever-changing world. The quantitative results show a positive but somewhat weak association between UIL and occupational mobility in general. Qualitative findings highlight the limitations of the temporarily scarce skills theory, that the theory omits the difficulties of signalling and screening workers' skills in real-world situations, and that the theory is only applicable when the recruitment of workers is highly 'skill-meritocratic'.

Next, *Chapter Six: More returns for the disadvantaged diligent?* sets out to investigate the extent to which the association between UIL and mobility is greater for RMWs. The *diligence dependence theory* is proposed. The theory predicts that the association between UIL and occupational mobility is greater for RMWs. It argues that generally a stronger 'learning-mobility' association exists for the disadvantaged, although the pattern only reflects disadvantaged background people's deprivation of skill- and non-skill-related resources for occupational attainment. The quantitative evidence highlights a stronger 'UIL-downward mobility' for the disadvantaged. In addition to unequal distribution of educational resources, the qualitative evidence provides another cause of the URW group's skill-advantage – an urban-biased definition of skills and knowledge in the urban labour market.

Chapter Seven (*Inequality in learning online?)* then sets out to investigate the extent to which RMWs and URWs have equal participation in UIL. Adopting a Bourdieusian perspective, the chapter proposes a *practical action theory of UIL* to argue that UIL is a 'resource-reliant' activity and advantaged-background individuals could have better access to UIL due to the 'rich resources' they have accumulated. Thus, the theory predicts that URWs are being more active in UIL. The quantitative findings show that RMWs and URWs differ in the rates of internet adoption and UIL participation. In addition to economic and cultural resources as highlighted in the practical action theory of UIL, the qualitative findings further highlight that inequality of social network resources might also play a role in explaining the differences in active internet use and UIL between RMWs and URWs.

After getting results for each research question, Chapter Eight (*Mitigation? Reproduction!*) gives an extended discussion on the role of UIL in mitigating the inequality of occupational mobility. The result turns out to be a *negative selection phenomenon*, that is: *while RMWs seem to be able to acquire more labour market benefits from UIL, they are also less able to participate in UIL*. The results show no sign that UIL mitigates the inequality of occupational mobility. Instead, as argued in Chapter Eight, the negative selection phenomenon in UIL demonstrates the way that privileged individuals constantly reproduce their advantages in an ever-changing world.

Finally, the concluding chapter summaries the findings of the thesis, provides policy suggestions to address issues of unfair recruitment in the urban labour market, inequality in UIL participation, the lack of access to educational opportunities and the *hukou*-related economic inequality in China, and highlights the limitations of this study.

1.6. Potential contributions

This study brings new empirical evidence and theoretical insights concerning the role of the internet in the continual production and reproduction of the processes of equality/inequality of URWs and RMWs by focusing on the relationship between UIL and occupational mobility. Empirically, this study provides new evidence to show the ineffectiveness of relying on the internet as a new learning tool to equalise pre-existing unequal occupational mobilities. Additionally, the findings from each chapter provide new empirical evidence to indicate the general landscape of inequality of occupational mobility between RMWs and URWs, the role of UIL in the contemporary labour market in urban China, the heterogeneity of the relationship between UIL and occupational mobility for RMWs and URWs, and issues of inequality in internet use and UIL between RMWs and URWs.

In addition, this study contributes to the existing knowledge base with some new theoretical insights. The *temporarily scarce skills theory* in Chapter Five contributes a new perspective to the field of social stratification by articulating the impact of information communication technology (ICT) and the internet on the obsolescence of work skills in a rapidly changing world, and highlighting the routinisation of 'learning labour' to reproduce scarce skills to secure economic life chances. The *diligence dependence theory* in Chapter Six contributes a perspective to interpret the stronger 'learning-mobility' association for the disadvantaged as a sign of their resource-deprivation. The *practical action theory of UIL* in Chapter Seven articulates the 'resource-dependent' nature of UIL, which contributes a new way to explain the translation from structural inequality to the differences in participating in learning online. Lastly, the discussion in Chapter Eight contributes a new perspective to interpret that UIL plays a role in reproducing the pre-existing social inequalities in an ever-changing world.

Although not being able to provide detailed guidelines for policy-making, the research findings can suggest some useful ideas for effective policy responses to address the issues of the disadvantage of RMWs in the urban labour market as well as the structural inequality between rural and urban origin populations to support the ongoing nationwide *hukou* reform project. In addition, the research findings offer useful ideas for designing effective measures to widen access to learning opportunities, digital technologies, and UIL.

Chapter Two: Background

2.1. Introduction

This chapter introduces three key themes on the background knowledge of this study. First, it introduces China's urban-biased *hukou* system, and the consequences of rural-urban inequality, massive rural-to-urban migration since the economic reform, and most importantly the issue of economic disadvantage of RMWs in urban China. Second, after briefly sketching some competing theoretical arguments on the role of social mobility, the chapter contends that China, like many other industrialised societies nowadays, views social mobility through individual hard-work and engagement in market competition as a key strategy to secure individual economic well-being. Nevertheless, in urban China, RMWs are found to be disadvantaged in the 'free-competition' of occupational mobility, and the reduction of skill-deficiency for RMWs is seen as the key solution to improve their competitiveness. Third, the chapter will introduce that since the *World Wide Web* became widely available, the internet has been considered as a powerful tool for widening access to learning opportunities, especially given the abundance of shared information resources online.

2.2. From the *hukou* system to the RMW-URW divide in urban China

2.2.1. The *hukou* system

The word *hukou* in Chinese literally means nothing more than 'household and population'. Across centuries, there have been numerous '*hukou'* related institutions in China that functioned for different purposes (e.g., statistics collection, categorization of populations and households, taxation, military recruitment, population control, lands, and property re-distributions) (Song, 2016). But today the *hukou* system refers to the household registration system implemented since the 1950s, a few years after the Chinese Communist Party (CCP) took power and established the 'rural-urban dichotomy' (i.e., populations were categorized as either agricultural or non-agricultural populations according to their residences) as one of its key features.

When looking back historically, the senior state officials have defended that the *hukou* system as an 'inevitable measure' at that time, since China was longing for a rapid industrialisation whilst there was a deprivation of resources to support the ambitious project of industrialisation (Naughton, 2007, pp. 55-83; Chan, 2009; Zhang and Chai, 2012, pp. 22). Therefore, a system with unequal resources distribution (i.e., those who worked for industry in urban areas being rewarded more than rural agricultural workers) was introduced as a strategy. The post-1949 state attempted to adopt the Soviet model to provide jobs, food, and housing to all urban citizens (Cheng and Selden, 1994). Considering that peasants can grow their own grains for self-consumption (Zhang and Chai, 2012, p. 22) and the prioritisation of rapid industrial development in urban areas, peasants in rural areas were then not provided with subsidized food, welfare benefits, and/or social services (Zhang and Chai, 2012, p.22; Chan, 2009; Cheng and Selden, 1994). Furthermore, under the planned economic system, through the well-known 'price scissors' policy[2], the prices of agricultural products were suppressed in order to support heavy industrial development in urban areas. As the freedom of migration and residence was not restricted before 1953 (e.g., see the Article 5 from the '1949 temporary constitution' *Common Program of The Chinese People's Political Consultative Conference* (*CPPCC*, 1949)), a large number of rural populations chose to move to cities with the attempt to find industry jobs (Chan, 2009). Facing the rural influx, also in conjunction with the issue of unemployment and the refugee crisis after the civil war (Cheng and Selden, 1994), the populations in the urban areas grew to such an extent than what the state could support (Zhang and Chai, 2012, p. 18). Thus, the state council and the party's central committee made statements[3] to discourage further rural-to-urban migration, and degradingly labeled the migrants as the 'blind flows'

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[2] Originally, the term refers to the measures to extract profits from peasants in rural sector to subsidise industry sector workers, in order to speed up the capital accumulation process (Preobrahensky, 1926).

[3] For example, *Guanyu fangzhi nongcun renkou manmu wailiu de zhishi* (Instructions on Preventing Aimless Rural-to-Urban Migration) in December 1956 (Zhou and Chen, 1956); *Guanyu fangzhi nongcun renkou manmu wailiu de buchong zhishi* (Additional Instructions on Preventing Aimless Rural-to-Urban Migration) in March 1957 (Zhou, 1957) and *Guanyu zhizhi nongcun renkou manmu wailiu de zhishi* (Instructions on Restraining Aimless Rural-to-Urban Migration) in December 1957 (CCPCC and State Council of the People's Republic of China, 1957).

(*Mangliu*), which means aimless migrators and troublemakers (Chan, 2009). In 1958, the most important legislation *Zhonghua renmin gongheguo hukou dengji tiaoli* (Regulations on Household Registration in the People's Republic of China) was promulgated by the National People's Congress (SCNPC, 1958). The regulation officially declared the citizens' obligation to register their *hukou* status according to their residence and their prohibited free migration without official permission (normally either through marriage or obtaining an employment in the state sector in the cities) (Ibid.). Furthermore, in 1963, the department of public security officially adopted 'whether or not entitled to state grain rations' as the criteria by which populations were classified into agricultural (those with no entitlement to state grain rations) and non-agricultural (those with entitlement to state grain rations) groups (Zhang and Chai, 2012). It was at this point that the new *hukou* institution was officially formed.

2.2.2. The rural-urban divide

One of the main consequences of the new household registration system was that it dichotomized rural and urban society. Since China was completely under the 'planned economy' system before the 1978 reform, decisions on resource allocation rested fully with the state. As mentioned above, like many other Stalinist style communist countries, an urban-biased developmental strategy was adopted by the state in order to support the capital-intensive heavy industry in urban areas.

Table 2.1. The Rural-Urban Dual System in Mao's Era

Economy	
Industry	**Agricultural/Rural**
Priority Sector	Nonpriority sector
State owned	Nonstate sector
State support and control	Self-reliance
Monopoly profits through unequal sectoral exchange	A provider of cheap resources for the state sector
Society	
(based on the *hukou* classification)	
'Non-agricultural' Households	**'Agricultural' Households**
State protection; subject to political control	Self-reliant; subject to less central control
State-provided employment and welfare	Employment and welfare based on local collectives
Restricted entry	Tied to land and agricultural-exit restricted

Source: Chan and Zhang (1999).

Table 2.1 summarises the dual economic and societal system during Mao's era. During the planned economy period, most of the urban industry had been transformed into state-owned or state-private enterprises, whilst collective ownership was the typical way of organising agricultural economy in rural areas (Cheng and Selden, 1994). Although there seemed to be a high degree of freedom, the rural economy was still subject to state control, for example in the way that the price of agricultural goods was 'manipulated' by the state. Also because of this double-standard 'self-reliance,' rural households could not receive any additional resource stipend even though selling agricultural goods was not profitable under the state's monopoly. In contrast, their privileged urban counterparts were entitled to state-provided life necessities, such as secure employment and welfare benefits (Zhang and Chai, 2012, p. 30). Furthermore, in accordance with the urban-biased policy and the prioritization of heavy industry development, there was also a differentiation of public resources supply and infrastructures investments between rural and urban areas, including but not limited to medical care, school and educational resources, water and electricity supply, and public transportation (Zhang and Chai, 2012, p. 34).

2.2.3. The economic reform, migration, and the RMW-URW disparity in cities

China launched its own economic reform *Gaigekaifang* (Economic Reform and Opening-up) in 1978 that coincided with a global *laissez-faire* trend at that time (Harvey, 2005, p. 120). It is claimed that the purpose of the reform was to develop 'socialism with Chinese characteristics,'[4] which gave market and privatized economy an important role in organising economic activities (CCPCC, 1984*).* Alongside the economic reform in the post-Mao China, the migration ban was eased and a new wave of massive rural-to-urban migration began (Chan, 2014). It was estimated that there were 30 million rural migrants in 1989 (Li, 2008). In 2019, the number of rural migrants rose to 290 million (National Bureau of Statistics, 2020).

The boom of the rural-to-urban migration was due mainly to: a) the loosening of migration controls by the authorities (e.g. the launch of the 'Temporary Residence Certificate system' in order to 'adapt to the trend of economic reform and opening') (Solinger, 1985; Ministry of Public Security, 1985; Chan and Zhang, 1999); b) surplus rural labourers as a result of the rural economic reform (i.e., the de-collectivization of agricultural sector in rural areas) (e.g. Yang, 1993; Chan, 1996); c) more rural-to-urban travel[5] for

[4] There is a noteworthy reminder from Tisdell (2008) that although it seems impossible to find an exact definition of the term 'Socialism with Chinese Characteristics', and that nowadays the term is used to refer to different things for different purposes under different circumstances, when people firstly started to use it to refer to the goal of China's economic reforms, there were certainly some elements related to 'free and open market'; 'professionalism and performance orientation'; 'the rules of law'; 'the transition from state ownership to private ownership'; and 'economic incentives and stimulus to productivity.'

[5] A reminder from Chan (1996) is worth-mentioning that even before 1978, people were

agricultural goods trading due to the allowance of free-trading of goods (e.g. Goldstein and Goldstein, 1985; Yang, 1993; Chan, 1996); d) the expansion of temporary employments by both the private and state sectors, especially in low-end factories and service jobs (e.g. Yang, 1993; Chan, 1996; Chan, 2012); and e) the remaining large gaps in living standards between cities and rural areas (e.g. Li, 2008; Chan, 2014).

The new trend of rural-to-urban migration was then followed by the issue of inequality between RMWs and URWs in cities, as Chan (1996) comments:

> '*Though the role of the hukou system has declined in the reform period, the classification still means a lot and has produced a relatively clear social and economic stratification.*' (p.194)

Strictly speaking, those who migrated to cities without the change of household registration status are still classified as 'temporary' residents or *de Facto* populations in cities (Chan, 1996; Chan and Wang, 2008). Although being allowed to reside in cities, RMWs are not entitled to the state-supplied welfare benefits and social services (including but not limited to social security, health insurance, children's access to public school, house-allocations and unemployment insurance) (Chan et al., 2008), due to their agricultural *hukou* status. Thus, RMWs are almost entirely reliant on income from their work to secure their economic well-being in cities.

Moreover, RMWs are also at a disadvantage in the urban labour market. In the urban labour market, the jobs RMWs have undertaken are more likely to be low-paying, insecure, and in poor working conditions (Li, 2004; Li, 2008; National Bureau of Statistics, 2016). It is known that the RMW-URW inequality in the urban labour market is strongly related to occupational segregation (e.g. Chan 1996; Li 1999, 2004; Chan 2009; Démurger et al. 2009; Liu 2017). The division in participation in the state sector used to play a role.

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never banned from 'travelling' to other areas, but they were not allowed to reside in the areas they travelled to.

RMWs were much less likely to work in the state sector and that meant that they did not secure all those advantages that state sector employment used to carry, namely employment security (Chan, 1996; Liu, 2017). In the 1990s, job opportunities in the state sector were further restricted to local *hukou* status (Chan, 1996). That being said, the extent to which the state/non-state division still matters is up for debate after the state sector reforms of 1997 which replaced the promised lifetime job security with an efficiency-driven competition system (Fung, 2001). Bian et al. (2006) argue that even after the state sector reforms, compared to the non-state sector, the state sector still had a slightly stronger 'resources re-distributive' characteristic. However, studies like Démurger et al. (2009) show that the sectoral effect on labour reward is negligent and fails to explain the RMW-URW earnings differences.

More importantly, RMW-URW occupational segregation is related to the differentiation of jobs with different skill levels. Following the labour market segmentation theory (Reich et al., 1973), Li (2004) argues that in urban China, the manual/non-manual labour division can explain the RMW-URW differentiation to a large degree. RMWs are often found to be linked to low-income and unskilled '3-D' (i.e., dangerous, dirty and demeaning) jobs in manufacturing, construction and low-end service industries (Chan 2009; Chan, 2012). The massive 'low-cost and exploitable' labourers contribute to China's economy boom, by supporting the strength of cheap labour-price for the export-oriented manufacturing industry and infrastructure-building projects in the construction industry (Chan, 2012). It is harder for RMWs to obtain occupations with good economic renumeration and this is thought to be related to the specific skill-deficiencies of RMWs. Empirical evidence by Liu (2017), Démurger et al. (2009), and Li (2008) shows that to a large degree, the RMW-URW gaps in earnings and benefits can be explained by skill-related factors (i.e., educational backgrounds and training experiences). The failure to obtain advanced work skills is considered to be a consequence of the 'urban-biased' developmental policies that prioritised rich economic, cultural, and educational resources for supporting education and trainings, which are being exclusively hoarded in urban areas (e.g. Li, 1999). Liu (2017) argues that although the *hukou* status has no direct effect on restricting RMWs to attain skilled positions, the in-competitiveness of RMWs is at least indirectly affected by the institutional discrimination in the distribution of educational resources. In addition, since the *hukou* system has a hereditary effect, being born into an urban family naturally bestows on that person a richer social and economic stockpile of resources for their personal development.

2.3. Climbing the social ladder to improve economic well-being?

2.3.1. The theoretical debate

The inequality relevant inquiry of mobility firstly emerged in the early 1980s (Heath, 1981, p.11; Morgan, 2006; Goldthorpe et al, 1982). It is said that the concern for mobility 'strikes at the heart of debates over what makes a good and fair social and political order' in the context of modern industrial societies where liberal capitalism is the dominant model of social organisation (Atkinson, 2015, p. 104). On the one hand, in such a context, there are fewer legal constraints and more freedom on what a person can do and achieve in their lives, providing the basis for the possibility of 'free movement' (Ibid.). On the other hand, stratification in societies is still allowed or even supported, with the claim that it is a way to maintain efficiency and a just social order (Ibid.). A famous supporting account is the *functional theory of stratification* by sociologists Kingsley Davies and Wilbert E. Moore (Davis, 1942; Davies and Moore, 1945). The theory, underpinned by the dominant sociology paradigm *structural functionalism*, argued that the stratification of *positions*[6] is necessary since some positions are either more important for the so-called 'functioning and order-maintaining' of the society or because they require more talent and diligence from individuals. Therefore, rewards should be given differently to them as a kind of incentive to ensure that the positions are always filled by the most qualified persons (Davis, 1942; Davies and Moore,

[6] The term *position* in Davies' (1942) work broadly means '*a place in a given social structure.*' It serves as an abstract conceptual tool (as he said when representing and analysing social structure, the use of highly abstract concepts is inevitable) but can be specified into different forms (e.g. *status*, *office* in his conception), depending on the context and purpose of the study (Davies, 1942).

1945). Specifically, in the context of modern industrial societies, occupation has become the foundation of the stratification system rather than the hereditary caste and feudal estate (Blau and Duncan, 1967). As Cooley (1956) commented, ‘an ideal class society [is] by achievement rather than inheritance.’ For early functionalists, the inequality of rewards was not considered problematic. However, they believed that inequality of opportunity to participate in advantaged positions was a huge concern because the misallocation of talents and skills would contribute to the issue of inefficiency and instability for a society and would therefore damage the right social order (Lipset and Bendix, 1959; Blau and Duncan, 1967).

While functionalists considered mobility as a critical issue of their version of ‘inequality’ (i.e., the inequality of opportunity for career success), left-wing scholars considered the ‘mobility concern’ as ‘bourgeois problematic’ (Poulantzas and Fernbach, 1975, p. 33). Firstly, social mobility is premised upon social stratification. Poulantzas and Fernbach (1975, p. 33) argued that in a capitalist society, even when there was a fluid mobility between the bourgeoisie and the proletariat, the fundamental principle of capitalism would still exist and therefore there would still be exploitative relations between agents. Similarly, John Westergaard and Henrietta Resler (1975, p. 280) also criticised that ‘they [those who advocate mobility] concern the recruitment of people to classes; not the brutal fact of the existence of class.’ Furthermore, some are also concerned that upward mobility will hinder a revolutionary shift to a classless society. Although Karl Marx (1991; 2003) himself did not leave a systematic analysis of mobility, he remarked that a ‘constant flux’ is a way to strengthen the hold of the ruling class by recruiting the most talented individuals from the bottom while weakening the formation of class consciousness of the suppressed groups. In a similar vein, Eric Olin Wright (1997) commented that low mobility helps the suppressed group develop a consciousness of their own common situation, and therefore a *class for itself* would more likely to be formed.

2.3.2. The agenda of social mobility

In contemporary society, it is often the functionalists' version of equality (i.e., equality of opportunity for mobility) that dominates equality discourses. The mainstream political agenda in modern industrial economies allege to tackle the issues of economic injustice by attempting to promote equal opportunities for the so-called 'meritocratic' occupational mobility (Brown, 2013; Littler, 2017). It is the principle of 'meritocracy' that underpins the advocacy of occupation-based social mobility for personal success (Atkinson, 2015, p. 104), especially after the late 1970s when neoliberal ideology gained a global foothold. By focusing on reducing redistributive welfare provision and emphasising career success and economic security via individual competition, neoliberalism transformed the popular narrative on equality (Harvey, 2005, p. 3; Littler, 2017, pp. 47-72). Over the world, 'the ladder of opportunity' has been adopted as a key metaphor (especially in modern workforces) for meritocracy: the idea that only an individual's merits can determine their achievements and rewards (Atkinson, 2015, p.104; Littler, 2017, p. 28). Public discourses with the underpinning ideology of meritocracy advocates a 'level playing field' (all players should start from an equal footing), which, on first glance, appears to attempt to reduce inequality. However, it actually obscures the issue of inequality by diverting the public's attention away from the actual unequal acquisition/distribution of resources among individuals and instead focuses on the so-called 'equality of opportunity' which encourages individuals to fight for a relatively advantaged position (Littler, 2017).

In the era of economic reform, China proclaims the prioritization of efficiency for continuous economic growth by adopting a market-driven developmental process, while economic inequality is tolerated in order to stimulate competition and continuous growth (Harvey, 2005, pp. 120-151; Whyte, 2012). During the Third Plenum of the 11th Central Committee at the end of 1978, Deng Xiaoping's '*let some get rich first*' speech (1989, cited in Li, 2012) initiated a market-oriented economic reform. While the economic growth is accomplished alongside rising inequality, redistributive welfare provision was not increased but rather reduced, and workers' lifelong employment job security ended (Chan et al., 2008). This marked a shift in responsibility of achieving economic well-being from the state to the individual. Individuals were encouraged to actively pursue wealth to secure their economic well-being through career advancement and entrepreneurial success through fierce competitions (Li, 2012). Individuals' social mobility through hard-work and engagement in fierce competitions has been phrased as 'the important passcode for China's prosperous development' by the CCPCC's official newspaper *People's daily* (Li, 2019a). It is said that since the economic reform, the development of China's socialist market-economy conditions the possibility of individuals' social mobility (Ibid.). In addition, it is said that each individual's social mobility will also unleash the dynamic for China's continuous social development (Ibid.).

Even though occupational mobility through individual hard-work and competitive participation has been phrased as a solution to improve individual economic life chances, it is worth noting that the condition of 'equal opportunity for success' has not been achieved. Studies indicate that in urban China, RMWs were found to be disadvantaged when it came to occupational mobility. Although research (e.g. Li, 1999, 2004; Li 2010; Zhang 2011) consistently shows that RMWs change their jobs more frequently than URWs, they do so mainly due to the lack of job security rather than to further career advancement. Using the International Socio-Economic Index of Occupational Status (ISEI), Li's (1999, 2004) research firstly documents that the first- and second-time job changes among RMWs (after their labour market entry) shows significantly less ISEI increase than URWs. Regarding the job insecurity and low upward mobility chances of RMWs, currently the state identifies that the skill-deficiency of RMWs is the major issue to be resolved (Li, 2019a). It is argued that the key is to improve the *Jishusuyang* (skill quality) of RMWs with the provision of learning and skill-development opportunities, in order to let them to be adaptable to the continuing industrial development and stay competitive in the urban labour market (Han, 2006; Li, 2019a).

In such a context, the rural-urban skills gap is pointed out to a main cause of disparity in occupational mobility between RMWs and URWs. And therefore, encouraging RMWs to engage in further learning and training for skill-development is suggested to be a means to improve their social mobility. At the beginning of the 21st century, skill policies like *2003 – 2010 Quanguo Nongmingong Peixun Guihua* (Plans for skill training for rural migrant workers between 2003 and 2010) (State Council of the People's Republic of China, 2003) and *Nongcun Laodongli Zhuanyi Peixun Jihua* (Plans for transferring rural labour and skill-training) (Ministry of Education of the People's Republic of China, 2003) were proposed with an aim to reskill rural background workers and to enable them to find skilled industrial jobs in urban areas. The state council (State Council of the People's Republic of China, 2006a) commented that in order to incorporate surplus rural labour into urban labour market, the support for learning and reskilling opportunities for RMWs should be considered as essential. In the aftermath of the 2008 global financial crisis, 'learning and reskilling' were again presented as a strategy by the Ministry of Human Resources and Social Security to help RMWs secure jobs and increase chances for career progression (Ministry of Human Resources and Social Security of the People's Republic of China, 2009). However, as Feng (2020) noticed, the primary goal of those previous skill policies for RMWs was merely for the sake of efficiency for the national economic production (i.e. to efficiently transfer rural surplus labour into urban labour market to boost national productivity) in which workers were simply treated as elements for production, rather than to improve the economic well-being of rural background individuals. Echoing the new national scheme to alleviate poverty, policy and media narratives have started to change their tongues since 2019 by articulating the value of individuals' social mobility and economic achievement when encouraging RMWs to engage in further learning (e.g. *Dangdai zhongguo fanrong de zhongyao mima* (The key passcode for China's prosperity) (Li, 2019a); *Guanyu Cujin Laodongli He Rencai Shehuixing Liudong Tizhi Jizhi Gaige De Yijian* (Opinions on reforming the institution for labour and human resources mobility) (State

Council of the People's Republic of China, 2019a)) (Feng, 2020). Those narratives articulate the consistency between the prosperity of the national economy and personal career achievement in a modern society (Feng, 2020). In particular, for the *Lianghousheng* (under-educated poor rural background youngsters), empowerment by work skills is adopted as the main strategy to reduce poverty within the national poverty scheme (e.g. Ministry of Human Resources and Social Security of the People's Republic of China, 2020).

Despite the proposal for active engagement in further learning and reskilling to reduce the skills gap between rural and urban background individuals, RMWs actually did not receive enough support for participation in learning. Two years after plans *2003 – 2010 Quanguo Nongmingong Peixun Guihua* (Plans for skill training for rural migrant workers between 2003 and 2010) (State Council of the People's Republic of China, 2003) and *Nongcun Laodongli Zhuanyi Peixun Jihua* (Plans for transferring rural labour and skill-training) (Ministry of Education of the People's Republic of China, 2003) were announced by the state council calling the local authorities to expand training opportunities for RMWs, investigation in 2005 showed that the provision of learning opportunities and support was far below the set target (*Xinhua*, 2005). Nearly 80% of RMWs who did not finish high school education failed to receive any training support (Ibid.). Latest records show that until 2017, nearly 70% of RMWs had not received any form of training for non-agricultural jobs (National Statistics Bureau, 2018). Lacking access and support to traditional adult learning programs for RMWs has been an on-going issue. In general, RMWs had low enrolment and completion rates in vocational training programs supported by employers, government, or training institutes (Xu, 2013; Li, 2018). Despite the call for expansion of training programs for RMWs, in reality, public funding for vocational training for RMWs is still very limited (Xu, 2013). Although a few government-supported training schemes are available, they are not sufficient to meet the demand from such a large number of RMWs (Ibid.). Moreover, RMWs have more difficulties to access employer-provided training programs, since employers tend to think that investment in RMWs, who are thought to have low literacy and lack stable settlement in cities, will not bring great economic returns to organisations (Zhu, 2004; Xu, 2014).

Lately, the state has started to call for using the internet to facilitate learning and skill-development for RMWs. In statement *Guowuyuan Guanyu Jiejue Nongmingong Wenti De Ruogan* (Several suggestions from the state council for resolving rural migrant related issues), the state council suggested that local governments and authorities should consider promoting multiple modern and innovative forms and channels (e.g. television) to expand learning opportunities for RMWs (State Council of the People's Republic of China, 2006a). In 2010, the state council further recommended the promotion of using the internet and online learning to RMWs, considering the versatility and efficiency by using the internet (State Council of the People's Republic of China, 2010). Since the 'Internet Plus' strategy, the application of the internet to promote innovative development of conventional industries and government services (*China Daily*, 2015), has been adopted by the state with the aim to increase efficiency of public service, RMWs are encouraged by the state to fully engage in digital life to enjoy the dividends of 'staying connected' in the information age (Zhang, 2015). In the subsequent *Zhi Ye Jineng Tisheng Xingdong Fangan (2019-2021)* (Plans for advancement of vocational skills 2019 to 2021), the internet is introduced to be the main tool to facilitate learning for under-educated RMWs (State Council of the People's Republic of China, 2019b). Most recently, since the COVID-19 crisis has come, the state has initiated a new round of 'Internet+ Learning' scheme (Ministry of Human Resources and Social Security of the People's Republic of China, 2020). This new learning scheme claims to stipend high quality online content creators and to fund learning platforms to share content for free (State Council of the People's Republic of China, 2020; Ministry of Human Resources and Social Security of the People's Republic of China, 2020). It is said that the new learning scheme is aiming at three goals (i.e. increase rural-background workers' skill-level, reduce social contact and help individuals secure jobs during the economic crisis) to help the country cope with the economic and social crisis (State Council of the People's Republic of China, 2020; Ministry of Human Resources and Social Security of the People's Republic of China, 2020). As introduced, currently the internet is increasingly seen as a versatile and efficient tool to facilitate learning and skill-development for migrant workers. And since the ‘skill-meritocratic’ model is still in place determining individuals’ economic well-being and the COVID crisis is expected to last for a period of time, it is very likely that the promotion of UIL will stay as a strategy to help RMWs develop skills and secure occupational achievement.

2.4. The internet and the abundance of resources for learning

2.4.1. From a nuclear-proof tool to the World Wide Web

In *The Internet Galaxy*, Manual Castells remarks that the internet is the first communication medium that allows a worldwide scale many to many interaction, which has strengthened interactive ‘networks’, an old form of human practice, to transform into a powerful new form as ‘information networks’ (2002, p. 3). Although the use of the internet is now so prevalent, originally, the internet was only for military use by the Advanced Research Projects Agency Network (ARPANET) in the USA in the 1960s (Fuchs, 2007). It used to be a decentralized military computer-based communication network (Fuchs, 2007, p. 122), and its supporting idea was, at first, a radical ‘nuclear-proof’ solution to guarantee command and control communications with no vulnerable central point to be attacked once nuclear weapons started to fall (Baran, 1960; Ryan, 2010). After having been through many waves of internet-based application development, the most popular application currently, the *World Wide Web* (*WWW* or the *Web*), was released in 1991, designed by Tim Berners Lee and his colleagues at the European Organization for Nuclear Research (CERN) in Switzerland (Poe, 2010, p. 214). During his time at CERN, Berners-Lee had realized that the core value of a network is not the technical connection between computers, but the connection between real people and through that to access a wide range of information by sharing documents (Ibid.). Thus, the *Web* he designed, with the application of Hypertext Transfer Protocol (HTTP), is more like a worldwide information space for global resource-sharing with Uniform Resource Identifiers (URI) to identify the resources of the interest (Jacob, 2004).

2.4.2. The abundance of resources for learning

The internet, especially the application of the *World Wide Web,* has become a powerful tool for resource-sharing for people around the world, as Berners-Lee describes: a 'pool of human knowledge' (Berner-Lee et al., 1993). The barriers to participate in learning and inaccessibility to knowledge are seen being challenged by many optimists (Selwyn *et al*., 2001). Educationalists are spreading a 'transformative effect' narrative about the profound implications of the internet for widening access to learning and education (Selwyn et al., 2001; Gorard and Selwyn, 2005). For example, the former director of United Nations Educational, Scientific and Cultural Organization (UNESCO), Irina Bokova, had shown her optimism on the potential of the internet for learning purposes:

> '*New technologies and broadband internet access offer formidable opportunities for increasing access to education. They make new learning opportunities possible. They add a new dimension to how we deliver literacy programs, train teachers, manage schools and share knowledge*' (UNESCO, 2011).

In particular, the internet has provided access to abundant information resources for learning. First, the abundance of online information resources is related to digitalisation, which has made informational content *reproducible at a low cost*. The information resources online are all digitalised resources. Digitalisation can be seen as a process of integrating things in everyday life with the use of digital technologies by the digitisation of everything that can be digitised (Thomas, et al., 2015). Digitisation, a necessary part of digitalisation, refers to 'the conversion of text, picture and sounds into a digital format that can be processed by a computer' (*Oxford Dictionary*, 2007).

Before digitalisation, only fixed forms of cultural objects, such as paper books, were used to contain informational content (Poster, 2006, p. 194). Information, unlike physical objects, cannot be used up, and likewise is not unavailable for others when it is being used, due to its 'non-rivalrousness' (May, 2004; David, 2010, p. 45). A very good example illustrated by David (2010, pp. 45-46) is that while no one else can be using the hammer and nails that are currently being used by another person, the *idea* of using hammer and nails can be held by as many people as possible at the same time. However, to access information, one needs to get access to a physical medium (e.g., owning a printed copy of a book) that information attached to and the physical objects have the nature of rivalrousness. The production of these fixed-form cultural objects requires the consumption of considerable amount of scarce resources (e.g., printing machines and papers for printed books) (Poster, 2006, p. 194). This fixity creates a clear division between producers and consumers, with consumers being in a relatively weak position (Poster, 2006, p.195). Since the production of each fixed object consumes a considerable amount of material resources, the copies follow the economics of scarcity, can be commodified, and have exchange value (Ibid). Therefore, in many cases, the distribution of these fixed cultural objects follows a market mechanism (i.e., pay to obtain) and acquires exchange value (Ibid).

Cultural objects in digital forms, however, are not subject to the same logic as they lack 'natural scarcity.' Compared to getting access to fixed forms of cultural objects, acquiring digital forms of resources is very low-cost, thus expanding the potential for further accessibility to knowledge. Information can be easily stored and transmitted due to the technique of digital compression (David, 2010, p. 32). The reproduction and distribution of cultural objects in digital form incur almost no cost, which has also made the commodification of digital copies much harder (Poster, 2006, p. 195; David, 2010, pp. 31-32). Digital forms of information resources, like ideas, 'do not diminish when they are given away' (Poster, 2006, p.195). The inexpensiveness of reproduction leads to a blurring boundary between producers and consumers (Poster, 2006, p. 195) as anyone can easily reproduce the copies on their own digital devices, and thus exemplifying Toffler's (1984) term 'prosumer.' Although capitalists have attempted to maintain scarcity for the purpose of profit-maximisation through the appropriation of intellectual property rights (May, 2004), different forms of resistance (e.g., peer-to-peer sharing platforms based on file-sharing protocols) have emerged to fight against the monopolization online (David, 2010, pp. 29-31).

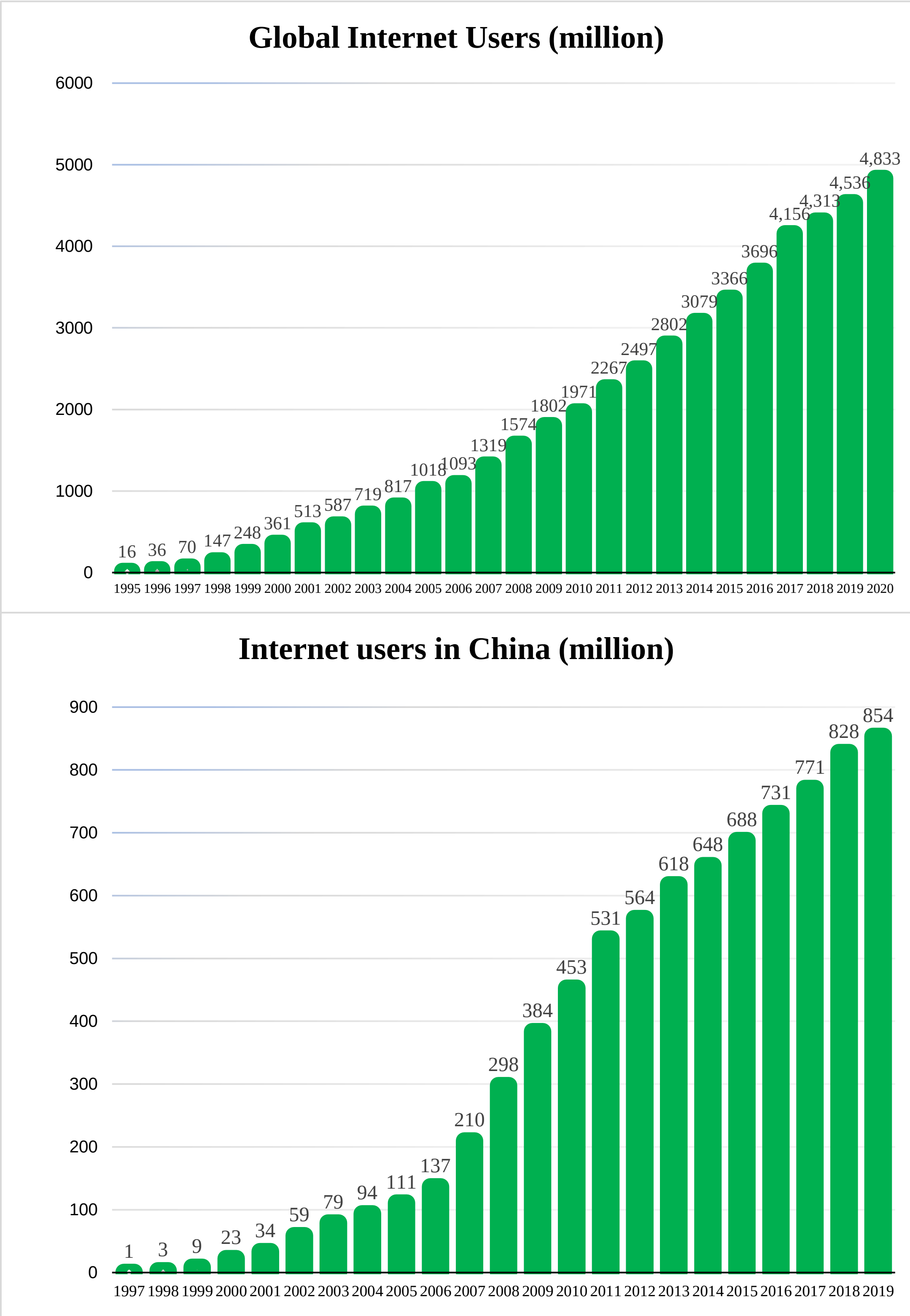

Figure 2.1. The estimation on internet users by year (source: Internet World Stats, 2020; CNNIC, 2014; 2019)

Second, in addition to the low cost of reproduction, *global connectivity via the internet* enables a full, global exchange of information resources. Information in digital form could be distributed easily based on *infrastructural convergence*, which allows different kinds of communication links and equipment to be combined in order to enable multimedia digital communication (Van Dijk, 2012, p. 7). Moreover, what makes this network valuable is its tremendous number of current users. This is related to what is known as the *network effect*, understood simply as the potential for sharing resources will likely increase as the number of members increase since the potential inter-member links increase for every new member's (Hendler and Goldbeck, 2008).

Following the release of more and more user-friendly browsers for the *World Wide Web* (e.g. Mosaic by Microsoft in 1993) and the ubiquity of multimedia computers and mobile devices, internet usage has increased dramatically and 'surfing the net' has become a popular activity since the mid-1990s (Poe, 2010, p. 215). The use of the internet, especially the *World Wide Web,* has become massively diffused into people's daily lives in the aspects of economic, social, political, educational, cultural and so on (Norris, 2001, p. 68; Van Dijk, 2005, p. 2). In 1995, it was estimated that there were 16 million internet users in the world (Internet World Stats, 2020). The figure is estimated to have exceeded the first billion in 2005 (around 15.8 % of the world's population) and reached nearly 4.8 billion in 2020 (accounting for more than 60% of the world's population) (Ibid.). China currently has the largest number of internet users in the world (Ibid.). With more than 100 million internet users since 2005, it is estimated that as of 2019, the number of internet users in China is 854 million (CNNIC, 2014, 2019). Chinese internet users might face more obstacles in accessing globally shared information resources. For example, the so-called 'Great Firewall,' a key part of internet censorship in mainland China, blocked many foreign websites (Zhang, 2020). However, whilst the 'Great Firewall' may have caused more difficulties for many to access some foreign websites, individuals could still use virtual private networks and other tools to 'bypass' the censorship (Ibid.). Besides, even taking into account the internet censorship, information resources shared by hundreds of millions of Chinese netizens can still be seen as abundant, supported by the previously mentioned network effect.

Since the popularity of the internet has blossomed, a wider range of information is now acquirable online owing to this powerful means of communication. Van Dijk (2012, p. 30) argues that with the advent of the internet, the scope of human social interaction has not only intensified and increased, but so has the previously-limited social circle been extended well beyond what was once considered possible along with the reach of information retrieval and communication (Ibid.). Consequently, the internet has been portrayed as the largest library in human history, and rich cultural resources are immediately available to those who connect to this global network (Ibid.).

2.5. Concluding remarks

In short, this chapter has introduced the three key themes of the background of this study, which are: a) the *hukou* system in China and the economic disadvantage of RMWs in China's urban areas, b) occupational mobility being promoted as a practical pathway to improve economic well-being whereas inequality of mobility between RMWs and URWs still exists, and c) the internet being seen as a tool to provide new learning opportunities that challenge inaccessibility to knowledge, especially given the abundance of shared information resources online. These three foundations frame the design of this research project. As mentioned in 2.3.2., the state has identified continued development of RMWs work skills, along with participation in additional learning and training opportunities as a key measure to improving their occupational mobility in the urban labour market. Yet, it has traditionally been the case that mainstream educational and training programs are far from affordable or accessible for RMWs, the very cause of their skill-deficiency in the first place (Lei, 2004; Zhu, 2004; Xu and Liu, 2005; Xu, 2014). The internet, considered the new so-called powerful tool for facilitating and widening access to learning, has not been fully studied regarding its potential to promote occupational mobility for RMWs. For this reason, this study chooses to explore the potential of UIL for mitigating the unequal occupational mobilities between RMWs and URWs. Based on the background knowledge introduced in this chapter, the next chapter will explain the research design of this study in detail.

Chapter Three: Research design

3.1. Introduction

The preceding chapter introduced the background of this study. As a legacy of China's *hukou* system, RMWs became an economically disadvantaged group in China's urban areas. Currently, the state encourages people to improve their economic well-being through hard work thus achieving occupational mobility, yet, inequality of opportunity for mobility between RMWs and URWs is still an on-going issue. For the state and some scholars, the improvement of work skills through on-going learning for RMWs is seen as the major solution to reduce their disadvantage in occupational mobility. Whilst the internet is seen as a powerful tool for the facilitation of people's learning and widening of access to knowledge, the effect of UIL on the inequality of occupational mobility between RMWs and URWs is not yet known.

After the introduction of background knowledge in the preceding chapter, this chapter will introduce the research design of this study. The first section will outline and explain the rationale of the central question (i.e., the role of UIL in mitigating unequal occupational mobilities between RMWs and URWs), the evaluation framework, three derived research questions, and definitions of key concepts in this study. Regarding the ways to answer the research questions, the second section will give an overview of the guiding methodological principles of this study; details of the analytical techniques will not be presented here as they will be presented in the following chapters where I address each research question respectively.

3.2. The research focus

3.2.1. The central question

Chapter Two has outlined the context of the urban labour market in contemporary China, where RMWs are at a disadvantage when it comes to occupational mobility. As introduced in the last chapter, the skills gap between RMWs and URWs plays a big role in the formation and continuation of the inequality in occupational mobility between them in the urban labour market. At least partly, this skill-gap is due to China's different economic organisation in rural and urban area. Under China's *hukou* system and for the sake of rapid industrialisation and modernisation, the urban areas were encouraged and financially supported to develop diverse modernised manufacturing and service industries, whilst the major economic activity in rural areas is farming. (Chan and Zhang, 1999). Rural and urban areas appreciate different kinds of labour power, and therefore those who only possess knowledge and capability to do farming works might not be easily appreciated as skilful in the urban labour market.

However, more importantly, the RMW-URW skill-gap is due to unequal distribution of various kinds of resources (especially education resources). As introduced in Chapter Two, China prioritises industrial development in urban areas and therefore put heavy investment in urban areas whilst rural areas receive very little financial support. During the planned economic period, China adopted the 'price scissors' policy to exploit rural labourers by suppressing the prices of agricultural products in order to subsidise food and welfare benefits to urban individuals (Zhang and Chai, 2012, p.22; Chan, 2009; Cheng and Selden, 1994). The urban-biased developmental strategy has barely changed after the 1978 economic reform, as the state still prioritises the economic and social development in urban areas (Chan, 2009). Schools and universities are exclusively invested in China's urban areas, whereas individuals from rural areas have very limited access to educational opportunities in their local areas (Zhang and Chai, 2012, p. 34). Lacking access to educational opportunities and economic resources to support educational attainment and completion leads to rural background individuals' poor educational achievement, which is highly related to rural background workers' 'skill-deficiency' (e.g. Li, 1999; 2012; 2018; Liu, 2017; Zhang, Li and Xue, 2015).

Moreover, lacking effective compensatory support for adult learning also helps sustain the skills gap between RMWs and URWs. To promote social mobility for RMWs, the state identifies the skill-deficiency of RMWs as the main issue to be addressed (e.g., State Council of the People's Republic of China, 2003; Li, 2019a). Studies of occupational attainment of RMWs (e.g., Han, 2006; Tian et al., 2013) often conclude with a simple suggestion: RMWs should further develop their skills to improve their employability. However, it is still an ongoing issue that RMWs had not received sufficient support for participating in adult learning programs. In fact, RMWs had low enrolment and completion rates in vocational training programs supported by employers, government, or training institutes (Xu, 2013; Li, 2018). In workplaces, employers are less willing to give training opportunities to RMWs since they are considered to lack certainty of settlement in cities and are less trainable due to their low-literacy (Zhu, 2004; Xu, 2014). As an economically disadvantaged group in cities, RMWs are less able to purchase training courses and self-learning materials from for-profit private providers (Lei, 2004; Zhu, 2004; Xu and Liu, 2005; Xu, 2014). Furthermore, the provision of government-supported training schemes is still not sufficient to meet the demand as the funding on training schemes is limited (Xu, 2013).

Whilst the internet is portrayed as a convenient and powerful learning tool that can possibly challenge inaccessibility to knowledge, we still know very little about the potentials of UIL for helping disadvantaged background people’s skill-development and occupational mobility. Is the internet really an effective tool that can facilitate individuals’ learning and skill-development and therefore help individuals achieve occupational mobility in the contemporary labour market? Does the use of the internet empower rural background individuals’ by providing them a more accessible and convenient tool for learning and upskilling due to the abundance of information resources online and the global connectivity? Would the pre-existing structural inequality between RMWs and URWs therefore be challenged due to UIL, or translate into one or various kinds of digital inequality that continuingly facilitate the reproduction of the advantage of urban background individuals in the urban labour market. To solves those puzzles, further studies are definitely required to critically analyse the link between UIL and inequality in occupational mobility in the contemporarily labour market.

Thus, this research sets out to explore UIL's implications for the inequality of occupational mobility between RMWs and URWs in urban China. It is of course too naive to fantasize that the issue of inequality of occupational mobility could be tackled by UIL alone, since occupational attainment is affected by a variety of factors at different levels (e.g., the institutional, organisational, or individual). Although a complete equalisation of occupational mobility is certainly not possible, it is still worthwhile to explore whether, and to what extent, UIL plays a role in challenging the existing inequality of occupational mobility. In theory, some degree of mitigation of unequal mobilities would be able to challenge the reproduction or deepening of pre-existing inequalities at the structural level and to thus allow RMWs to enjoy fairer opportunities to improve their life chances at the individual level. As such this research will focus on this central question:

> ***To what extent does UIL mitigate the unequal occupational mobilities between RMWs and URWs in China's urban labour market?***

3.2.2. The evaluation framework and three derived research questions

The evaluation of the mitigation of unequal occupational mobilities considers two aspects of the effect of UIL simultaneously: *the compensatory effect of UIL* for the disadvantaged (is it the case that RMWs enjoy more labour market returns due to UIL?) and *the inclusivity of UIL participation* (is it the case that RMWs and URWs have equal participation in UIL?). The idea originates from Bukodi's (2017) methods on assessing the effect of further education on promoting equalised social mobility in Britain. On the one hand, it is often speculated that the availability of new learning opportunities is more helpful for the disadvantaged since those new learning opportunities could offer disadvantaged background individuals a second chance to upgrade their skills after full-time education (Ibid.). On the other hand, some are concerned that if the disadvantaged are excluded from accessing learning opportunities, the availability of new learning opportunities simply magnifies the gap between the advantaged and disadvantaged (Ibid.). To effectively assess the impact of new learning opportunities on promoting more equal social mobility, those two aspects of the effect of UIL must be considered simultaneously (Ibid.).

Following the evaluation method, three research questions are then proposed. Firstly, we have a foundational question:

1) To what extent is UIL related to occupational mobility in general?

The purpose of this foundational question is to *make a clear sense* of the relationship between *UIL and occupational mobility* in the contemporary labour market, before setting foot on the discussion for the mitigating effect. This question is addressed in Chapter Five.

After that, the following two questions are directly related to the evaluation of the mitigation effect of UIL:

2) Given the same participation in UIL, is there a stronger UIL-mobility association for RMWs?

And

3) Do RMWs and URWs have similar participation in UIL?

The two questions above set out to investigate the compensatory effect of UIL for the disadvantaged (i.e., the extent to which RMWs enjoy more labour market returns to UIL) and the inclusivity of UIL participation (i.e., the extent to which RMWs and URWs have equal participation in UIL) respectively. The second question is addressed in Chapter Six and the third question is addressed in Chapter Seven. Afterwards, a combined discussion is given in Chapter Eight based on the findings from Chapter Five to Chapter Seven to gain a full picture of the evaluation. Table 3.1 shows the possible outcomes and their interpretations regarding the mitigation of the unequal occupational mobility. While an extended discussion will be given in Chapter Eight, here I only briefly mention those optimal outcomes. Among all the outcomes, only three of them (those in green colour) show some notable signs of the mitigation effect (i.e., RMWs and URWs are equally active in UIL whilst UIL is more effective for the mobility of RMWs; the effect of UIL on mobility is equal but RMWs are more active in UIL; not only are RMWs more active in UIL, UIL is also more effective for the mobility of RMWs).

Table 3.1. Possible outcomes and the interpretations

Participation in UIL	Effectiveness on occupational mobility	Interpretation
URW>RMW	URW>RMW	Unequal mobility chances deepened
URW>RMW	URW=RMW	Unequal mobility chances deepened
URW>RMW	URW<RMW	Unequal mobility chances remained
URW=RMW	URW>RMW	Unequal mobility chances deepened
URW=RMW	URW=RMW	Unequal mobility chances remained
URW=RMW	URW<RMW	Unequal mobility chances mitigated
URW<RMW	URW>RMW	Unequal mobility chances remained
URW<RMW	URW=RMW	Unequal mobility chances mitigated
URW<RMW	URW<RMW	Unequal mobility chances mitigated

Changes in occupational mobilities: Mitigation No changes or unclear Deepening

3.2.3. Definitions of the key concepts

In this study, UIL is defined in a broad sense referring to *all kinds of work-relevant learning activities with the use of the internet to assist*. Since this study attempts to gain an overview of the potentials of the internet for facilitating learning and the impact on occupational mobility, this broad definition serves its purpose. However, there is one limitation that each specific kind of learning activity with the use of the internet has not been fully explored.

This study adopts *China Labour Bulletin*'s (2020) standard to define RMWs and URWs, considering individuals' registered *hukou* type, employment, and place of residence. RMWs are defined as those who hold *an agricultural household registration*, have *a non-agricultural job* in an urban workplace, and *reside in an urban area*. URWs are those who hold *a non-agricultural household registration*, have *a non-agricultural job*, and *reside in an urban area*.

By saying occupational mobility, this study mainly concerns itself with those 'vertical mobilities' (i.e., upward and downward) as they are more directly related to changes in individuals' economic life chances.

3.3. A mixed-methods research design

This study adopts a mixed-methods design to obtain new knowledge to answer each research question. Figure 3.1 summarises the rationale of the design. The constructed knowledge for each research question aims to provide *an accurate description* of the patterns of a) the overall relationship between UIL and occupational mobility (for the first research question), b) the extent of the difference in the 'UIL-mobility' association between RMWs and URWs (for the second research question), and c) the extent of the difference in the participation in UIL between RMWs and URWs (for the third research question). In addition, the constructed knowledge also aims to provide *a plausible explanation* of the mechanisms behind all the observed patterns.

Firstly, drawing on the scholarship of existing theoretical and empirical studies, *a preliminary theory* is proposed to predict the patterns and to offer a provisional explanatory account of the underlying mechanisms of the observed patterns for each research question. As will be introduced from Chapter Five to Seven, these preliminary theories are: *the temporarily scarce skills theory* for the first research question, *the diligence dependence theory* for the research question, and *the practical action theory of UIL* for the third research question.

Next, analysis of empirical evidence is carried out. This study uses both quantitative and qualitative data. The way of mixing methods is *complementarity*, meaning that different methods are used to address different parts or aspects of the inquiry since each method has its own unique strengths (Hammersley,2002). The quantitative analysis is employed first to gain an overview of the patterns for each research question. After describing the general patterns, additional qualitative analysis is carried out to refine the explanation when making sense the observed patterns. Since quantitative methods have the strengths of providing robust results of comparisons and measuring general patterns and regularities (Maxwell, 2016), quantitative evidence can give an accurate description of the general patterns for answering each research question. As such, quantitative analysis drawing on the data from a large-scale social survey ‘the China Family Panel Studies (CFPS)’ is conducted to examine the hypotheses on the general patterns derived from the preliminary theories. Next, since qualitative evidence provides detailed and rich descriptions for gaining an in-depth understanding of social phenomena, and creates openness to explore under-discovered factors and mechanisms, qualitative evidence is used to refine the interpretation of the mechanisms behind the observed patterns. To do so, qualitative analysis drawing on data from 24 semi-structured interviews is subsequently carried out to point out limitations and imperfections of the provisional explanatory accounts derived from the preliminary theories, and supplement new elements in order to provide an explanation of the observed phenomena.

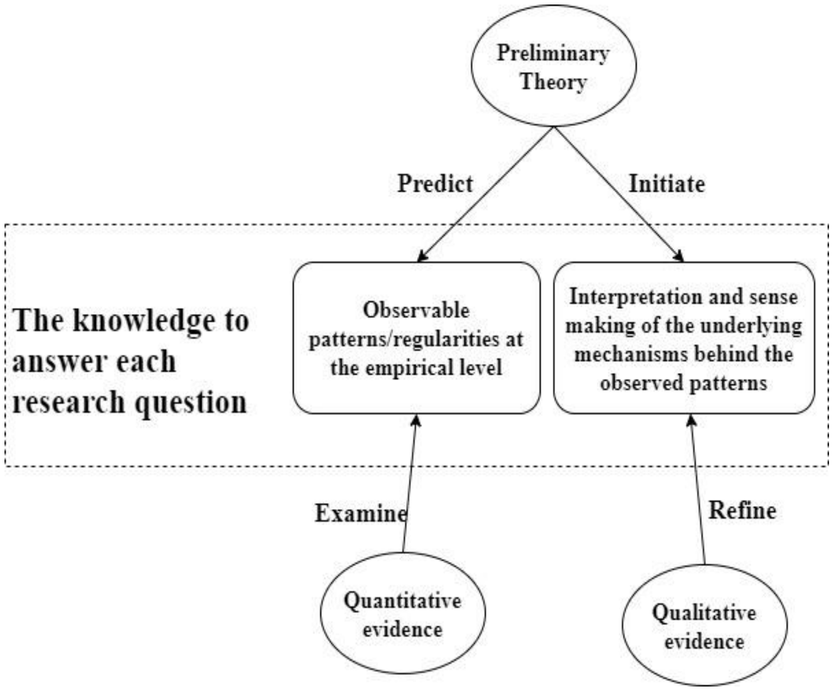

Figure 3.1. A mixed-methods design

3.3.1. Quantitative data and analysis

Quantitative data analysis is conducted to measure the patterns of a) the general associations between UIL and occupational mobility, b) the heterogeneity of the 'UIL-mobility' association between RMWs and URWs, and c) the differences in participation in UIL between RMWs and URWs. At first, hypotheses on the relevant observable phenomena were given by each preliminary theory for each research question. Subsequently, quantitative analysis of the CFPS data was carried out to test those hypotheses. The data collected from CFPS are the most suitable for this study because as a large-scale, nationally representative, and longitudinal survey of Chinese communities, families, and individuals, CFPS contains the variables (including variables measuring internet use for learning, *hukou* type, and occupation) needed for answering the research questions of this study. The sample was drawn through a three-stage stratified sampling (by selecting counties, cities, villages or equivalent and households). In CFPS 2010, there are 33,600 valid individual cases with an approximate 79% response rate. Currently, there are four waves of data available (2010, 2012, 2014, and 2016). For each wave, it contains individual-level data sets (e.g., CFPS2010adult and CFPS2010child), family-level data set (e.g., CFPS2010fam) and community level data set (e.g. CFPS2010com). Among them, CFPS2010, 2014 and 2016 contain valid variables about adult respondents' internet usage, *hukou* status, occupations and other useful variables. Thus, data from CFPS2010adult, CFPS2014adult and CFPS2016adult is used. To fit the research purpose, I only selected cases with a non-agricultural job and urban residence as the valid sample for the study (i.e., I filtered out cases living in rural areas, being unemployed, or working as agricultural workers). The analysis was then carried out to measure the overall association between UIL and occupational mobility, the differences in 'UIL-mobility' associations, and the differences in participation in UIL. Analyses are mainly done by running mixed-effects models with *Stata* and packages in *R* environment. As mentioned in the introduction of this chapter, I will introduce the technical details of the analysis in the following chapters when I address each research question separately.

3.3.2. Qualitative data and analysis

The preliminary theories offer an initial explanatory account to make sense of the observed patterns reported by quantitative findings. To further refine the interpretation of the mechanisms behind the observed patterns, qualitative data analysis of 24 semi-structured interviews is conducted. The interviews took place in the city of Guangzhou between August and October 2018. The reason I chose Guangzhou as a site to collect the primary data was that Guangzhou, one of the developed cities in the country and the main manufacturing hub of the Pearl River Delta, is one of the most popular migration destinations for individuals with rural backgrounds seeking non-agricultural jobs (e.g. Li, 2004; Chan, 2009).

During each interview I asked the participants to cover four aspects of their personal life experiences as well as their perceptions: occupation trajectories, learning activities, the use of the internet, and the use of the internet for learning (see Appendix B for the full interview guide). Although a small sample, one main strength of the qualitative data is to provide a rich description to understand individuals' occupational attainment and learning activities with the use of the internet. In addition to the richness, another key strength is the openness provided by semi-structured interviews. Compared to data collected from close-ended questions in quantitative analysis, semi-structured interviews have the benefit of allowing new ideas to be brought up by participants. The openness helps discover new elements from participants' own accounts, which might not have been documented in any previous studies.

The qualitative inquiry is mainly drawn upon a combination of purposive and snowball sampling. Although not being able to yield a random sample for statistical inference and to exclude all unknown characteristics related to the selection of participants (Griffiths et al., 1993), purposive sampling can still yield a logically representative sample of the target population since the selected individuals have to meet a variety of key characteristics that are relevant to the analysis (Lavrakas, 2008). In particular, purposive sampling has the convenience of achieving the maximal variation (to cover as much variation and diversity as possible) within a small sample qualitative study (Flick, 2014, p.122). In this study, I recruited male and female RMW and URW participants from different types of starting occupations in the urban labour market. To make *type of starting occupation* manageable, I sought to cover two big types: first job as manual and first job as non-manual position in the urban labour market. At first, I recruited my participants via leaflet-distribution in industrial parks in *Panyu* district and office building blocks in

Tianhe district[7] in Guangzhou. Additionally, referrals from the interviewed participants and my extended social networks helped me reach potential participants meeting the target characteristics. This combination of purposive and snowball sampling can guarantee that the sample meets the required characteristics for theoretical representative on the one hand, and the ease of accessing the targeted populations on the other hand (Atkinson and Flint, 2001; David and Sutton, 2011, p.232). The plan for data collection had been ethically approved by the ethics committee in the Department of Sociology at Durham University before any interview took place (see Appendix A).

Table 3.2 and Appendix C summary some key characteristics of the interview sample. Initially, I interviewed 22 participants and all of them were internet users. However, as the quantitative results in Chapter Five and Seven will show, the internet non-users still account for a considerable proportion of the working populations in China's urban areas, and the inequality in internet adoption between RMWs and URWs still exists. To gain more understanding about no active use of the internet, I later added two more interviews with internet non-users. Thus, eventually, I did 24 interviews. However, one limitation is that the sample of the internet non-users lack demographic diversity because both of them were manual workers, agricultural *hukou* type, male, and above 45-year-old. Among the internet-using participants, only two RMW participants did not have experience of UIL. The sample has 15 RMW and 9 URW participants. Most participants were young adult labourers age 18 to 40, the major labour force in urban areas who are expected to be more active in both UIL and occupational mobility. Whilst focusing on young adult workers does allow a control for influences of aging and/or generational effects, at the same time it is a source of limitation since the analytical findings might not be generalisable to workers who are more mature. Overall, the sample has a balanced ratio of male and female and manual and non-

[7] Industrial parks in *Panyu* district are the places where most manual working populations gather whilst office building blocks in *Tianhe* district are where most white-collar working populations centre. The purpose was to try to access both manual and non-manual working populations.

manual origin workers. The sample covers workers from various educational backgrounds although there is only one case under secondary education.

Table 3.2. Key characteristics of the interview sample

	RMW		URW		Total	
	n	%	n	%	n	%
Age						
18-40	13	86.67	9	100.00	22	91.67
41-60	2	13.33	0	0.00	2	8.33
Gender						
Male	9	60.00	6	66.67	15	62.50
Female	6	40.00	3	33.33	9	37.50
Ethnicity						
Han	14	93.33	9	100.00	23	95.83
Ethnic minority	1	6.67	0	0.00	1	4.17
Education						
Primary education or lower	1	6.67	0	0.00	1	4.17
Secondary or high school	8	53.33	1	11.11	9	37.50
Higher education	6	40.00	8	88.89	14	58.33
First occupation in the urban area						
Manual	8	53.33	2	22.22	10	41.67
Non-manual	7	46.67	7	77.78	14	58.33
Current occupation in the urban area						
Manual	7	46.67	1	11.11	9	37.50
Non-manual	8	53.33	8	88.89	16	66.67
Internet users	13	86.67	9	100.00	22	91.67
UIL experience	11	73.33	9	100.00	20	83.33
Total	15	62.50	9	37.50	24	100.00

All interviews took place in a public setting (e.g., a cafe, a restaurant) where I treated participants to a drink (non-alcoholic) or some food as a token of my gratitude for their time. On average, each interview took around 30 minutes. All interviews were audio-recorded by two audio recorders with the interviewees' consent. I transcribed the audio recordings and translated them into English.

Data was then analysed by a narrative analysis approach. Narrative analysis is an approach sensitive to the temporal sequence of key events in the past accounted by participants (Bryman, 2012, p.582; David and Sutton, 2011, p.374). Not only can narrative analysis identify 'what actually happened' in the past, it also gains a sense of 'how do they [participants] make sense of what happened', stories that participants employ to account for events (Bryman, 2012, p.584). In this study, the narrative analysis aims to map out

a) the sequential order of the actual events experienced by participants regarding occupational mobility and learning activities with the use of the internet, and b) the way that participants made sense of the events they experienced from their storytelling. In participants' accounts, elements of casual assertions are often used when people are making sense of events that happened in sequence (Boje, 2001, p.95). It is possible that participants' accounts are not always consistent with the explanations derived from the preliminary theories. However, as Boje (2001, p.38) suggests, juxtaposing various sources of accounts and explanations provides a channel into a fuller understanding of the mechanisms linking the events. Counter-narratives should not be used to reject and dismiss the developed explanatory accounts, but should be employ to critically analyse and redevelop the existing theories (Boje, 2001, p.43). Thus, the inconsistencies between participants' storytelling of their life experiences and the provisional explanatory accounts derived from the preliminary theories then provide good material for highlighting the imperfections of the preliminary theories (regarding the way of making sense of the mechanisms behind the observed general patterns measured by the quantitative findings). Whilst an initial thematic code-list was derived from the major concepts from the preliminary theories, after thoroughly reading through the transcriptions twice, the initial code list was modified by a) making some adjustments of the original codes based on the familiarity of the texts and b) doing some open coding. After that, I started to code text by text in multiple rounds with more manifest coding in the beginning whilst more latent coding in the later rounds. In the next phase, the comparative analysis started. Inconsistencies between participants' storytelling and explanatory narratives from the preliminary theories were then highlighted. Discussions were then followed to find out what limitations the preliminary theories might have when interpreting the mechanisms behind the observed patterns, and how to make a better sense of the observed patterns. I used the qualitative data analysis package MAXQDA throughout the process.

3.4. Summary

Firstly, this chapter introduced the research focus of the study. This study investigates a central issue: *to what extent does UIL mitigate the unequal occupational mobilities between RMWs and URWs in China's urban labour market?* To achieve the goal, three research questions (*To what extent is UIL related to occupational mobility in general? Is there a stronger UIL-mobility association for RMWs? Do RMWs and URWs have similar participation in UIL?*) were then proposed. To answer each of the research questions, a mixed-methods approach is adopted. Quantitative and qualitative data are used in a complementary manner. Initially, for each research question, a preliminary theory was proposed to give hypotheses on observable patterns and a provisional explanatory account to interpret the mechanisms behind the patterns. Given the strengths of providing robust comparisons for measuring general patterns and regularities, quantitative evidence is used to give an accurate description of the general patterns. Given the strengths of providing detailed and rich descriptions and creating openness, qualitative evidence is used to refine the interpretation to make a better sense of the observed patterns.

Chapter Four: An overview of the unequal mobility

4.1. Introduction

Before embarking on the 'journey' of evaluating the potential of UIL in mitigating the unequal mobility, it is helpful to firstly gain an overview of the latest situation of the inequality of occupational mobility between RMWs and URWs. Thus, this chapter aims to investigate the overall extent of equality of occupational mobility between RMWs and URWs, by presenting a series of bivariate analyses (i.e., the outflow table methods, the comparison of the numeric scores of mobility, and the comparison of mobility types) drawing on data from CFPS, after briefly introducing the comparison methods and describing an estimated occupational structure in China's urban labour market.

4.2. Data and analytical methods

Data from CFPS2010adult, CFPS2014adult, and CFPS2016adult are used since those waves contain valid information about individuals' employment status, occupation, and *hukou* type. By using that valid information, I aim to compare RMW and URW samples' occupational changes within the periods 2010-2014, 2014-2016, and 2010-2016.

Table 4.1 summarises the process of valid sample selection. In step one, I selected the valid sample in accordance with our target population (i.e., urban-living and employed as non-agricultural occupations); I had 5,457 eligible cases for the 2010-2014 and 2010-2016 periods, and 6,226 for the 2014-2016 period. Next, the following two steps deal with the missingness. As shown by Table 4.1, the issue of item-missing is not serious, but the wave-missing rates (or attrition) are not very low. Complete case analysis was conducted after listwise deletion. While the sample sizes were large enough for each round of the statistical analysis, the analysis retains a potential limitation of sample bias, as the missing might not be completely at random.[8]

Table 4.1 The process of valid sample selection

		2010 to 2014	2014 to 2016	2010 to 2016
Step One: Eligible cases selection	1. Total nationally representative sample from wave a (within the 'a to b' period)	33, 600	34, 731	33, 600
	2. Eligible sample selection: urban-living and employed as non-agricultural worker	5, 457	6, 226	5, 457
Step Two: Missing value of *Hukou* at wave a		5, 453 (4 item missing, 0.07%)	6, 179 (47 item missing, 0.75%)	5, 453 (4 item missing, 0.07%)
Step Three: Attrition, and item missing at wave *b*	1. Remain at wave b	3, 695 (1, 250 dropouts, 22.9%; 508 individual questionnaire not given, 9.32%)	4, 999 (659 dropouts, 10.67%; 521 individual questionnaire not given, 8.43%)	3, 458 (1, 457 dropouts, 26.72%; 538 individual questionnaire not given, 9.87%)
	2. Employment status at wave b	3, 159 (57 item missing, 1.54%; 479 economically non-active, 12.96%)	4, 328 (149 item missing, 2.89%; 522 economically non-active, 10.44%)	2, 791 (102 item missing, 2.95%; 565 economically non-active, 16.34%)
	3.Among the employed, valid information about occupation at wave b	3, 035 (Originally: 347 item-missing, 11.13%; After imputing 266 values from wave 2016: 81 item missing, 2.67%)	4, 213 (115 item missing, 0.27%)	2, 733 (26 item missing, 0.94%)

[8] Mainstream multiple imputation techniques might not be able to easily input highly reliable values for the missing data in this case. This is because for the wave-missing, the imputation needs to estimate the values for two variables in sequence (i.e., *whether staying active in the labour market* and *occupational class*). Instead, the study conducted complete analysis after listwise deletion whilst compared the sample characteristics before and after the listwise deletion. The comparison of the sample characteristics gives a sense of the possible biases caused by the missing. The comparison of the sample characteristics is presented in Appendix D.

Occupation classification: the use of EGP class scheme

The data sets contain a variable *egp* measuring individuals' occupation category at each wave based on the Erikson-Goldthorpe-Potocarero (EGP) class scheme[9] (Erikson, Goldthorpe, and Potocarero, 1979). Despite being criticized for a lack of consideration of the role of culture (Savage, 2015), and a failure to capture differentiation of the elites (Atkinson, 2015, p.55), the EGP scheme is considered to be a useful tool to measure occupational class among working populations, especially for the purpose of comparing social mobility in terms of economic life (Atkinson, 2015, pp.50-53; Goldthorpe, 2016). Mainly influenced by a neo-Weberian tradition, the EGP scheme aims to group occupations based on a similar market situation (specifically this scheme looks at income, economy security and economic advancement) and work situation (authority and control in the workplace) as important indicators of individuals' economic life chances (Erikon and Goldthorpe, 1992; Goldthorpe, 2007; Atkinson, 2015, pp. 50-53). In terms of its applicability in China, Zou's (2015) study shows that the scheme has a good constructive validity in measuring individuals' economic life chances in China's urban labour market despite China's different economic and political institutions. In practice, leading empirical studies in comparative social mobility in China (e.g., Wu and Treiman, 2007; Zhou and Xie, 2017) also preferred to adopt this class scheme.

However, one point needs to be noticed that these categories cannot be regarded as completely ordered (Bukodi and Goldthorpe, 2018, p.23). For the intermediate classes (i.e., Routine non-manual, Self-employed, and Manual supervisor in this scheme), it is difficult to claim which one is definitely above the others (Ibid.). So, whilst other classes were treated as ordered, the three intermediate classes were seen as categorically, but not hierarchically,

[9] Categories: 1=Higher managerial and professional, 2= Lower managerial and professional, 3= Routine non-manual, 4=Self-employment, 5=Manual supervisor, 6=Skilled manual, 7=Semi-unskilled manual, 8=Agricultural workers

different. Thus, I also created a variable *egps* to measure the completely ordered occupational class scheme[10].

Hukou

In accordance with our definition of RMWs and URWs, the combination of information of individuals' current residence and *hukou* type could indicate whether they belong to RMWs or URWs. As all the cases were working populations living in urban areas when the survey took place, the variable *hukou* type can indicate whether they are RMWs (if the *hukou* type is agricultural) or URWs (if non-agricultural *hukou* type).

Comparison a: the outflow table method

The outflow table method is a useful way to compare mobility patterns between individuals from different original occupations, and is highly compatible with the use of EGP class scheme (Atkinson, 2015, p.108). It is a two-way table (the original occupation in the row, the destination occupation in the column) showing the row percentages of occupational destination grouped by occupational origin. But because our main purpose is to compare the occupational mobility of RMWs and URWs, the comparison actually goes three ways. However, instead of using a three-way table, which is cumbersome, I chose to use a heatmap (see Figure 4.2) with the use of colour to illustrate the RMW-URW differences in mobility conditioned on the same original occupation. In addition, Chi-square test results are attached to give further information on the inference of the RMW-URW differences in mobility at the population level.[11]

[10] Ordered: 1=Higher managerial and professional, 2= Lower managerial and professional, 3= Routine non-manual, Self-employment, and manual supervisor, 4=Skilled manual, 5=Semi-unskilled manual, 6=Agricultural workers

[11] Every unit of a test is based on a two-by-two table grouped by *Hukou* type (row) and whether or not entering a certain position (column), for those who were from same original occupation.

The analysis in this chapter includes all the cases that were still economically active[12] (both the employed and unemployed who had an intention to work) at the later wave whilst excludes those who did not have any intention to seek a job at the later wave. However, as the next two analyses (i.e., comparison b and c) mainly focus on the degree and the type of vertical mobility, the samples for the following two sections do not contain those who are unemployed at the later wave.

Comparison b: The comparison of the numeric scores of mobility

The next analysis uses a scale variable to describe the degree of vertical occupational mobility. To achieve this, I created a scale variable *occupational change score (*$=egps_{it}-egps_{it-1}$*)*. Thus, a positive value of the *occupational change score* stands for upward mobility, a negative value stands for downward mobility, and the absolute value counts how many levels a person changed. The initial idea was simply to use the comparison of means. However, as shown by Figure 4.4, some conditional groups' distributions do not follow a normal distribution, and for these I supplemented mean scores with a nonparametric Wilcoxon Mann Whitney test.

Comparison c: The comparison of mobility type

This part mainly aims to compare the proportions of each type of vertical mobility (upward, downward, and no vertical mobility) between RMWs and URWs, regardless of the magnitude of mobility. For each unit of comparison, a Chi-square test result is attached.

The comparison of the distributions of the scale variable of mobility (i.e., the *occupational change score*) and the mobility type has different strengths and weaknesses. The former gives more information about the magnitude of the

[12] Economically active includes those currently having a job (i.e., the employed) and those trying to get employed but failing to get a job (i.e., unemployed). Thus, those who are not employed for other reasons (e.g., education, no intention to get a job) are not included.

mobility whilst the latter can better indicate the general chances of having each type of mobility. For all the analyses, longitudinal weighting was applied.

4.3. The overall occupational structure

Figure 4.1 shows the estimated overall occupational structure of the employed rural migrants, urban residents, and the aggregation of them in the urban labour market in 2010, 2014, and 2016, with the adjustment of cross-sectional weighting. In general, across the years, semi-unskilled manual workers accounted for a large proportion of the total workforce. And among all the samples, manual workers were still the majority. This somewhat echoes the perception of China as being the so-called 'world factory' with a large number of low-waged manual workers, especially in the manufacturing industry (Li, 2019b, pp.203-204)[13]. In contrast, the category *manual supervisor* was merely a minority group in all the samples.

Compared to the figures in 2010, there were apparently more semi-unskilled manual workers in all the samples in the subsequent two waves. Further, for both RMWs and URWs, the ratios of higher managerial and professional staff reached the highest in 2010 and the lowest in 2014. As this is based on the use of panel data, there is a possibility that this was due to attrition rather than the structural change of the labour market. However, the expansion of semi-unskilled manual labour somewhat echoes Li's (2019, pp.203-204) finding of increasing unskilled manual labourers after 2000. While some fantasized a 'post-industrialised modernization' trend of urban China's economy in the new century, the number of unskilled manual labourers actually increased (Ibid.). Nonetheless, despite some small differences, the whole occupational structure in the urban labour market (i.e., the total sample) can be seen as stable overall.

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[13] Strictly speaking, this perception is not completely correct, as it only focuses on a perceived image of urban China. If we look at the whole of China, according to data from *The 2010 Population Census of the People's Republic of China* (National Bureau of Statistics, 2011), 46.49% of the population were still peasants.

Over the six-year period, the occupational structure of RMWs had shifted from a more diamond-like shape to a more pyramid-like shape, whilst the structure of URWs tended to stay more or less similar across the years. In comparison, it is clear that over this period of time, URWs had a larger proportion of managerial and professional staff (both at the higher and lower level) and routine non-manual workers. In contrast, RMWs had a larger ratio of manual workers, especially the semi-unskilled. In addition to this manual/white-collar divide, the proportion of self-employed workers within the RMWs sample was larger. Despite having a small proportion of higher managerial and professional staff, the ratio of lower managerial and professional RMWs doubled in 2016 compared to 2010, whilst the proportion of self-employed staff shrank between 2010 and 2016.

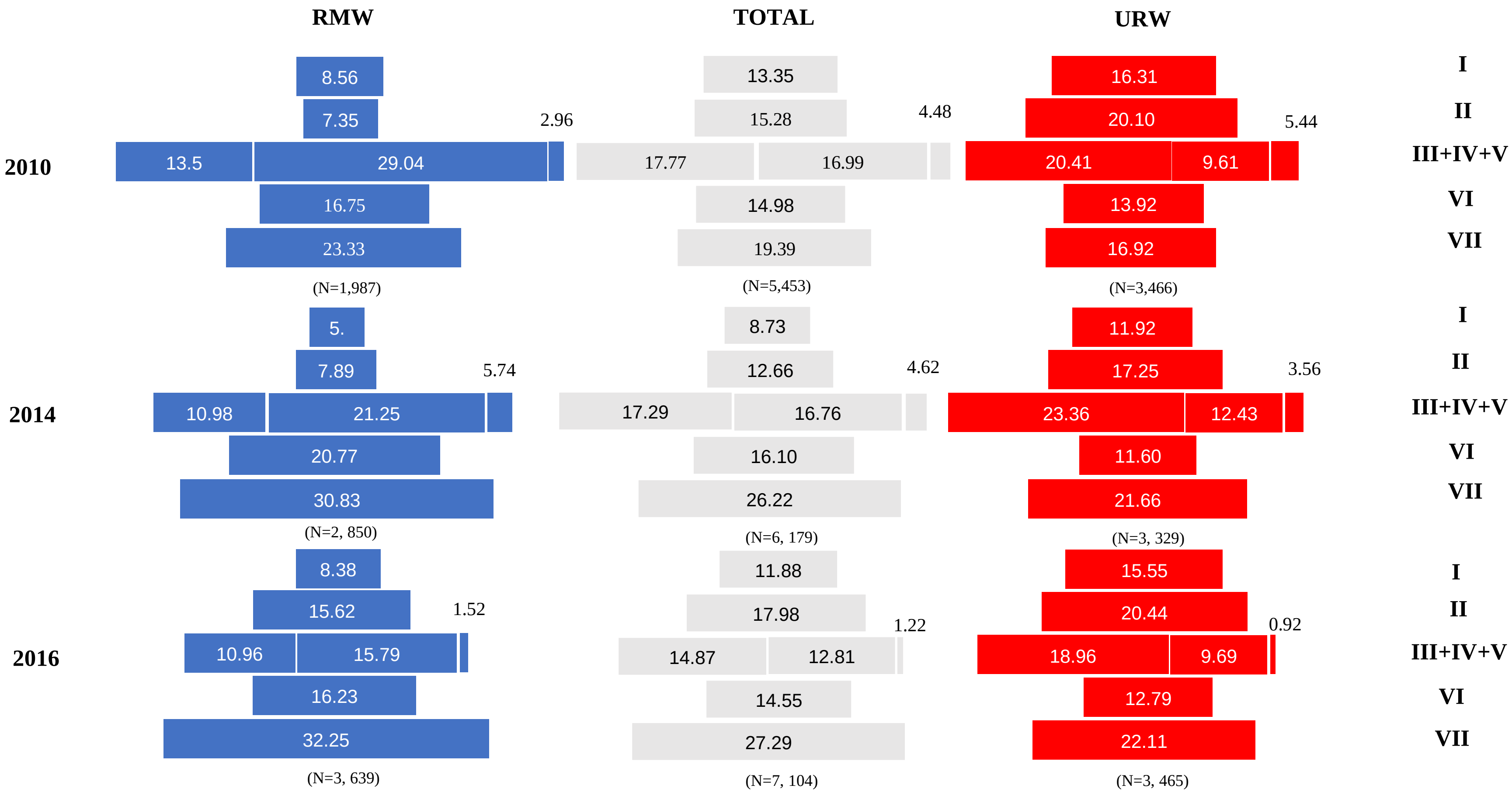

Figure 4.1 Occupation distributions (%) of the employed population in 2010, 2014 and 2016. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, IV=Self-employed, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

4.4. The RMW-URW difference in occupational mobility

4.4.1. Comparison a: the outflow table method

Before getting into the comparisons, it would be useful to start by looking at the overall pattern of mobility across all the original occupations. Table 4.2 shows the outflow tables of occupational mobility of all economically active participants in the periods of 2010-2014, 2014-2016, and 2010-2016. As shown, except for those who started as manual supervisors, all other categories had the largest proportion of workers staying in their original positions across all the observed periods. Individuals from all occupation categories were not very likely to become agricultural workers, although, in a relative sense, the self-employed workers and semi-unskilled manual workers had a higher chance. Even though having some small degree of change, workers who started in non-manual positions were more likely to do non-manual jobs subsequently, whilst manual workers were more likely to stay as manual workers.

Next, three heatmaps (Figure 4.2) were plotted to compare the row percentages of occupational mobility between RMWs and URWs, based on the figures from grouped outflow tables. Within each heatmap, the red colour means that URWs had a higher proportion in that cell, while a blue cell represents the other way. In addition, a Chi-square test was conducted with the asterisks showing the levels of statistical significance on the differences in the outflow distributions of occupational changes between RMWs and URWs[14].

At first glance, for all the graphs, the first three columns are more dominated by red shades, meaning that regardless of the original occupations, URWs were more likely to take over professional and managerial positions or work

[14] Every unit of a test was based on a two-by-two table grouped by *hukou* type (row) and a binary outcome of whether or not entering a certain occupational class at the later wave (column), for those who were from the same original occupation at the previous wave.

as routine non-manual workers in general. In contrast, in all the graphs, blue cells dominate the right-hand side, especially the right bottom but does not include the last column ‘unemployment’ (i.e., upper classes’ downward mobilities), suggesting a greater tendency for RMWs to move to or stay in the lower level occupations, regardless of their original occupations. Speaking of becoming agricultural workers, the ‘VIII’ column shows a consistent blueness with many cells showing a statistically significant difference over all the observed periods, indicating that RMWs from all the occupation groups had a much stronger tendency to become agricultural workers presumably in the rural areas than those who held a non-agricultural *hukou* status. This gap is expected as those who hold a non-agricultural *hukou* type would not normally move to rural areas and undertake an agricultural job. However, the last column does not show any clear pattern of RMW-URW difference in becoming unemployed. Longitudinally, the ‘red-dominance’ on the first three columns and the dominance of blue-shades on the right of the graphs are more apparent within the overall six years (2010-2016), but less salient within only two years (2014-2016).

It is clear from Table 4.2 that attaining a managerial and professional level or routine non-manual level was very rare for those whose original jobs were in manual occupations. However, in comparison, the chance (of entering I, II and III) was higher for a non-agricultural *hukou* holder, as we can see from Figure 4.2 (the first three columns of the first two rows) that there are some red-shades suggesting the advantage of URWs in occupational mobility and star signs indicating that the difference is sometimes statistically significant.

Within those intermediate categories (i.e., routine non-manual, self-employed, and manual supervisor), the category ‘manual supervisor’ appears to be closely correlated to manual occupations. Regarding the mobility of the manual supervisors, compared to the rural migrant manual supervisors, the urban resident manual supervisors had a strong likelihood to stay as manual supervisors (red shades in 2010-2014 and 2010-2016) or at least to be skilled manual workers (red shades in all the periods and a significant difference within the first four years), but a small chance to be semi-unskilled manual workers (blue shades in all the periods and a significant difference within 2010 to 2014). However, there are some small indications that more RMWs took over the higher managerial and professional positions, indicated by consistent blue shading in all the periods and a significant difference (but only at 90% level) within six years. Whilst the pattern in the 2014-2016 period is less clear, in the other observed periods, the URWs, who started as self-employed individuals, were more likely to take over managerial and professional positions than their RMWs counterparts and the difference is estimated to be significant in the first four years.

Among those who started from routine non-manual or lower managerial and professional categories, although the urban residents did not have an absolute advantage in their further upward mobilities, they were significantly more likely to stay in their original positions than the rural migrants. As for higher managerial and professional background staffs, among them the urban residents had a noticeable advantage in avoiding a severe degree of downward mobility (the red shades in the first three cells), especially within the whole six years, indicated by both the dark red-shades and the significant differences. As mentioned, Table 4.1 has already shown that those who started from routine non-manual or managerial and professional levels were not likely to become manual workers subsequently. But in comparison, RMWs were relatively more likely to turn into semi-unskilled manual workers, indicated by the blue shades in column 'VII' of the last three rows. This pattern is more evident within the 2010-2016 period as both dark blue shades and some statistically significant differences can be observed.

To sum up, the heatmaps have shown some clear evidence of URWs over RMWs in occupational mobility in the urban labour market. They also show some dynamics of a further occupational segregation between RMWs and URWs over the manual/white-collar divide. The estimation of occupation structure from Figure 4.1 has already shown an RMW-URWs divide in undertaking manual and non-manual jobs. However, the above findings further show that across the years the gap was widening rather than narrowing down. URWs were consistently more likely to take over managerial, professional, or at least routine non-manual positions, even though some of them did not work on those positions at an earlier time point. On the other hand, even though some RMWs started from managerial, professional, or routine non-manual positions, they were subject to a higher risk of downgrading to manual (especially the semi-unskilled manual) workers.

Table 4.2 The outflow tables of occupational mobility of all economically active population in the period of 2010-2014, 2014-2016 and 2010-2016

2010				2014					
%	I	II	III	IV	V	VI	VII	VIII	U
I	43.23	12.56	18.61	5.65	1.48	7.42	9.03	1.56	0.45
II	15.94	55.55	13.32	2.39	0.43	2.06	6.6	2.47	1.22
III	16.09	10.63	42.97	5.29	0.13	6.55	14.4	2.4	1.53
IV	3.67	11.06	4.51	41.35	0.82	5.95	18.48	11.57	2.6
V	6.96	10.5	2.36	1.08	33.35	30.93	12.5	1.67	0.63
VI	2.13	2.28	6.98	5.49	5.07	46.56	25.96	3.65	1.87
VII	1.47	4.59	8.58	5.06	0.91	9.78	59.85	8.12	1.64

Valid N=3, 078

2014				2016					
%	I	II	III	IV	V	VI	VII	VIII	U
I	60.8	11.89	13.45	4.45	0.76	3.38	3.38	1.07	0.75
II	9.82	60.25	18.25	2.21	0	2.76	4.63	1.36	0.71
III	12.33	11.07	52.05	3.9	0	5.61	11.54	1.59	1.9
IV	3.69	22.83	8.89	43.33	0.26	4.06	12.06	4.01	0.87
V	7.33	2.24	4.19	2.02	0.21	67.95	11.99	4.09	0
VI	4.13	4.93	3.98	6.44	0.5	51.08	23.86	3.48	1.55
VII	3.83	3.81	8.05	6.73	0.33	11.81	56.11	6.88	2.46

Valid N=4,282

2010				2016					
%	I	II	III	IV	V	VI	VII	VIII	U
I	41.47	18.66	15.35	3.81	1.64	4.95	8.22	5.28	0.63
II	21.37	52.18	10.87	1.05	0.63	3.38	7.43	2.62	0.46
III	21.82	11.5	41.83	3.71	0.25	4.55	12.1	3.31	0.93
IV	3.67	17.34	9.54	28.91	0.11	7.3	20.18	10.94	2.03
V	4.75	3.07	7.23	2.11	1.79	65.95	10.62	3.9	0.58
VI	4.67	6.03	7.38	6.18	2.56	44.27	25.09	3.36	0.47
VII	4.88	4.24	8.5	3.43	0	14.09	53.13	10.74	0.99

Valid N=2,764

Immobility
Upward mobility
Horizontal mobility
Downward mobility

I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, IV=Self-employed, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual, VIII=Agricultural worker, U= Unemployed; Source: CFPS adult 2010, 2014 and 2016

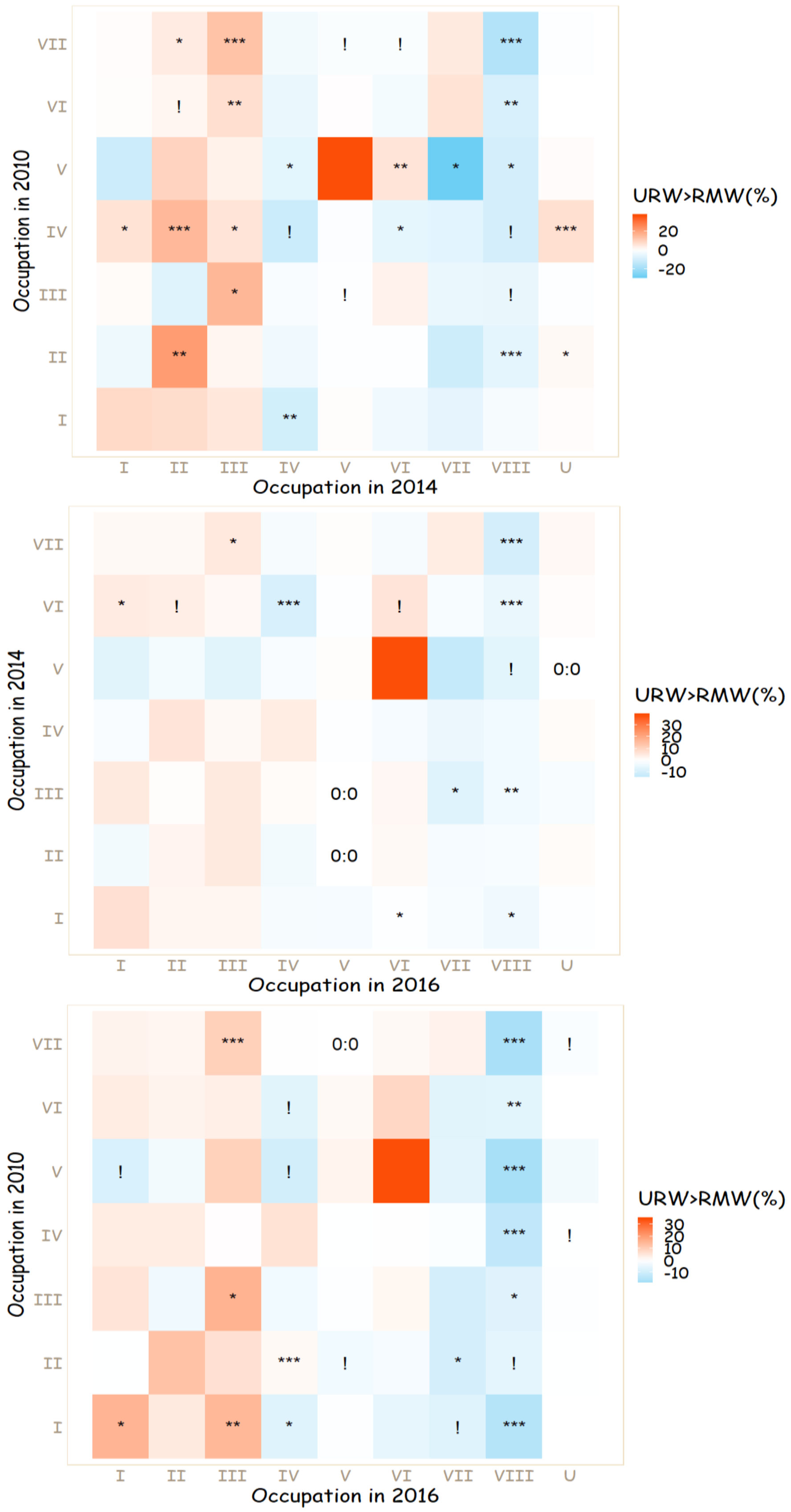

Figure 4.2. Heat maps on comparative occupational mobilities between RMWs and URWs (Redness stands for URW having a higher proportion and blueness stands for RMW having a higher proportion) with Chi-squared test result (*** p<0.001, ** p<0.01, * p<0.05, ! p<0.1, 0:0 no case in both RMW and URW groups). I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, IV=Self-employed, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual, VIII=Agricultural worker, U=unemployed; Source: CFPS adult 2010, 2014 and 2016

4.4.2. Comparison b: the comparison of occupational change scores

As a preliminary step before this comparison, Figure 4.3 summarises the distributions of the occupational change scores - the scale variable of occupational mobility across all the samples within each observed period. The distributions of the scores appear to have a nearly symmetrical distribution with a small degree of left-skewness, as there was slightly more downward mobility than upward mobility. In addition, the distributions seem to be leptokurtic as more than 40% of the cases did not have any vertical (i.e., upward or downward) occupational mobility. Mobility becomes more salient within a longer period of time (2010 to 2016) than for only two or four years. The range is from -5 (i.e., from higher managerial and professional positions to agricultural labourers) to 4 (i.e., semi-unskilled manual workers) as this study only includes those who started as urban-living non-agricultural workers and they could end up taking an agricultural job in the rural areas due to mobility, both occupational and geographical. Compared to having a short distance vertical mobility (e.g. -1,1), a long-range mobility was very rare (e.g. -4, 4) to be seen, which of course is partly due to the fact that different starting occupations had different ranges of values (e.g. the value '-4' only exists for the managerial- and professional-origin individuals).

Next, Figure 4.4 shows the comparison of the distribution of occupational change scores between RMWs and URWs, grouped by the original occupation and the observed period. The initial idea was to compare the mean values of occupational change with error-bars showing the 95% confidence intervals. However, since the violin plots show that the distributions of the occupational change scores are not close to normal for some groups (e.g., those who started from managerial, professional and semi-unskilled manual workers), the validity of simply comparing means is questionable for those groups. To address the issue, I supplemented with a Wilcoxon Mann Whitney test.

Overall, Figure 4.4 shows that URWs were more likely to get a larger value for the occupational change scores (i.e., when changing jobs, URWs are more likely to obtain a higher position), in comparison to RMWs. The shapes of the distributions of the violin plots look quite similar for those who started from the same occupation, except for the distributions for the individuals who started from self-employed workers in all the periods and the distributions for skilled manual workers within the first four years. However, the plots for managerial and professional background urban residents had a ‘sharper end’ than the urban resident counterparts’ within the four-year (2010-2014) and six-year (2014-2016) periods, indicating that URWs had fewer small negative values (i.e., long-distance downward mobility). Across all the groups in all the periods, the sample mean values for URWs are higher than the mean values for RMW, indicating that on average URWs are more likely to achieve better occupational mobility. Also, the differences are significant at the 95% confidence level for those whose original occupation were managerial, professional, or semi-unskilled manual within 2010-2014, routine non-manual or self-employed within 2014-2016, and higher managerial, higher professional, and self-employed within 2010-2016. To mitigate the issue of the possibly unreliable results for the distributions with non-normality, a nonparametric test, the Wilcoxon Mann Whitney test, was applied. There are significant RMW-URW differences in the distributions of the occupational mobility among those who started from managerial, professional, self-employed, or semi-unskilled manual workers within 2010-2014, those who started from self-employed or manual workers within 2014-2016, and those who started from managerial, professional, self-employed or manual workers within the overall six years. All in all, it is evident that RMWs tended to have a lower value of the occupational change score when compared to URWs, which further confirms a pattern that the overall situation of occupational mobility is better (i.e., they are able to obtain or secure a higher position more easily) among URWs.

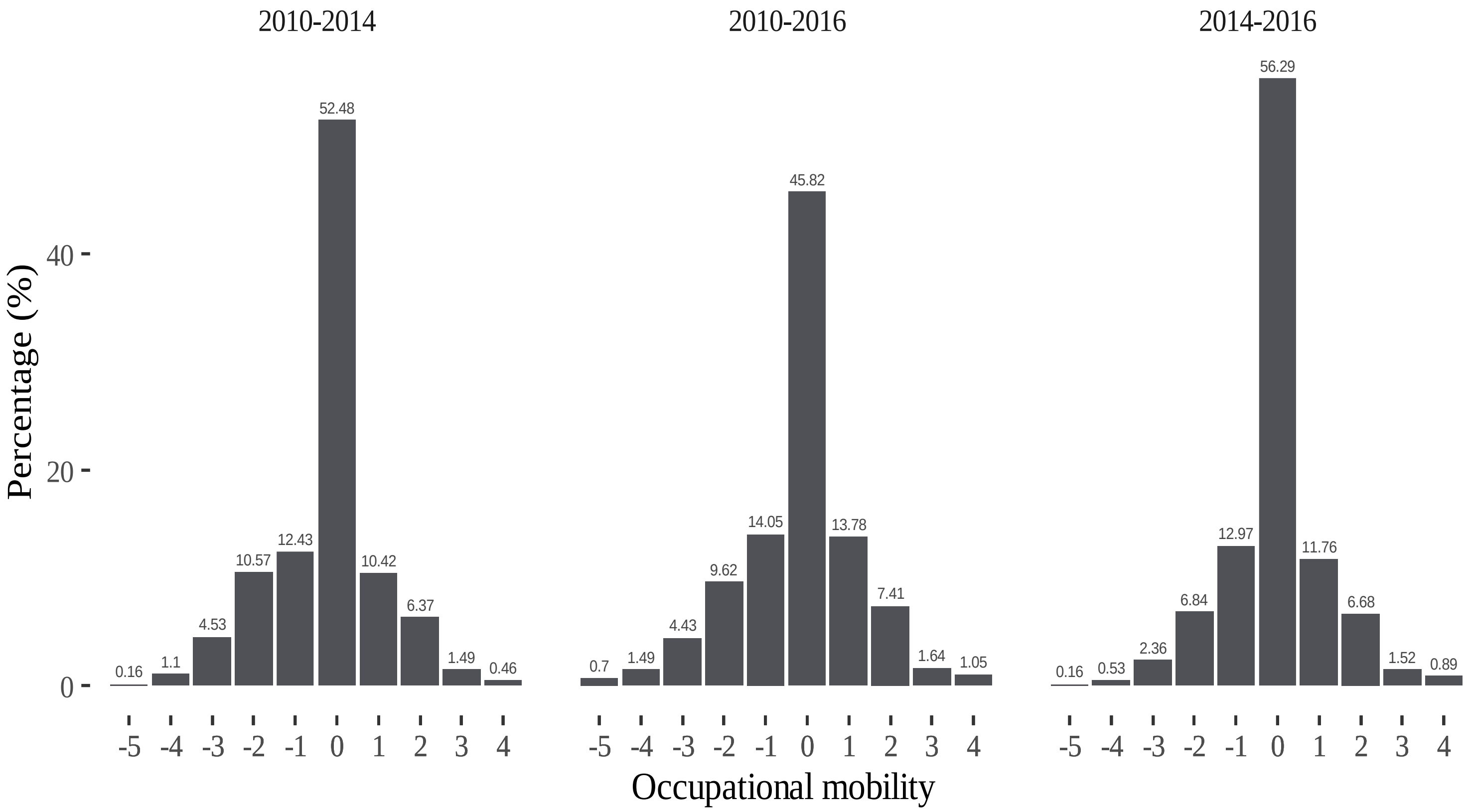

Figure 4.3 Histograms on the values of occupational change by year, reporting percentages. Source: CFPSadult2010, 2014, 2016

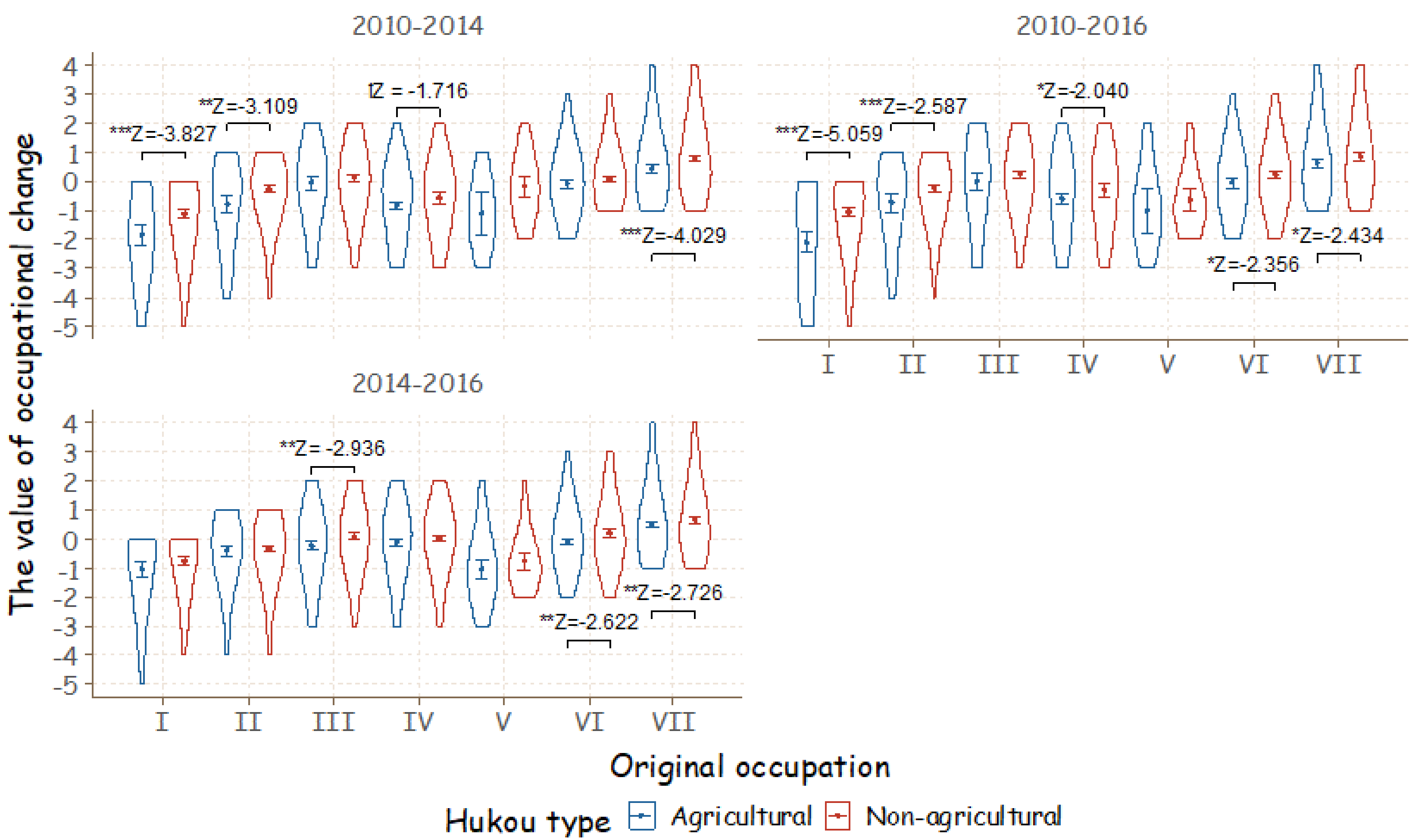

Figure 4.4 Comparing the values of occupational mobility between RMWs and URWs with the comparison of means with error bars (95% confidence intervals), violin plots (showing the distributions of values), and the results of Wilcoxon Mann Whitney test (only showing the significantly different results, *** p<0.001, ** p<0.01, * p<0.05, † p<0.1), grouped by year and original occupation. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, IV=Self-employed, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

4.4.3. Comparison c: the comparison of mobility types

Finally, the comparison of the distributions of mobility types (i.e., upward, staying and upward) between RMWs and URWs with the 95% confidence intervals and Chi-squared test results is presented by Figure 4.5. As the key focus is on vertical mobility, I simply call both immobility and horizontal mobility as 'staying'. At first glance, across all the observed periods, even though the URW samples do not always have a higher upward mobility rate (not the case for group VII within 2014-2016, group V within 2010-2016, and group III in both 2010-2014 and 2010-2016), they usually had a lower chance of experiencing downward mobility (except for group V in 2014-2016 and 2010-2016).

Indicated by the results of Chi-squared tests, within the first four years (2010-2014) the distributions of mobility types were expected to be significantly different between the RMW and URW populations, if their original occupations were professional, managerial, self-employed, or semi-unskilled manual workers. Among the managerial, professional, and semi-unskilled manual occupation backgrounds workers, URWs had a significantly lower chance of experiencing downward mobility. In addition, within this period, it was estimated that urban resident self-employed individuals had a higher chance of 'moving up' to the managerial or professional category.

Next, the Chi-square test results further suggest that within the subsequent two years (2014-2016), the differences in mobility type distributions were likely to happen among the individuals who were manual, self-employed, or routine non-manual workers in 2014. Especially, rural migrant semi-unskilled manual workers had a much higher chance of becoming agricultural workers.

Within the overall six-year period (2010 to 2016), the Chi-square test results suggest an at least 90% confidence level significant difference in the distributions of occupation mobility type for the groups of people who started from managerial, professional, routine non-manual, or semi-unskilled manual occupations in 2010. Again, the rural migrant semi-unskilled manual workers were expected to be much more likely to move back to rural areas and work as agricultural workers in 2016 than the URW counterparts. Although the rural migrant routine non-manual sample had a slightly higher upward mobility rate, they also had a lower rate of staying in a similar level occupation (i.e., a higher downward mobility rate).

To sum up, while not indicating the magnitude of mobility, the comparison of mobility types shows a disadvantage for RMWs in occupational mobility, especially in downward mobility (i.e., a higher downward mobility risk). Possibly because the magnitude of upward mobility is not measured here, the comparison of the mobility types did not document a salient URW strength in upward mobility. However, the relatively high risk of downward mobility for RMWs is notable, especially among those who were originally managerial, professional, or semi-unskilled manual workers.

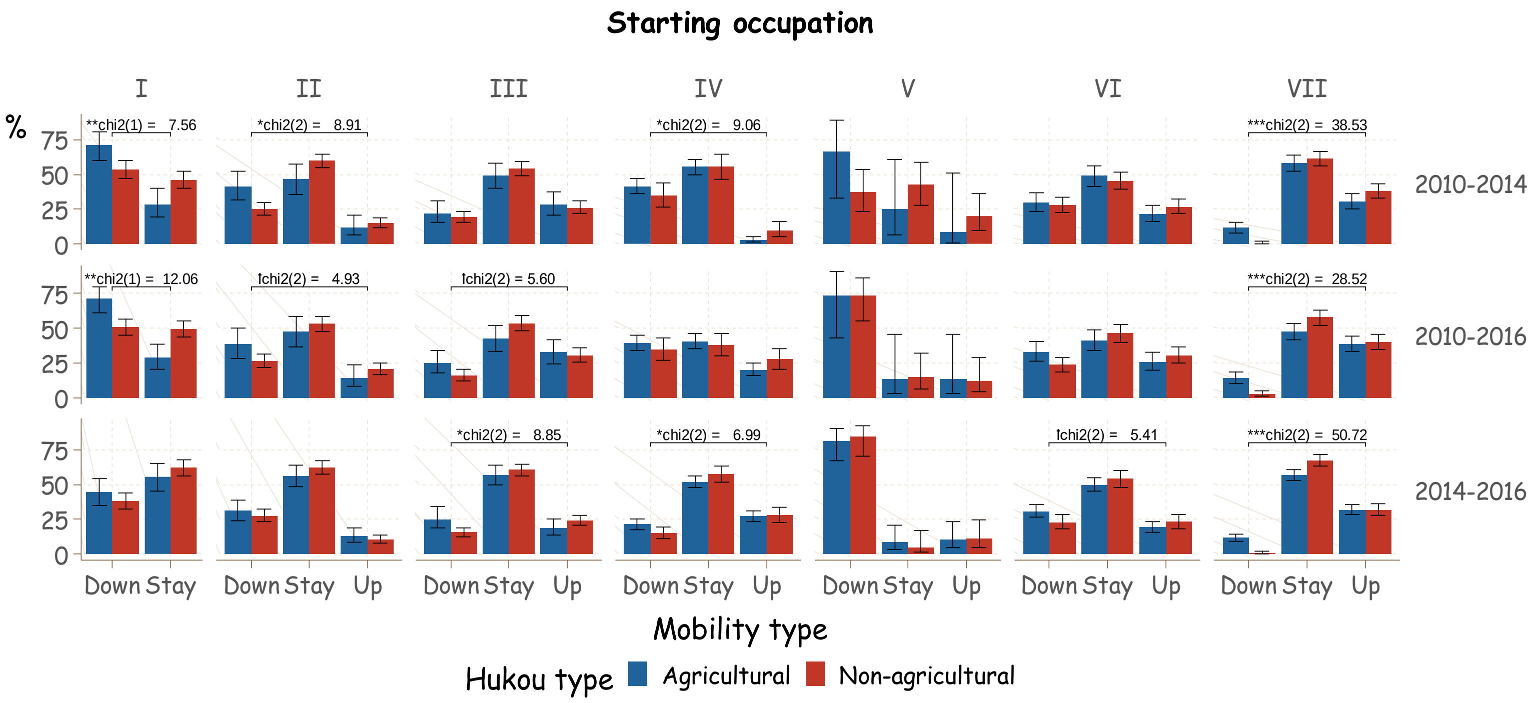

Figure 4.5 Comparison on the distributions of different mobility types between RMWs and URWs with the error-bars of estimated percentages (95% confidence intervals) and Chi-squared test results (only showing the significantly different results, *** p<0.001, ** p<0.01, * p<0.05, † p<0.1), grouped by observed period and original occupation. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, IV=Self-employed, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

4.5. Summary

To summarise, three bivariate analyses have shown the disadvantage of RMWs in occupational mobility in the urban labour market with different features. Regardless of the occupational origin, the outflow table method captures the relatively high tendency of becoming agricultural workers for RMWs over time. However, given the fact that the overall rates of becoming agricultural workers for each original occupation was not very high in general, it is possible that it might not need to be taken seriously. In addition, the combined results of Figure 4.1 and Figure 4.2 suggest a possible further manual/white-collar occupational segregation between RMWs and URWs in the urban labour market. Additionally, the results also show that urban resident manual workers (both the skilled and semi-unskilled) had a relatively high chance of becoming managers, professional, and routine non-manual workers. Whilst, in a relative sense, the rural background managers, professionals, and routine non-manual workers had a high chance of losing their privileged occupations and becoming manual labourers.

When using a scale variable (i.e., the occupational change score) to measure the magnitude of vertical mobility, Figure 4.4 shows that RMWs and URWs had significantly different distributions of occupational mobility, with a prominent feature that URWs tend to have a higher value for the occupational change scores. When concerning the rates of different types of mobility (upward, downward, and no vertical mobility), the results highlight rural migrant managerial, professionals, and semi-unskilled manual workers' higher risk of experiencing downward mobility.

Were RMWs found to have any advantage in occupational mobility? Very rarely and the results might not be entirely reliable at the population level. For instance, Figure 4.2 shows that the rural background manual supervisors had a relatively high chance of entering the higher managerial and professional category in 2016, although the evidence is weak. From Figure 4.5, we can see that the rural migrant routine non-manual worker sample sometimes had a slightly higher upward mobility rate than the urban resident counterpart sample. Also, if we further scrutinise routine non-manual workers' upward mobility by checking Figure 4.2 again, we find that the rural migrant routine non-manual worker sample indeed had a slightly higher chance of becoming a lower level manager or professional, but not a higher level one.

Chapter Five: Learning and moving

5.1. Introduction

The internet has long facilitated new ways of delivering formal education, such as the practice of Massive Online Open Courses (MOOCs) (e.g. McAuley at al., 2010; Pappano, 2012; Glennie and Mays, 2013). Most recently, the COVID-19 crisis has put remote teaching and learning in the spotlight, with most schools and universities worldwide ‘going online’ (e.g. Bao, 2020; Zhang *et al*., 2020). Moreover, the abundance of online information also largely enables individual self-directed, informal learning with flexibility and autonomy (e.g., Imel, 1999; Gray, 1999; 2004; Peters, 2000; Livingstone, 2002). However, to what extent are internet-based new learning activities related to workers’ occupational mobilities? Before discussing UIL’s mitigation potential on the inequality of occupational mobility, the question above must first be addressed. Thus, this chapter focuses on the first research question to make sense of the relationship between UIL and occupational mobility in the contemporary labour market. First, after reviewing the existing empirical evidence and theoretical knowledge on the relationship between learning and mobility in general (see Section 2), I put forward a *temporarily scarce skills theory* (see Section 3) to account for the link between UIL and occupational mobility in the contemporary labour market. Next, in Section 4, findings from the quantitative analysis are reported to measure the general association between UIL and occupational change among the working population in urban China. Finally, Section 5 reports the qualitative findings on further highlighting the limitations of the *temporarily scarce skills theory* when making sense of the patterns of the ‘UIL-mobility’ relationship.

5.2. Learning and ‘moving’, what do we already know?

The main purpose of this section is to give an overview of the existing scholarship on learning and occupational mobility, and to critically discuss the usefulness and limitations of our current knowledge. I will start by pooling and highlighting some relevant empirical findings, which might give a hint to the general patterns of learning and mobility. After that, I will engage in a critical discussion of theoretical accounts which attempt to provide a plausible explanation for the learning-mobility association.

5.2.1. Relevant empirical evidence

Utilising online learning resources to help move up the career ladder is often mentioned within particular public discussions (e.g., Gulati, 2008). But to the best of my knowledge, there does not appear to be any empirical studies directly investigating the relationship between UIL and occupational mobility. Nevertheless, there are two kinds of loosely related research findings which are still helpful in understanding the UIL-mobility relationship. The first kind is the traditional 'education/learning-mobility' studies, and the second is studies broadly researching labour market outcomes related to internet use. This section will briefly summarise the key findings of those two areas of study.

Firstly, there are rich empirical findings showing the strong relationship between learning activities and occupational attainment. Most sociological works identify Blau and Duncan's *The American Occupational Structure* (1967) as the founding study that inspired future research into the role of education in status-attainment in industrial societies. Blau and Duncan (1967, p. 170) and Duncan's earlier investigation (Duncan and Hodge, 1963) showed that individuals' educational achievements play a far more important role in job attainment than social origins (indicated by father's education and occupation). Follow-up investigations by Ridge (1974) and the Oxford Social Mobility Group's 1972 study (Heath, 1981, pp. 138-166) confirmed a similar pattern (i.e., education as the strongest predictor in job attainment) in the UK. Based on their comparative studies in 21 countries, Treiman and Yip (1989) claimed that this achievement-based (i.e., educational attainment) occupation attainment is widespread in industrialised countries. Later mobility studies by the Nuffield school scholars (e.g., Goldthorpe, 1987; Erikson and Goldthorpe,

1992) shifted the focus onto the intergenerational mobility of economic-based occupational class and the historical change of the 'Social Origin – Education – Destination (OED)' relationship (e.g., Goldthorpe, 2003). Studies in Britain and other European countries showed that the 'Education – Destination (ED)' relationship remains strong, although historically the association has been becoming weaker (e.g., Breen and Goldthorpe, 1999; 2001; Goldthorpe and Mills, 2004; Jackson, Goldthorpe and Mills, 2005; Breen and Luijkx, 2004; Whelan and Layte 2002; Iannelli and Paterson, 2007; Bukodi and Goldthorpe, 2018)[15].

In addition to studies examining the role of educational background before labour market entry, studies of workers' adult education and learning also show links between learning and positive labour market returns. Regardless of gaining new qualifications or not, active participation in learning is generally found to be related to better subsequent labour market outcomes (e.g., wage increase) (Jenkins *et al.*, 2003; Vignoles *et al*., 2004). In particular, evidence shows a clear positive relationship between gaining a higher-level vocational qualification and positive outcomes like occupational mobility (e.g., Blanden, et al., 2010; Gloster, 2016; Bukodi, 2017; Virdia and Schindler, 2019) and income-boosting (e.g., De-Coulon and Vignoles, 2008; Dorsett, 2011; Blanden, et al., 2012) in countries like the UK and Germany. However, the impact of a lower-level vocational qualification is unclear (e.g., Jenkins et al., 2003; Jenkins et al., 2007).

Although the role of education in job attainment in pre-1978 China[16] was less

[15] The OD association is generally unchanged, and the OE association has been becoming weaker most likely due to education expansion. Those studies (especially the studies from the Nuffield school scholars) were mostly used to criticise the liberal industrialisation/modernisation theory from functionalists like Blau and Duncan (1967) and Treiman (1970), who believed there would be a trend of education-based-meritocracy whilst social origin would gradually play a less important role compared to education.

[16] For example, Nee (1989; 1983) showed that the income return on education could be seen as negligible in Mao's era (although income difference between occupations was small at that time), whilst Zhou, Tuma and Moen (1996) showed education still played a role in occupation attainment. But scholars generally agreed on the relative uselessness of education

clear, it is less disputed that education has become crucial for job attainment after China's market economy transition. After the economic reform, when a) free job mobility was allowed and b) income inequality between occupations grew, most evidence suggests that educational attainment has become one of the most crucial determinants for well-paid position acquisition (Nee, 1989, 1996; Bian and Logan, 1996; Zhou, Tuma and Moen, 1996; Zhou, 2000; Bian, 2002; Bian and Zhang, 2002; Zhou and Zhao, 2002; Nee and Cao, 2003; Liu and Zhang, 2013) and career progression (Walder, 1995; Walder et al., 2000; Cao, 2001) in both the state and non-state sectors. Most of these studies focused on the urban labour market which is often seen as 'modernised' and 'industrialised' in the view of the modernisation theory (e.g., Treiman, 1970), but some investigations (Parish, Zhe and Li, 1995; Nee and Keister, 2000) also show that educational attainment matters significantly in stratifying non-agricultural occupations in Chinese rural areas. Although studies rarely focused on the role of adult learning, there is some scattered evidence hinting that workers' active participation in further training or learning activities is helpful towards career progression (e.g., Han, 2006; Fan and Li, 2015).

Additionally, there are some studies showing that the use of the internet can be related to some positive labour market outcomes. DiMaggio and Bonikowski (2008) firstly show that internet use in 2000 was associated with U.S. workers' subsequent earnings growth in 2001. Even for those who switched off the internet at the later wave, their income growth rates were still higher than those who did not use the internet at the earlier wave (Ibid.). Later investigations (e.g., De los Rios, 2010; Forman et al., 2012; Atasoy, 2013; Katz and Callorda, 2013) further confirmed that internet adoption is generally linked to a subsequent wage increase and employment growth in many other countries. In addition, adopting the EGP class scheme, Eynon, Deetjen and

for higher position (e.g., cadre) attainment compared to political capital, as a common characteristic of the statist socialism contexts (Djilas, 1957; Nee, 1989; Bian and Logan, 1996; Zhou, Tuma and Moen, 1996). Also, the state policies changed dramatically from time to time and sometimes educated individuals were devalued in workplaces (e.g., see Rosen, 1982; Lu, 2004: 32-34)

Malmberg (2018) found that in Britain, internet use plays a role in maintaining and improving class position during one's life-course. Whilst those findings present a positive association between internet use and labour market outcomes, the evidence is not sufficient to imply that UIL and occupational mobility are related.

5.2.2. Some existing theoretical perspectives

Given the rich evidence on the link between learning and occupational mobility, how do scholars make sense of the observed patterns? In this section, I examine some existing theoretical perspectives that are frequently used to explain the learning-mobility relationship.

Credentialism and signalling and screening

The basic idea of credentialism is: not that jobs require skills, but that credentials themselves work as an 'entrance ticket' (similar to Bourdieu's (1986) concept of institutionalized cultural capital) for specific job attainment, as a way of social closure for occupational attainment (e.g., Collins, 1979). The theory does not deny the importance of specialised skills for work performance. However, credentialism suggests that workers only learn the most relevant skills through on-the-job training, after individuals have already used their credentials as a 'cultural currency' to enter a monopolized workplace, while formal education usually provides no basis for specific technical work skills (e.g., Illich, 1970; Randall, 1979; Labaree, 1992). Credentialism provides a critical account interrogating the effect of education and of credentials as a barrier to succeed in social mobility.

Economists' signalling theory (Spence, 1973) and screening theory (e.g., Stiglitz, 1975) are similar to credentialism theory in the way that employers do not actually look at potential employees' actual work skills (because they are unable to discern potential employees' real capacities). Rather, employers use some additional information (e.g., qualifications) as indicators of actual work abilities to sort individuals. Similarly, job seekers also use additional information to signal to employers that they might have the required skills to work.

Functionalists' perspective

Functionalism underpins earlier social mobility studies, the status-attainment approach. For functionalists, stratification is a functional necessity within a societal system (Davies and Moore, 1945). Different positions in a society are attached to different duties (Ibid). For the maintenance of the existing social order and the efficiency of the system, rewards must be given unequally according to the functional importance of the role for the existing social system and the scarcity of the available personnel (Ibid). Functionalists believe in a progressive trend of universal industrialisation characterised by growing rationality and efficiency in production, manifested by rapid technological development and the increasing division of labour (Parsons, 1971, p.139; Blau and Duncan, 1967, p. 429). Thus, they envisage a trend of merit-based position attainment rather than the earlier one based on ascription (e.g., inheritance). Compared to pre-industrial societies, class barriers and immobility are seen as problematic in industrial societies for functionalists who sought technological progress, especially when industrial production require the use and support of those who held professional knowledge and skills regardless of their social origins (e.g., Lipset and Bendix, 1959; Blau and Duncan, 1967, p.431; Treiman, 1970). Blau and Duncan (1967, p. 6, p. 430) argued that it is a universalistic principle in all modern industrial societies that a high rate of occupational mobility relies on 'objective merits' (e.g., education) in response to the needs of industrial production.

Human capital theory

The human capital theory is one of the most influential theoretical accounts that attempt to make sense of the relationship between learning activities and economic rewards. The basic idea is that within the context of trading labour for economic rewards, certain kinds of human characteristics (knowledge, skills, abilities, health, etc.) can be counted as a source of 'capital' that enable individuals to get better rewards (Schultz, 1960; 1961; Kiker, 1966; Becker, 1993). According to the human capital theory, those human characteristics are beneficial resources for boosting overall productivity. Thus, workers with those characteristics receive better 'rewards' than others (Schultz, 1961; Melton, 1965; Weisbrod, 1966; Becker, 1993). Despite the fact that sociologists often show contempt for the human capital theory (Goldthorpe, 2014), they are still impressed by the theory's attempt to differentiate different kinds of labour (earlier neoclassical economists treated labour simplistically as homogenous units) (Bowles and Gintis, 1975).

For the human capital theorists, individuals' knowledge and skills are a form of capital (just like other tangible forms of capital such as property and machines), which are gained by individuals' investment, as written by Schultz (1961):

> 'Although it is obvious that people acquire useful skills and knowledge, it is not obvious that these skills and knowledge are a form of capital, and this capital is in substantial part a product of deliberate investment […] The failure to treat human resources explicitly as a form of capital as a produced means of production, as the product of investment, has fostered the retention of the classical notion of labour as a capacity to do manual work requiring little knowledge and skill, a capacity with which […] labourers are endowed about equally' (pp. 1-3).

In this sense, Schultz (1961, p. 3) made a very bold claim that 'labourers have become capitalists' by the possession of knowledge and skills that have economic value.

The Marxian approach

According to classical Marxian theory, the most relevant 'toolkit' for understanding the UIL-mobility relationship is the concept of *labour power* from the labour theory of value. For Marx, the main function of the concept labour power was first to debunk the illusion that capitalists buy workers' labour with money (Marx and Engels, 1993), and then to illuminate the exploitative nature of the capitalist form of labour process (Harvey, 2010, p.119-133). When working for those who own the means of production, wage workers do not get paid for the value of their labour, but for the minimum amount of money that can barely support the production and reproduction of their capacity to perform work, the labour power (Marx and Engels, 1993). Workers are subjected to this arrangement in order to survive, rather than having real freedom to arrange their labour in the way they prefer (Marx and Engels, 2009). As a result, surplus value is extracted by the capitalists in order to accumulate more capital and to strengthen the power of their dominance over society (Marx and Engels, 1993; Marx, 2013).

The idea of labour power can be used to make sense of the stratification among wage workers. The stratification among workers is not simply a reflection of the division of labour, but the revelation of the difference in the production of work capacity, as the production of other kinds of commodity (Marx, 2013, p. 115). If labour power is sold as a commodity, different kinds of labour power value differently, depending on the socially necessary labour-time for its production and reproduction (Ibid.). Some work positions require the capacities that take a longer time or special effort to produce and reproduce. For example, for some manual works without extensive training, their wage is paying for simply the labourers' survival (e.g., food, clothing, fuel, and housing) (Ibid.). Regarding the positions that require specialised skills and knowledge, the cost of the labour power also includes the necessary labour-time (learning, training, and work experience) to produce those requisite skills and knowledge (Ibid.).

After the massive transformation of industrial societies in the twentieth century, Marx's two-class framework had become increasingly ineffective in mapping out many aspects of stratification (Atkinson, 2015, pp. 25-26). For example, with increasing demand for 'knowledge possessors' to join the workforce (Bell, 1973), the long-neglected skill-related stratification among wage workers needed to be further highlighted (Ibid.). Erik Olin Wright (1978) has provided an effective solution with his notion of 'contradictory class location.' His idea is: not to reclassify ambiguous occupations (e.g., the professionals) into a new category like what Poulantzas and Fernbach (1975) did, but to recognize and study the real contradictory nature of one's occupation within class relations (e.g., the professionals do not own or control the means of production but have better control on their own labour than unskilled workers) (Wright, 1978).

According to Wright (1979, pp. 79-109; 1980; 1985, pp. 82-86; 1997, pp. 18-27), the scarce skills possessors, are in a contradictory location. On the one hand, skilled wage workers are still those who have no control over the means of production or other important resources and sell their labour power for a living. On the other hand, the degree of exploitation has been undermined. The scarcity of skills enables workers to have the power to better control their labour and this helps workers to bargain for a better reward for selling their labour power (1985, pp.65-104). In other words, they are not exactly like the traditional proletariat who completely lost control over their own labour. Advanced skills and knowledge are definitely related to the growth of productivity, but for Wright (1985, pp. 75-77; 2015, p. 7) that only explains part of the story regarding the differentiation among wage workers. In the market, there is a demand for highly productive labour capacity (Ibid.). But equally important is that the access to knowledge and skills are highly exclusive (Ibid.). The inaccessibility of learning and educational resources, and therefore scarce skills, restrict the supply of workers available to take those positions. Eventually, those who have acquired scarce skills, gain better control over their labour, and can enter work from an advantaged position

(Wright, 1997, pp. 18-20). For Wright (1980, p. 350), the reward for scarce skills holders could be higher than the actual cost for the production of their labour power, as argued by Marx.

Discussion

In addition to what has been covered above, Table 5.1 summarises some key features of those theories discussed.

Among the theoretical accounts discussed above, credentialism and signalling and screening may not be sufficient in explaining the whole story of the relationship between UIL and occupational mobility. As mentioned, the internet greatly empowers informal learning which usually has no actual qualifications except for the in-demand knowledge and skills in return. If we simply reduce the UIL-mobility relation to a ‘credential-job-attainment’ relation, the power of using the internet will be massively undermined by ignoring those non-credential-oriented learning activities, unless a theory predicts that the actual job skill development literally has nothing to do with occupational mobility. However, neither of those theories agree with this point (that actual skills do not matter). Credentialism and signalling, and screening theories do not deny the importance of actual work skills for work performance, but that is simply not the main focus of those theories. Those theoretical accounts might be more helpful for the context of qualification-oriented formal learning, but they are not that valuable as a way to account for the whole effect of UIL.

Table 5.1. A summary of different theoretical perspectives on addressing the learning-mobility relationship

Theoretical perspectives	Most relevant learning outcomes	Primary analytical unit	Nature of wage labour	Nature of 'learning activities' related stratification	Nature of occupational mobility
Credentialism (e.g., Collins, 1979)	Credentials, as the most useful cultural currencies	Social relation	Not specific	The socially constructed nature of the hierarchy of skills and occupations. The construction is subject to pre-existing power-relationship. Opportunity hoarding by credential holders and class-based exclusion for credential acquisition	Rhetoric of meritocracy-based mobility is merely a dominant group's ideology, for concealing the fact of social closure. Credentials serve as a barrier for mobility.
Signalling (Spence, 1973) & Screening (Stiglitz, 1975)	Credentials or other indicators of work abilities	Individuals characteristics	Selling labour as a commodity in the market, under the framework of neo-classical economics	Subject to the supply and demand conditions of the market, highly productive labourers earn higher rewards. Credentials or other information serve to signal potential work capacities	Change in productivity leads to rewards change. Use credentials or other information to discern or signal the change in productivity related work capacities.
Functionalists' status attainment approach (e.g., Davies and Moore, 1945; Blau and Duncan, 1967; Treiman, 1970)	Productivity related skills	Individuals characteristics	Role-duty performance and achievement based (rather than ascription based) rewards, for the functioning of existing social order of industrial societies	It is just to stratify positions, based on positions' functional importance and the scarcity of available personnel in the society.	Achievement and position attainment; Meritocracy-based modernity
Human capital theory (e.g., Schultz, 1961; Becker, 1993)	Productivity related skills	Individuals characteristics	Selling labour as a commodity in the market, under the framework of neo-classical economics	Subject to the supply and demand conditions of the market, highly productive labour earns higher rewards	Change in productivity leads to rewards change
Classical Marxism (e.g., Marx and Engels, 1993; Marx, 2013)	Productivity related skills	Social relation	Selling labour power in exchange for earnings and the exploitation of surplus labour values	Different exchange value of labour power, depends on the socially necessary labour time for the production and reproduction	The change of exploitative relation
Scarce skills account (e.g., Wright, 1979; 1985; 1997)	Productivity related skills	Social relation	Selling labour power in exchange for earnings, and the exploitation of surplus labour values	The scarcity of skills enable labourers to have a better control over their labour	The change of exploitative relation

Based on the functionalists' approach, one could argue that learning activities with the use of the internet could enable individuals to gain skills and abilities that are required for prestigious work positions. For the maintenance of the right social order and the efficiency of the system, individuals with acquired skills should be assigned to the positions with better rewards. The functionalists' approach has one distinctive merit: it articulates the historical difference in position/status-attainment between the pre-industrial and industrial societies (i.e., more achievement/merit-based attainment rather than ascription) (e.g., Blau and Duncan, 1967; Treiman, 1970).

Nevertheless, a fundamental flaw in their interpretation of social order leaves the functionalists' theory unable to unveil the true nature of social stratification and mobility. For the functionalists, upward mobility is a progression from a less important position to a more important one for the functioning of a publicly-consenting social order. Social stratification works as a 'functional necessity' to reward more resources to more important positions to maintain a good social order (Davies and Moore, 1945). Functionalism sees existing norms and social orders as a product of value consensus whilst simultaneously failing to notice its coercive elements (Dahrendorf, 1959). The maintenance of the existing social order is also affiliated with the dominant groups' interests, in order to maintain their own advantages (Ibid.). At the same time, functionalistic rhetoric like 'value-consensus' and 'functional necessity' conceal the coercive nature of the social world and provide a misleading interpretation on the nature of social mobility.

For those who apply the human capital theory, UIL might be broadly related to the development of individuals' skills and knowledge that can boost productivity. Those who have UIL activities and who have accumulated more 'human capital' might yield a profit of getting a work position with better earnings and rewards. The human capital theory simply treats wage workers as a kind of 'free trader', who sells labour as a commodity according to the market labour price. For this 'free and fair-trading logic,' Marx's (2013, pp.105-112) chapter, *Contradictions in the general formula of capital* in his *Das Kapital* already provided an insightful critique. Imagine all traders are within the same market in a simple M(Money) -C (Commodity) -M' (Money afterwards) circulation. If the commodity 'labour' has been sold for a market price, how can an employer get any extra profit, as M' cannot be larger than M (i.e., no surplus value) (Ibid.)? In Marx's labour theory of value, the exploitative relationship forms the basis of employment, of which we have already had an extensive discussion. Even John Goldthorpe who rejects a Marxian *a priori* concept of exploitation (e.g., Goldthorpe and Marshall, 1992), also criticises human capital theory's mis-conceptualisation of wage labour as selling every unit of labour as a commodity for remuneration (Goldthorpe, 2014). In the real world, he said, workers are offered an employment contract, they take on a job, and then they accept the authority of the employer(s), performing all kinds and amounts of work-tasks as laid out by their employer(s) (Ibid.). Both Marxian scholars and John Goldthorpe make a clear distinction between wage workers and those who work in the occupations of selling their labour more freely (e.g., the petty bourgeoisie in the Marxian approach; the self-employed workers in Goldthorpe's occupation classification).

Laid side by side, the Marxian approach offers a more critical insight into the learning-mobility relationship. The distinctive merit is its focus on real social relations of production and allocation of social resources as the primary unit of analysis. Both functionalism and the human capital theory explain the success of upward mobility as that person's individual merit or achievement for productivity which enables them to attain a position acquiring more rewards. The image of 'climbing a social ladder' is often used to depict the scene of social mobility in a stratified world (Littler, 2017, p.2). However, Wright (1997, p. 26) criticised that the 'individuals' positions changing' metaphor could be misleading, since it discourages us from reflecting on the socially constructed nature of production and reproduction of a stratified social world, as well as the so-called objective standard of 'merit'. In Wright's

(1997) view, mobility should be interpreted as a change of social relations regarding production and allocation of social resources. What workers can gain from learning activities are skills or labour power that matter for the productivity for the workplace, an important aspect that the human capital theory and functionalism also mention. But more importantly, labour power or skills can also be seen as a source of power from the worker's point of view, a bargaining chip which a worker can use to negotiate a better economic remuneration within an exploitative production relation. This point goes unnoticed in both human capital theory and functionalism.

Both Marx and Wright are committed to the relational approach and have provided their accounts on skill-related occupation stratification (the labour power account and scarce skills account). However, in comparison, Wright's scarce skills account might be more useful for two main reasons. First, Wright's scarce skills account has clearly articulated the contradictory situation of skilled workers (i.e., they have better control over their labour compared to unskilled workers but are still subjected to some degree of exploitation within an employment relationship). In comparison, the main purpose of Marx's concept of labour power was developed to complete his labour theory of value, however it fails to provide a detailed explanation of the special situation of skilled workers. Second, Marx's labour theory of value is more useful in an ideal-typical context characterised by a capitalist mode of production, where the value created by the labourers is extracted by the owners of the means of production. In comparison, Wright's explanation (1984) can be applied to diverse types of exploitative employment relationship in different types of workplaces based on the control of different kinds of important resources (e.g., means of production, organisational assets, political power).

Thus, given the relative insightfulness, relevance, and usefulness, this study adopts Wright's scarce skills account to form the basis of the theoretical framework to articulate the UIL- mobility relationship, as will be shown in the following section *5.3. Temporarily scarce skills theory*.

5.3. Temporarily scarce skills theory

This work proposes the temporarily scarce skills theory as a means to explain the 'UIL-mobility' relationship in the contemporary labour market. As indicated by the name, this theory mainly aims to contribute to Wright's scarce skills account by introducing and emphasizing the temporality of the scarcity of skills[17], which should be seen as crucial in an age when information resources online for learning are abundant. If scarce skills matter for one's occupational attainment, then the study of mobility, which concerns the temporal character of one's occupational location, should also pay attention to the temporality of the scarcity of skills. It might sound common-sensical that the scarcity of certain skills varies temporally and spatially, but the pattern of the change of skills' scarcity might have something to do with the way that human beings produce and share knowledge in the internet age of contemporary society.

5.3.1. A tension

According to Wright's (1997, pp. 18-19) scarce skills account, within an exploitative employment relationship, the possession of scarce skills enables some employees to enjoy a 'privilege' with a relatively smaller degree of exploitation when selling their labour power. Wright attributes the emergence of this 'privileged appropriation location' to the mechanism of the scarcity of skills in the labour markets (caused by the limited accessibility to learning and educational resources) (Ibid.). In Wright's own words, the maintenance of obstacles to knowledge acquisition, which contributes to the scarcity of skills in the market, plays an important role in the privileged position

[17] In Wright's (1997, pp.19-20) *Class Counts*, he frequently used the couplet 'skills and expertise' to denote work capability as he worried that sometimes people use 'skill' only to refer to manual skills rather than some general idea of enhanced or complex labour power. Although inspired by Wright's scarce skills account, this study, in order to keep the language clear and simple, only uses the word 'skill' to denote all kinds of work capability.

maintenance for those scarce skills holders. However, when articulating the cause of the scarcity of skills, Wright (1997, pp. 18) only mentioned the obstacles to credential-oriented formal education opportunities. Currently, the internet is widely accessed and available, and information resources are abundant online. To some degree, the lack of access to learning resources, which is said to contribute to the scarce status of skills, is being challenged. Wright (1997) himself did not extensively discuss the temporality of the scarcity of skills, only giving a comment saying that skills are 'vulnerable to obsolescence' (p. 19). Despite the lack of specific discussion on this topic, Wright's scarce skills account can still be further developed to gain insight into the temporality of the scarcity of skills.

5.3.2. The risk of skill depreciation and the temporality of scarcity

Acquired skills might constantly face the risk of depreciation, which is at least partly related to changes in demand and supply of skills in the labour market.

Firstly, acquired skills can become obsolete or less in demand. For example, the demand for skills to use Adobe Flash, which used to be a mainstream tool to create digital interactive features, is fading (Tripp, 2020), which might be related to the production and appreciation of new productivity-related knowledge. When new productivity-related knowledge emerges and is shared and also appreciated by employers in a society, the skill demand in the labour market can change. Some new productivity-related knowledge, and the related skills, might be seen as better able to increase productivity and/or efficiency during production. Thus, new demand is created for those new skills in the labour market whilst the pre-existing skills become less valued. Consequently, the status of the scarcity of the pre-existing skills may be threatened. In this sense, the production of new productivity-related knowledge increases the risk of existing skills' depreciation.

More importantly, in addition to production, skill depreciation is also related to the sharing of knowledge, especially when the use of the internet has become so popular and widespread. As Fuchs (2010) highlighted, 'knowledge only needs to be produced once' (p.190). And once a kind of knowledge is produced and disseminated without being hoarded exclusively, the whole of society can share the idea without constantly reproducing it, since ideas are non-rivalrous and cannot be used up. In addition, information resources can easily be reproduced and disseminated in the internet age. Traditional ways of acquiring knowledge, such as paper books, opportunities for formal education, and on-the-job training are no longer the only sources in the digital age. Abundant information resources online become a new alternative means for learning, thus challenging the (previous) lack of access to knowledge. However, that also means that the scarce status of acquired skills, which had enabled some workers to enjoy an advantaged employment situation (e.g., better remuneration), is at risk. For the in-demand knowledge and skills, due to the increased accessibility to information resources online, more workers are hence engaged in learning certain kinds of knowledge and have successfully developed the relevant work skills. As a result, possessing those 'scarce' skills no longer make a worker distinctive. The supply of those once scarce skills is becoming more available and, as such, those acquired skills might now very well be gradually depreciated. Therefore, whilst inaccessibility to learning resources is being challenged by online sharing, the scarce status of certain skills and knowledge is also at risk.

Thus, it is better to assume that skills are only *temporarily scarce*, and they are constantly facing a possible risk of depreciation.

5.3.3. The labour of learning, skill development and occupational mobility

Thus, for those who are holding temporarily scarce skills, their privileged status in the labour market becomes less secure, since their work skills' scarce status might not be constant in the market. For them, learning activities, the labour to 'modify the human organism' (Marx, 2013, p. 116) in order to re-produce scarce work skills, are the means to protect their 'privileged status' in the labour market. Workers might have undertaken various ways to try to achieve the goal of scarce skills reproduction, and UIL is probably one of the convenient and popular means nowadays. It is in this way that UIL, the labour of learning with the assistance of the internet, is firstly related to the reduction of the risk of downward mobility at the personal level, although it might also be indirectly causing the risks of skill devaluation and non-learners' downward mobility at the societal level (i.e., workers competing to develop certain kinds of skills will lead to an abundance of those skills but then eventually a devaluation).

Nevertheless, UIL is also related to a higher chance of upward mobility, that is if the learning activities enable an outcome of developing new skills or advancing one's work skill level even *scarcer* than before. The abundant resources online do provide a new channel for those who did not possess temporarily scarce skills for learning and skill development. However, success in upward mobility, via learning and skill development, may require 'a race against time.' Workers need to successfully and constantly develop particular kinds of skills, before that skill has been devalued, in order to utilise the acquired skills as 'leverage' to achieve upward mobility.

5.3.4. 'Reskilling' as a new form of deskilling

In the end, the temporarily scarce skills theory can contribute to the labour process debate, especially to Braverman's *deskilling* claim in his *Labour and Monopoly Capital* (1998). Braverman argues that in order to maintain effective exploitation and domination within the labour process, workplaces tend to strengthen their control over the employed labour power. Thus, Braverman foresees a general trend of the removal of workers' skills and knowledge over the production process, so that they have less control over the production process and are thus more subject to workplace controls (Ibid.). His 'deskilling prediction' has faced empirical challenges as some empirical evidence shows no shrinking, but rather an expansion of educated non-manual workers (e.g., Wright, 1997, pp. 108-111). Here, the temporarily scarce skills theory offers another kind of 'deskilling' interpretation supporting the monopoly capital principle. Degradation does not require reducing workers to mindless production machines but can routinise mindful and cognitive labour. The motives and learning capacities of the workforce play a central role in the labour process nowadays (Livingstone and Sawchuk, 2004). When information resources are abundant online and the scarcity of skills is constantly being challenged, the possession of certain kinds of work skills and knowledge does not make workers look particularly skilful, even though they do have trained work capabilities. The dominant management theory has shifted the focus from the scientific management of workers' bodily movements to the well-designed organisation to motivate and enable workers' continual self-learning (Livingstone, 2004). As such, the expansion of non-manual skilled workers does not necessarily challenge Braverman's argument, and it is more important to look at the actual labour process.

5.4. Is UIL associated with mobility? The result of quantitative evidence

5.4.1. Analytical strategy

Quantitative evidence is used to provide a robust measurement of the overall association between UIL and occupational mobility in the contemporary urban labour market. As demonstrated in Chapter Four, a scale variable *occupational change score*, and two binary variables *downward mobility* and *upward mobility* were used to measure the degree and type of an individual's occupational mobility. Drawing on data from CFPS2010adult, CFPS2014adult, and CFPS2016adult, mixed-effects modelling was conducted with some additional measures to clarify the UIL-mobility relationship. The first measure was to lag the key explanatory variable *UIL* in the model (so UIL always happens before mobility), as a typical measure to overcome reverse causality. In reality, it might be common that occupational mobility conditions one's participation in UIL. Thus, the control of the reverse causality could make the correlation excluding elements like occupational mobility triggering one's participation in UIL. Furthermore, I added some known confounding variables into modelling, which could reduce the confounding bias to some degree.

Derived from the temporarily scarce skills theory, firstly, it is expected that there is an overall association between UIL and occupational mobility:

> ***H1.*** *Overall, UIL is associated with a higher occupational change score (H1a), a lower risk of downward mobility (H1b) and a higher chance of upward mobility (H1c).*

It is anticipated that one's formal educational background is associated with both a better career mobility outcome and the tendency of active UIL. Despite the confounding effect, the temporarily scarce skills theory predicts that the UIL-mobility association is a result of workers' constant production of scarce work skills, rather than simply reflecting well-educated workers' better prospect of career progression. So presumably, the UIL-mobility association will still exist after controlling for one's formal educational background. In addition, it is also expected that the UIL-mobility association will also exist independent of one's demographic characteristics and the industry and sector they worked in:

> ***H2.*** *After controlling for one's formal educational background, UIL is still associated with a higher occupational change score (H2a), a lower risk of downward mobility (H2b), and a higher chance of upward mobility (H2c).*

> ***H3.*** *After controlling for one's formal* educational background, *demographic characteristics (i.e.,* hukou *type, gender, age, and*

ethnicity), industry and sector, UIL is still associated with a higher occupational change score (H3a), a lower risk of downward mobility (H3b), and a higher chance of upward mobility (H3c).

In addition, in the context of 'skills vs. credential' debate (as discussed in 5.2.2), I also add the following hypothesis H4 to explore whether the 'UIL-mobility' association could be independent of gaining a higher-level qualification at the later wave. One can never have strong enough evidence to prove the pure effect of scarce work skills, but at least we can control for the confounding factor of the increase of one's educational level.

H4. *After controlling for one's formal educational background, demographic characteristics (i.e.,* hukou *type, gender, age, and ethnicity), industry, sector, and the likelihood of gaining a higher-level credential at the later wave, UIL is still associated with a higher occupational change score (H4a), a lower risk of downward mobility (H4b), and a higher chance of upward mobility (H4c).*

Furthermore, the temporarily scarce theory expects that a positive association between UIL and occupational mobility will exist across all kinds of wage workers from different employment-based occupational groups (i.e., self-employed not included). As such, H5 and H6 further predict that at the overall level and after adding controls, a positive association between UIL and occupational mobility exists across all the original occupational groups:

H5. *Across all the original occupational groups, UIL is associated with a higher occupational change score (H5a), a lower risk of downward mobility (H5b), and a higher chance of upward mobility (H5c).*

H6. *After adding all the controls, across all the original occupational groups, UIL is associated with a higher occupational change score (H6a), a lower risk of downward mobility (H6b), and a higher chance of upward mobility (H6c).*

Valid Sample

Using data from three waves and the lagged predictors design (UIL_{10} $\sim Mobility_{14}$; UIL_{14} $\sim Mobility_{16}$, will be discussed in the section *Statistical modelling*), there would be only two repeated observations (2010-2014; 2014-2016).

Table 5.2 summarises the process of valid sample selection for this part of the study. Similar to the sample selection in Chapter Four, the target population should be those who had a non-agricultural job and lived in urban areas at the earlier wave. Given that the temporarily scarce skills theory is only expected to be applicable to wage workers, the sample further excluded the self-employed. Firstly, I selected 4,618 eligible cases for the 2010-2014 period and 5,156 eligible cases for the 2014-2016 period. Among the eligible sample, the problem of item-missing was not too serious, so presumably listwise deletion will not create a very serious bias, even the missing might not be completely at random. However, the wave-missing rates were not very low (33% in 2014 and 19% in 2016). After dropping observations with item and wave missing and no activities in the labour market in the later wave, the final valid observations were 5, 466 from 3, 992 individuals. Given the large sample size, statistical power still remains. However, we should be aware of the possible bias created by the wave-missing.[18]

[18] Comparison of the sample characteristics is presented in Appendix D.

Table 5.2. The process of valid sample selection

		2010 to 2014	2014 to 2016
Step One: Eligible Cases Selection	1. Total Nationally Representative Sample From Wave a (within the 'a to b' period)	33, 600	34, 731
	2. Eligible Sample Selection: urban-living, employed as non-agricultural worker, and not self-employed at wave a	4, 618	5, 156
Step Two: Dropped cases with item missing at wave a	UIL	2 item missing	1080 item missing, imputed 699 from UIL2010
	Education	0 item missing	58 item missing
	hukou type	4 item missing	47 item missing
	Age	0 item missing	0 item missing
	Gender	0 item missing	0 item missing
	Ethnicity	10 item missing	65 item missing
	Industry	87 item missing	0 item missing
	Sector	42 item missing	92 item missing
	Remained N	4,480 (dropped 2.99% item missing)	4,657 (dropped 9.78% item missing)
Step Three: Attrition, and item missing at wave *b*	1. Remain at wave b	3,002 (1056 wave non-response; 422 no individual questionnaire; 67% remained)	3,789 (489 wave non-response; 379 no individual questionnaire; 81.36% remained)
	Dropped education missing at wave b	3,002 (no item missing)	3,763 (item missing=26)
	2. Employment status at wave b	2, 517 (34 unemployed; 407 out of labour market; 44 item missing, 1.74%)	3, 220 (56 unemployed; 417 out of labour market; 96 item missing, 2.98%)
	3.Among the employed, valid information about occupation at wave b	2,279 (238 item missing, 9.65%)	3, 198 (31 item missing, 0.97%)
	Valid N of observations	2, 279	3, 187
	Valid N of individuals	3, 992	

Key variables

Response variables This study used a scale variable *occupational change score* (positive values denote upward mobility, negative values denote downward mobility, and the absolute values measure the magnitude of mobility) and two binary responses *downward mobility* and *upward mobility* to measure occupational mobility, based on the EGP class scheme. Both of these were introduced in Chapter Four.

Explanatory variables To measure individuals' level of activeness in UIL, a variable *UIL* (Use the internet for learning? 1= No internet use, 2= Use internet but no active UIL, 3=Somewhat active UIL, 4=Active UIL) was created from recoding variables *ku301* (to what degree is learning an important part of your internet usage in last month, from 1 very unimportant to 5 very important) and *ku2* (the use of the internet? 1=Yes). Whilst CFPS2010adult does not contain a variable directly measuring an individual's time spent or other aspects of the actual activities of UIL specifically for work purposes, a combined usage of those two variables (i.e., *ku301* and *ku2*) could still indicate the variation of activeness in UIL to some extent. And as they are working individuals, presumably cases' activities of UIL are closely linked to their work. Therefore, I created a proxy variable *UIL* with 4 categories: 1= No internet use (indicated by variable internet adoption *ku2=0*, therefore implicates absolute no UIL at all), 2= Use the internet but not active UIL (those rated 1 or 2 for *ku301*), 3 = Use the internet with somewhat active UIL (those rated 3 for *ku301*) and 4=Active UIL (those rated 4 or 5 for *ku301*). Although it is not an ideal measurement, *UIL* is still useful in distinguishing the ordinal difference in UIL activeness.

In addition, I have also included *educational background*, *higher-level credential* (a higher -level credential compared to the previous wave), some demographic variables (hukou *type*, *age*, *gender*, *ethnicity*), also *industry* and *sector* (whether state sector or not) as control variables.

Statistical modelling

After showing the weighted descriptive statistics, mixed-effects linear (see (5.1)) and binary logistic regression (see (5.2) and (5.3)) models were constructed:

For the scale response:

$$\textit{Overall Mobility}_{it} = a + b^{*}\textit{UIL}_{it-1} + \ldots + \textit{year} + u_i + e_{it} \tag{5.1}$$

For the categorical responses:

$$\mathrm{Log}(\mathrm{P}(\textit{Up})_{it}/1-\mathrm{P}(\textit{Up})_{it}) = a + b^{*}\textit{UIL}_{it-1} + \ldots + \textit{year} + u_i + e_{it} \tag{5.2}$$

$$\mathrm{Log}(\mathrm{P}(\textit{Down})_{it}/1-\mathrm{P}(\textit{Down})_{it}) = a + b^{*}\textit{UIL}_{it-1} + \ldots + \textit{year} + u_i + e_{it} \tag{5.3}$$

Both models include a subject-specific random intercept (u_i) and a lagged explanatory variable $\textit{UIL}_{i\ t-1}$. The inclusion of a lagged explanatory variable is a common practice for studying the effect of training or education on career progression or intragenerational mobilities (e.g., Melero, 2004; Bukodi, 2017), as it can control for the reverse causality (i.e., mobility leads to more active UIL).

There were six steps of modelling. To test H1, the first model (Model 1: UIL) only includes *year*, *last wave UIL* and *last wave occupation* as the predictors to investigate the overall association between UIL and mobility. Based on Model 1, the second model (Model 2: UIL+ Edu) adds one's educational background, in order to test H2. To test H3, the third model (Model 3: Full) includes all demographic variables (hukou, *age*, *age-squared*, *gender*, *ethnicity*), and *industry* and *sector*. Based on the third model, the fourth model (Model 4: Full+Edu change) adds variable *higher-level credential*, which could be used to test H4. Model 5 (UIL x Occupation) includes a UIL (t-1) x

Occupation (t-1) interaction term and *year* to explore whether the overall UIL-mobility associations vary across different original occupations. Based on Model 5, Model 6 (UIL x Occupation + Controls) further adds all other controlled variables (*educational background*, *age*, *age-squared*, *gender*, *ethnicity*, *industry*, *sector*, and *higher-level credential*). Models 1 to 4 report regression coefficients. For the ease of interpreting interaction effect, Model 5 and 6 report the predicted means and probabilities (average marginal effects) by showing plotted figures.

5.4.2. Descriptive statistics

Firstly, descriptive statistics of the three response variables (*occupational change score*, *upward mobility*, and *downward mobility*) are summarised in Table 5.3. In addition, Figure 5.1 plotted two histograms of the response *occupational change score* (the scale indicator of occupational mobility), grouped by year. Longitudinal weight was applied. The results are similar to what was shown in Chapter Four.

From Table 3, we can tell that the means of *occupational change score* (a positive number indicates upward mobility) was -0.143 (S.D.=1.286) over 2010-2014, then increased to -0.007 (SD=1.190) over 2014-2016. That means on average that the vast majority tended to stay in their original positions, but downward mobility seemed to be slightly more likely to happen than upward mobility. More vertical occupational changes occurred between 2010 and 2014 than within the period of 2014-2016. Figure 5.1 shows that the distributions of *occupational change score* displace an approximately symmetrical distribution with a very small degree of left-skewness. Also, the distributions seemed to be leptokurtic as more than 50% of the cases did not have occupational mobility. The frequencies of +5 were zero, as +5 only stands for the mobility from *agricultural occupation* to *higher managerial and professional* but the sample includes no case originally from *agricultural occupation*. As shown by Table 5.3, the upward mobility rates were 21.98% in 2010-2014 and 20.72% in 2014-2016. The downward mobility rates were

25.33% in 2010-2014 and 22.01% in 2014-2016.

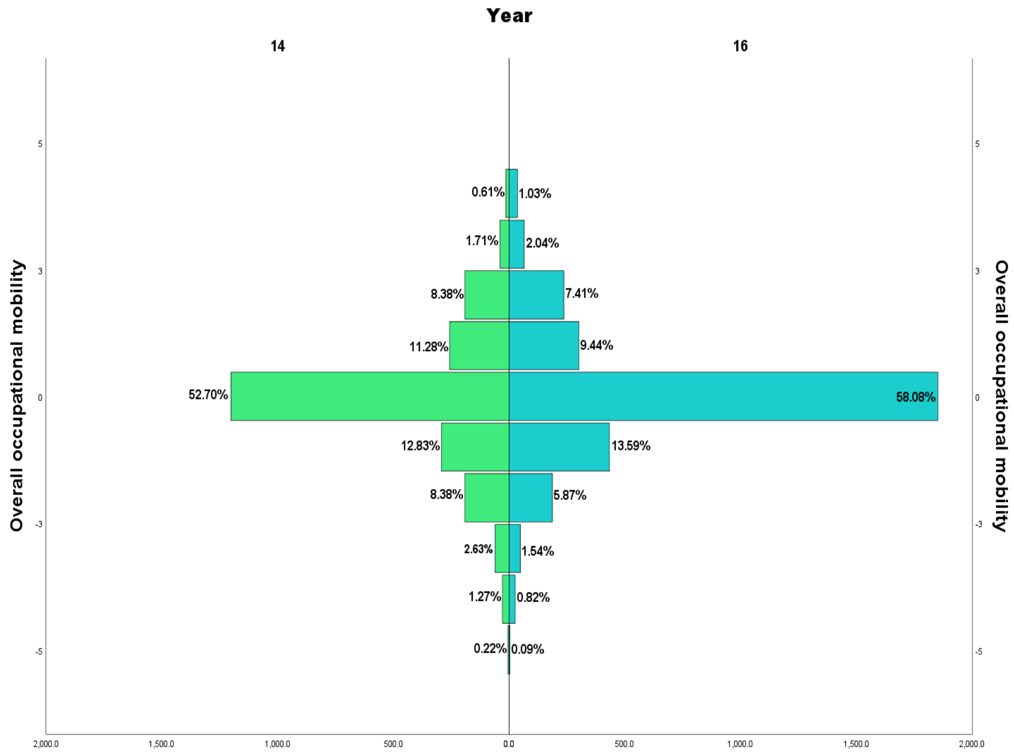

Figure 5.1 Back to back histograms on occupational change score (the scale indicator) by year, reporting frequencies and percentages. Source: CFPSadult2010, 2014, 2016

Table 5.3. Weighted descriptive statistics on response variables

	2010-2014	2014-2016
	Proportion/ Mean (S.D.)	
Occupational change score (The scale indicator)	-0.143 (1.286)	-0.007 (1.190)
Upward mobility rate (Binary)	0.2198	0.2072
Downward mobility rate (Binary)	0.2533	0.2201
N observations	2, 279	3, 187

Next, the descriptive statistics for the explanatory variables are shown in Table 5.4. Longitudinal weight was also applied. Looking at our main predictor *UIL* $_{(t-1)}$, around 60% of the individuals reported no internet use at each wave, less than 10% with non-active UIL activities, slightly more than

10% with somewhat active UIL activities and around 18 to 20% with active activities in UIL. The figures for the internet non-users seem to be higher than the estimation from the China Internet Network Information Center (CNNIC). According to CNNIC's survey report (CNNIC, 2018), the national internet adoption rates were 34.3% in 2010, and 47.9% in 2014. CNNIC estimated that the urban internet adoption rates were around 53.5% in 2010 and 62% in 2014 (CNNIC, 2018; 2013). Given that our samples were employed urban-living individuals, the estimated internet adoption rates were not supposed to be lower than the overall urban internet adoption rates estimated by CNNIC. So far, the cause of this discrepancy remains unknown[19], and we should be alerted to the potential inaccuracies of the internet adoption rate statistics from both sources.

Compared to the 2010-2014 sample, the 2014-2016 sample had fewer higher managerial and professional background cases but more cases whose original jobs were semi-unskilled manual. Also, the 2014-2016 sample had less well-educated, non-agricultural *hukou* type and state sector working cases. In other words, the 2014-2016 sample had less socio-economically better-off cases than the previous round. In addition, the mean difference in age between these two samples was smaller than 4, indicating the loss of older cases in 2014-2016 sample.

In both samples, there were more cases started from manual workers than any other category, especially the semi-unskilled manual workers. The majority of cases finished high school or middle school (Medium). Only 2.5 % of cases gained a higher-level qualification between 2010 to 2014. Within 2014-2016, only 0.8% of cases gained a higher-level qualification. Both samples had

[19] That could be caused by different sampling frames CFPS and CNNIC used. CNNIC acquired its sampling frame from registered individuals' landline and mobile phone numbers, provided by telecommunication companies (CNNIC, 2019). CFPS' sampling frame is local household registration information (i.e., lists of registered households residing in local areas) (Xie and Hu, 2014). It could be the case that CNNIC oversampled internet users, because those without internet access might also be those without a registered individual phone number and/or being less able to finish telephone interviews.

slightly more URW, males, and non-state sector workers. The majority worked in manufacturing, construction, and transportation related industries.

Table 5.4. Weighted descriptive statistics on explanatory variables

		2010-2014	2014-2016
		Proportion/ Mean (S.D.)	
Occupation (t-1)	Higher managerial and professional	0.142	0.095
	Lower managerial and professional	0.184	0.141
	Routine non-manual	0.182	0.179
	Manual supervisor	0.028	0.026
	Skilled manual	0.188	0.198
	Semi-unskilled manual	0.276	0.361
UIL (t-1)	No internet use	0.623	0.593
	Not active	0.068	0.073
	Somewhat active	0.110	0.145
	Active	0.200	0.188
Educational background (t-1)	Low	0.165	0.241
	Medium	0.556	0.531
	High	0.280	0.229
Higher level credential	Yes	0.025	0.008
Age (t-1)		41.703 (9.87)	43.305 (10.83)
Hukou type	Agricultural	0.322	0.452
	Non-agricultural	0.678	0.548
Gender	Male	0.613	0.624
	Female	0.387	0.376
Han ethnic group	Yes	0.957	0.958
State sector (t-1)	Yes	0.486	0.360
Industry (t-1)	Agricultural, forestry, animal husbandry	0.001	0.007
	Energy and utility	0.062	0.079
	Manufacturing, construction, transportation, storage, postal and delivery	0.427	0.404
	Public sector, organization and admin	0.184	0.120
	Real estate, rental, commercial service and finance	0.031	0.079
	Residential service, hotel and catering	0.113	0.063
	Retail and wholesale	0.070	0.088
	Scientific research, education, culture, sport and recreation	0.107	0.077
	Others	0.006	0.084
N observations		2,279	3,187

5.4.3. Occupational change on average

Firstly, I present the findings on the association between *last wave UIL* and *occupational change score* (the scale indicator of mobility). Table 5.5 presents the coefficients for the results of the linear mixed models (from Model 1 to Model 4) on *occupational change score*. The results of Model 5 and 6 will be presented in Figure 5.2 and 5.3 by plotted predicted means.

Model 1 only includes *last wave UIL* as the main predictor, and with *year* and *last wave occupation* as the controls, so the model can be used to describe the overall association between *last wave UIL* and *occupational change score*. Although the R-squared measure suggests that roughly 20% of the variance can be explained by the model, I suppose this is not because *last wave UIL* has a very good explanatory power on mobility but *last wave occupation* was included as a control, as Blau and Duncan (1967) remind us that the best predictor of mobility must be the starting occupation. The reference group was the observations in 2014 of those who started in higher managerial and professional category in 2010 and had completely no internet usage at that time. The intercept was -1.747, indicating that on average those who did not have any internet usage had a 1.7 degree of downward movement (between lower managerial and professional and intermediate levels).

Table 5.5. Linear mixed models on occupational change score (reporting coefficients and standard errors)

	(1)	(2)	(3)	(4)
	Model 1 (UIL)	Model 2 (UIL+ Edu)	Model 3 (Full)	Model 4 (Full+ Edu change)
Last wave UIL (Ref: No internet use)				
Not active	0.331***	0.173**	0.137*	0.135*
	(0.059)	(0.058)	(0.059)	(0.059)
Somewhat active	0.496***	0.265***	0.216***	0.212***
	(0.047)	(0.048)	(0.050)	(0.050)
Active	0.550***	0.295***	0.241***	0.236***
	(0.043)	(0.044)	(0.046)	(0.046)
Formal educational background (Ref: Low)				
Medium		0.402***	0.347***	0.345***
		(0.047)	(0.049)	(0.049)
High		1.035***	0.876***	0.890***
		(0.061)	(0.065)	(0.066)
Higher level credential (Ref: No)				
Yes				0.276**
				(0.100)
Constant	-1.747***	-2.303***	-2.197***	-2.277***
	(0.053)	(0.066)	(0.219)	(0.221)
Controls	a	a	b	b
Observations	5,466	5,466	5,466	5,466
Individuals	3,992	3,992	3,992	3,992
R-squared	0.202	0.236	0.252	0.254

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
a: year, last wave occupation; b: year, last wave occupation, age, age-squared gender, *hukou*, ethnicity, last wave industry, last wave sector; Coefficients of controlled variables presented in Table F1; Source: CFPS adult 2010, 2014 and 2016

A major finding from Model 1 is that there was a positive and linear relationship between UIL and the subsequent occupational mobility, meaning diligent learners with the use of the internet typically had better subsequent outcomes in occupational attainment. Compared to those who did not have the internet use at the last time point, those non-active leaners were associated with a smaller degree of average downward movement (Not active= 0.331, $p< 0.001$), and the average degree of downward movement was even smaller for those somewhat active learners (Somewhat active = 0.496, $p< 0.001$) and active learners (Active=0.550, $p< 0.001$). When holding other factors constant, at least the differences (on occupational mobility) between no internet use and other categories of UIL were estimated to be statistically significant at the 99.9% level, although no information is given on the differences between any two groups of other categories of last wave UIL. Nevertheless, I think the result offers sufficient evidence about the general association between last wave UIL and occupational change. As such, *H1a has gained some support*. Based on the findings of Model 1, we can say that there was an overall association between workers' last wave UIL and a better outcome of subsequent occupational change.

Model 2 further included formal educational background as one of the control variables, with an aim to eliminate the confounding effect of one's previous formal educational background. The result of Model 2 shows that even after controlling for one's educational background, last wave UIL was still independently related to a better outcome in overall occupational mobility. The reference group was the 2014 results for the higher managerial and professional staff who did not finish middle school education (i.e., low-level category) and who did not have any internet usage. The average value of their occupational change scores was -2.303, which suggests a downward mobility trend. In comparison, when holding other variables constant, not active in UIL was related to the reduction of the degree of downward mobility (Not active= 0.173, $p< 0.01$). When being somewhat active (Somewhat active=0.265, $p< 0.01$) and active activities in UIL (Active= 0.295, $p< 0.001$), the occupational change scores were much higher (compared to no internet use), although the score of active learners in UIL was not predicted to be substantively higher than somewhat active learners. However, an overall linear relation between last wave UIL and mobility can still be seen. In addition, the differences between no internet use and other categories of UIL were also statistically significant, at least at the 99% level. Like last wave UIL, formal educational background also showed a positive and linear relationship with occupational mobility, and presumably, the effect is much stronger although standardized coefficients are not shown here. This is consistent with all the literature on a strong positive relationship between formal education and job attainment that we have discussed above. Compared to the low-level educational background, the mobility score of the medium level (i.e., finished middle school or high school) was 0.402 higher and the high level's (i.e., finished higher education) was 1.035 higher, with both pairs of differences become statistically significant at the 99.9% level. Comparing the coefficients of Model 1 and Model 2, it is quite likely that the variable *education background* has mediated some effect of *last wave UIL* in the second model. Nevertheless, the important message we have got from Model 2 is that even after controlling for workers' formal educational backgrounds, their last wave UIL still matters for their subsequent occupational mobility, with the most active learners still predicted to be 'the winner' of occupational change. Therefore, *H2a has gained some support*.

Next, building on Model 2, Model 3 adds more controlled variables that were possibly related to individuals' occupational mobility. These were demographic characteristics (*age*, *age-squared*, *gender*, *ethnicity*, and *hukou type*), *last wave sector* (state or non-state sector) and *industry*. Overall, even after controlling for other mobility-related factors, there was still a persistent UIL-mobility association and the pattern was very similar to Model 1's and Model 2's. The result of Model 3 shows that the estimated average occupational change score for the reference group (the observations in 2014 of those *Han* ethnic female RMWs who started from higher managerial and professional occupation in the state sector and in manufacturing-related industry, with no higher than primary school educational background and no internet use at the last wave) was -2.180, indicating an overall downward mobility trend for the reference group. In comparison, when holding other variables constant, the growth of the activeness of UIL was associated with a gradual increase of the occupational change score (Not active = 0.137, $p < 0.05$; Somewhat active =0.216, $p < 0.001$; Active= 0.241, $p < 0.001$), and the coefficients were statistically significant. Educational background still strongly affected one's future occupational mobility in a positive way. Therefore, regardless of educational background, the demographic characteristics, and the starting sector and industry, UIL was still estimated to affect workers' prospects on career mobility. In this sense, *H3a is also supported*.

Additionally, Model 3 also presents us with the following findings (see Table F1 in Appendix F): being young, female, and from a non-agricultural population is related to better career mobility prospects; the non-state sector background was slightly related to a better outcome in occupational mobility than in the state sector.

As it is often discussed, the internet greatly empowers self-directed informal learning which enables learners to acquire needed knowledge and skills flexibly but not related to extra credential gaining (e.g., Imel, 1999; Gray, 1999; 2004). Model 4 further explores the role of UIL in mobility, regardless of whether or not gaining extra credentials takes place. So, in addition to all the variables we have in Model 3, Model 4 added one more variable *higher-level credential* (whether the educational level at the later wave was higher than the last wave). Furthermore, the result can have some implication for the 'skills vs. credentials' debate on the effect of learning activities.

So, in Model 4, the reference group was the 2014 results for the female *Han* ethnic RMWs who were from higher managerial and professional categories in the state sector and manufacturing related industries, with no higher than primary school educational background, no internet use at the last wave, and no higher-level credentials gained at the new wave. The average value of their overall mobility was -2.313, suggesting a downward mobility trend. Whilst educational background still stays as a strong predictor of occupational mobility like in the previous models, the occupational mobility score for getting a higher-level qualification was 0.277 ($p < 0.001$), higher than no change in qualification. However, regardless of getting a higher-level qualification or not by the later wave, UIL was still significantly related to workers' subsequent occupational mobility (Not-active=0.135, $p < 0.05$; Somewhat active=0.212, $p < 0.001$; Active=0.236, $p < 0.001$). Therefore, to some degree, the result gives some support for the claim that the relationship between UIL and subsequent occupational mobility is more than just extra-credential gaining. Thus, *H4a has gained some evidence*.

Next, Model 5 includes an interaction term between original occupation and UIL at the last wave, with a controlled variable *year*. The purpose is to explore whether the overall UIL-mobility associations differ across all the original occupations. Instead of reporting the exact coefficients, for the ease of interpreting the interaction, predicted means grouped by last wave UIL and original occupation were plotted in Figure 5.2. From Figure 5.2, we can easily tell that nearly all the original occupational groups show a somewhat positive line on the relationship between UIL and occupational change score. In particular, the positive relationship between UIL and occupational mobility for semi-unskilled manual workers was salient. For those who worked as semi-unskilled manual jobs at the last wave, being active in UIL was estimated to have a significantly higher *occupational change score* than no internet use and not being active in UIL. For those who were from higher managerial and professional and skilled manual background, being somewhat active or active in UIL is related to a significantly higher *occupational change score* than those who did not use the internet at all. For lower managerial and professional background individuals, although a linear association between UIL and mobility is seen, there is only a significant difference in occupational change score between being active in UIL and no internet use at the last wave. For the routine non-manual background workers, it seems the differences reside in whether people used the internet or not rather than how active they were in UIL, as the line goes flat after having used the internet. For manual supervisor background individuals, the predicted means of occupational change scores went down at being active in UIL after a rising trend from no internet use to being somewhat active in UIL. At the aggregated-level (i.e., the graph for overall), those who were active in UIL are estimated to have a significantly higher occupational change score than those who were not active in UIL or did not even use the internet. *H5a has gained some support*, as nearly all occupation groups show a somewhat linear and positive association between UIL and occupational mobility.

Next, based on Model 5, Model 6 adds all other variables as controls (i.e., *educational background*, *age*, *age-squared*, *gender*, *ethnicity, industry, sector*, and *higher-level credential*). Predicted means of occupational change scores were plotted in Figure 5.3, grouped by original occupation. Compared to Figure 5.2, it is obvious that after adding the controls, all the lines have become flatter, meaning a weaker UIL-mobility association for each original occupational group. For those who were originally semi-unskilled manual workers, the occupational change score still rises considerably with the activeness in UIL. However, for other groups, the lines are quite flat. *Thus, the evidence for H6a is very weak*.

To summarise, except for H6a, H1a to H5a have gained some evidence. The evidence suggests that workers' activeness in UIL is generally related to a better outcome of occupational mobility. Even after considering workers' previous educational backgrounds, gaining a higher-level credential at the new wave and some other factors, the positive UIL-mobility association still persists at the aggregated-level. When breaking down into each starting occupation, whilst an overall association between UIL and mobility exists, the associations have become weaker after controlling for education-related, demographic, industrial, and sectoral factors, except for those who started from a semi-unskilled manual background.

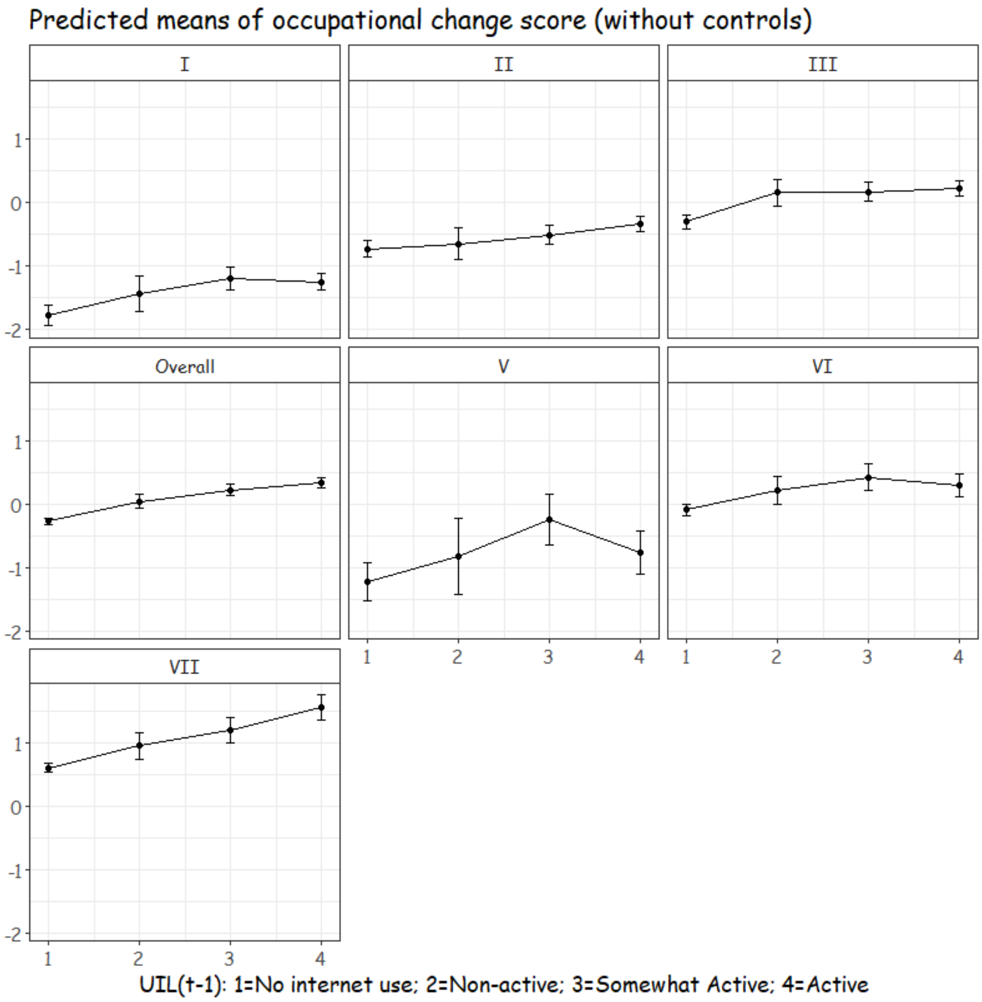

Figure 5.2. Average marginal effects of last wave UIL on occupational change score (the scale indicator) with 95% CI, estimation from Model 5, grouped by last wave occupation. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010,

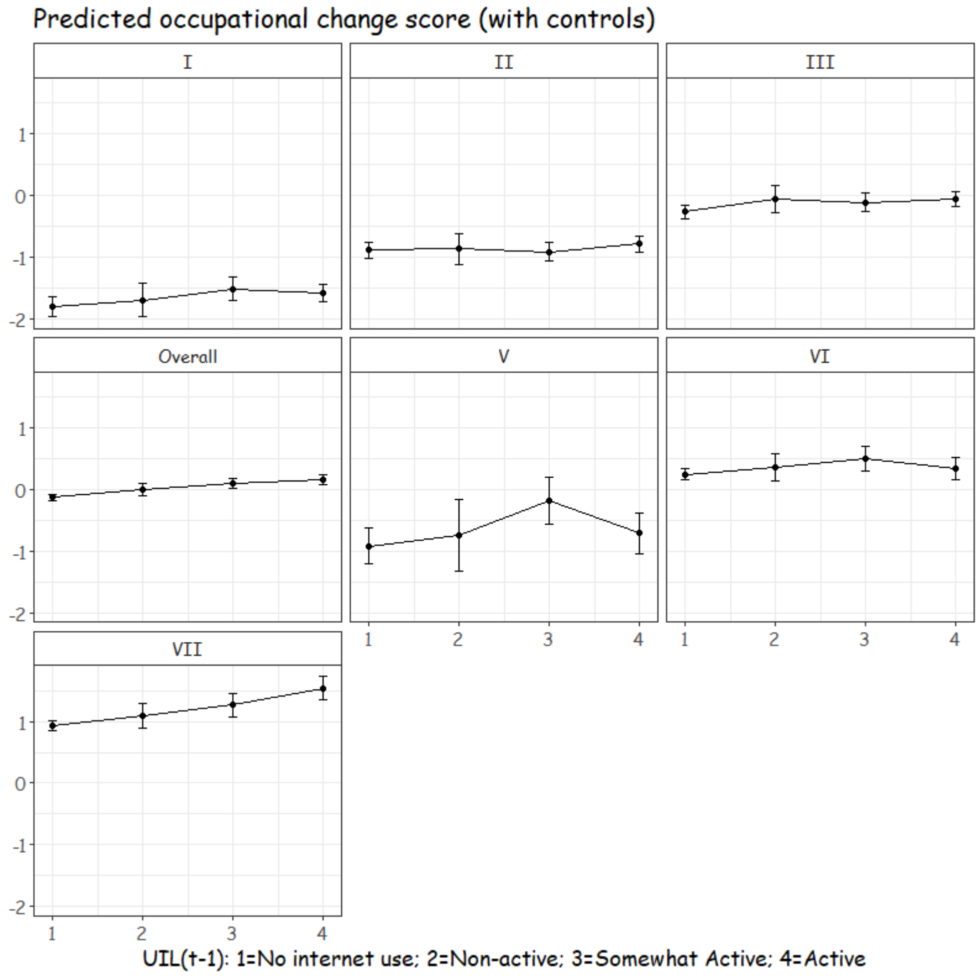

Figure 5.3. Average marginal effects of last wave UIL on occupational change score (the scale indicator) with 95% CI, estimation from Model 6, grouped by last wave occupation. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

5.4.4. The risk of downward mobility

According to the temporarily scarce skills theory, when information resources are abundant online, more and more people could access free information resources for learning. As a result, workers' developed skills might not be permanently scarce, and their original work positions might not be secure in the labour market. Workers will either have a higher risk of suffering downward mobility or will have to continually engage in learning activities to develop new temporarily scarce skills in order to fight against downgrading. Longitudinally, employers can raise the skills demand for the same positions if workers are more engaged in competition rather than collective rebellion.

Thus, in this section, I examine the role of UIL in offsetting downward mobility. As shown in Table 5.3, 25.33% of cases within 2010-2014 and 22.01% of cases within 2014-2016 experienced downward mobility. The analysis ran a mixed-effects binary logistic regression model with a binary variable *downward mobility* (1=Yes, 0=No) being used as the response. As usual, the first four models are summarised by a combined table (Table 5.6) which reports the model coefficients from Model 1 to Model 4. Model 5 and 6, which contain a '*last wave UIL* X *last wave occupation*' interaction terms, are presented by predicted probabilities in Figure 5.4 and 5.5.

Firstly, Model 1 only contains *last wave UIL* as the main predictor, as well as *last wave occupation* and *year* as controls. The estimated odds of suffering downward mobility for the reference (observations in 2014 of the higher managerial and professional staffs in 2010 who did not have internet use at that time) was 1.6, which indicates that they were more likely to suffer downward mobility than securing their original positions. Compared to no internet use, not being active in UIL was estimated to have a 33% lower odds of downward mobility ($OR_{\text{not active}}$ =0.672, $p < 0.01$). Additionally, being somewhat active and active in UIL were predicted to reduce 50% of the odds of downward mobility ($OR_{\text{somewhat active}}$ =0.465, $p < 0.001$; $OR_{\text{somewhat active}}$ =0.499, $p < 0.001$), although being active in UIL was not expected to reduce more odds than being somewhat active in UIL. All UIL coefficients were statistically significant. Thus, Model 1 shows us a general association between UIL and the risk of downward mobility, which gives some evidence to support H1b.

Table 5.6. Mixed-effects logistic regression models on downward mobility (odds ratios and standard errors)

	(1)	(2)	(3)	(4)
	Model 1 (UIL)	Model 2 (UIL+Edu)	Model 3 (Full)	Model 4 (Full+Edu change)
Last wave UIL (Ref: No internet use)				
Not active	0.672**	0.850	0.909	0.915
	(0.100)	(0.134)	(0.153)	(0.153)
Somewhat active	0.465***	0.672**	0.733*	0.736*
	(0.058)	(0.088)	(0.105)	(0.105)
Active	0.499***	0.758*	0.846	0.855
	(0.054)	(0.087)	(0.108)	(0.109)
Educational background (Ref: Low)				
Medium		0.445***	0.511***	0.514***
		(0.059)	(0.070)	(0.071)
High		0.152***	0.225***	0.219***
		(0.030)	(0.045)	(0.044)
Higher level credential (Ref: No)				
Yes				0.443*
				(0.145)
Constant	1.611***	5.279***	4.261***	7.597***
	(0.200)	(1.100)	(1.391)	(4.652)
Controls	a	a	b	b
Observations	5,466	5,466	5,466	5,466
Individuals	3,992	3,992	3,992	3,992
Wald Chi-square	228.5	210.1	204.4	205.2
df	9	11	24	25
Prob >chi2	0	0	0	0

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
a: year, last wave occupation; b: year, last wave occupation, age, age-squared gender, *hukou*, ethnicity, last wave industry, last wave sector; Coefficients of controlled variables presented in Table F2; Source: CFPS adult 2010, 2014 and 2016

Again, Model 2 adds formal educational background as one of the controls. The reference was the observations of the higher managerial and professional staff in 2010 with no higher than primary school educational background and no internet use at the last wave. For them, the risk of experiencing downward mobility was estimated to be very high, as indicated by a large odds of downward mobility (5.279). In comparison, having a better educational background, especially having finished higher education ($OR_{high} = 0.152$, $p < 0.001$), predicts a much lower risk of suffering downward mobility. In terms of UIL, compared to no internet use at the last time point, having somewhat active ($OR_{somewhat\ active} = 0.672$, $p < 0.01$) and active ($OR_{active} = 0.758$, $p < 0.05$) UIL activities were related to a 20% to 30% drop of the odds of downward mobility, whilst the model predicted no substantial difference between no internet use and non-active UIL. Therefore, from Model 2 we can tell that UIL was related to a lower risk of downward mobility, even after considering workers' educational background, although the evidence is not very strong. In this sense, *H2b has gained some weak support*.

Next, Model 3 adds more controls (*age*, *age-squared*, *gender*, *ethnicity*, *Hukou type*, *last wave sector* and *industry*) that were possibly related to workers' occupational mobility. For the reference group (the observations in 2014, female, *Han* ethnic RMWs, started in higher managerial and professional group in the state sector and manufacturing-related industry, with no higher than primary school educational background and no internet use at the last wave), it was four times more likely to suffer downward mobility than not having downward mobility, as indicated by the odds (4.261). Well-educated workers still had a lower risk of suffering downward mobility, as shown by the odds ratios ($OR_{medium} = 0.511$, $p < 0.001$; $OR_{high} = 0.225$, $p < 0.001$). In terms of UIL, the odds of downward mobility were predicted to be very similar between no internet use and not being active in UIL ($OR_{not\ active} = 0.909$, $p > 0.1$). But, compared to no internet use, being somewhat active in UIL was predicted to have a 26% lower odds of downward mobility ($OR_{active} = 0.733$, $p < 0.05$), and the coefficient was significant at the 95% level.

Thus, the result of Model 3 tells us that after considering some other factors that might be related to mobility, *there is still some weak evidence gained to support H3b* and showing that individuals' UIL was linked to a lower risk of downward mobility. Additionally, Model 3 also shows that RMWs and being male were related to a higher risk of downward mobility (see Table F2 in Appendix F).

Furthermore, Model 4 adds getting a higher-level credential as a control. When holding other variables constant, having a higher-level credential at the later wave is related to 55% lower the odds of downward mobility. But regardless of getting a higher-level qualification or not, being somewhat active in UIL was still related to a 26% drop on the odds of downward mobility. This indicates that if UIL really has an effect on reducing the risk of downward mobility, the effect is more than just the effect of a new credential as an outcome of UIL. However, the odds of downward mobility for being active in UIL is even higher than the odds of downward mobility for being somewhat active in UIL. *Thus, the evidence to support H4b is weak.*

Model 5 includes an interaction of *last wave UIL* and *last wave occupation*, with a variable *year* being the controlled. Figure 5.4 plots the predicted probabilities of downward mobility by different levels of UIL activeness at the last wave, grouped by original occupational group. At the aggregated-level (the overall graph), there is a generally negative association between downward mobility risks and UIL at the last wave. For those from higher managerial and professional backgrounds, a somewhat negative line could be seen. In particular, being active and somewhat active in UIL are predicted to have a significantly lower risk of experiencing downward mobility than not evening using the internet. However, the evidence is not strong enough to conclude that being active and somewhat active in UIL have a significantly lower risk of downward mobility than not being active in UIL, but at least with internet use. Among those who were originally routine non-manual workers, there is a significant difference in the downward mobility rate between internet users and non-users. However, among those who used the internet, the level of activeness in UIL does not seem to matter for routine non-manual and semi-unskilled manual backgrounds workers. All in all, *Figure 5.4 suggests that the evidence to support H5b is weak.*

Building on Model 5, Model 6 adds all other variables as controls. Figure 5.5 plots the predicted probabilities of downward mobility based on Model 6. Whilst the higher managerial and professional group was the only group showing a somewhat negative line on the relationship between UIL and downward mobility in Figure 5.4 (Model 5), Figure 5.6 shows that even for those from higher managerial and professional backgrounds, the association between UIL and downward mobility almost disappears, after adding controlled variables. For those who used to be semi-unskilled manual workers, a weak negative association between UIL and downward mobility can be seen. For other groups, there is almost no sign of a negative association between UIL and downward mobility. Therefore, *there is almost no evidence to support H6b*.

To sum up, the evidence shows that there is an overall negative association between UIL and risks of experiencing downward mobility at the aggregated-level. However, after controlling for formal educational background, getting a higher-level qualification and other related factors, the negative association between UIL and downward mobility becomes weak. When looking at each occupational group respectively and before adding other control variables, the negative association between UIL and risks of downward mobility is more salient among those who are from the higher managerial and professional background. After adding controls, for the managerial and professional background individuals, UIL does not seem to matter for downward mobility anymore. However, for semi-unskilled manual workers, a very weak negative association between UIL and downward mobility still exists, even after controlling for variables like education, demographic characteristics, sector, and industry.

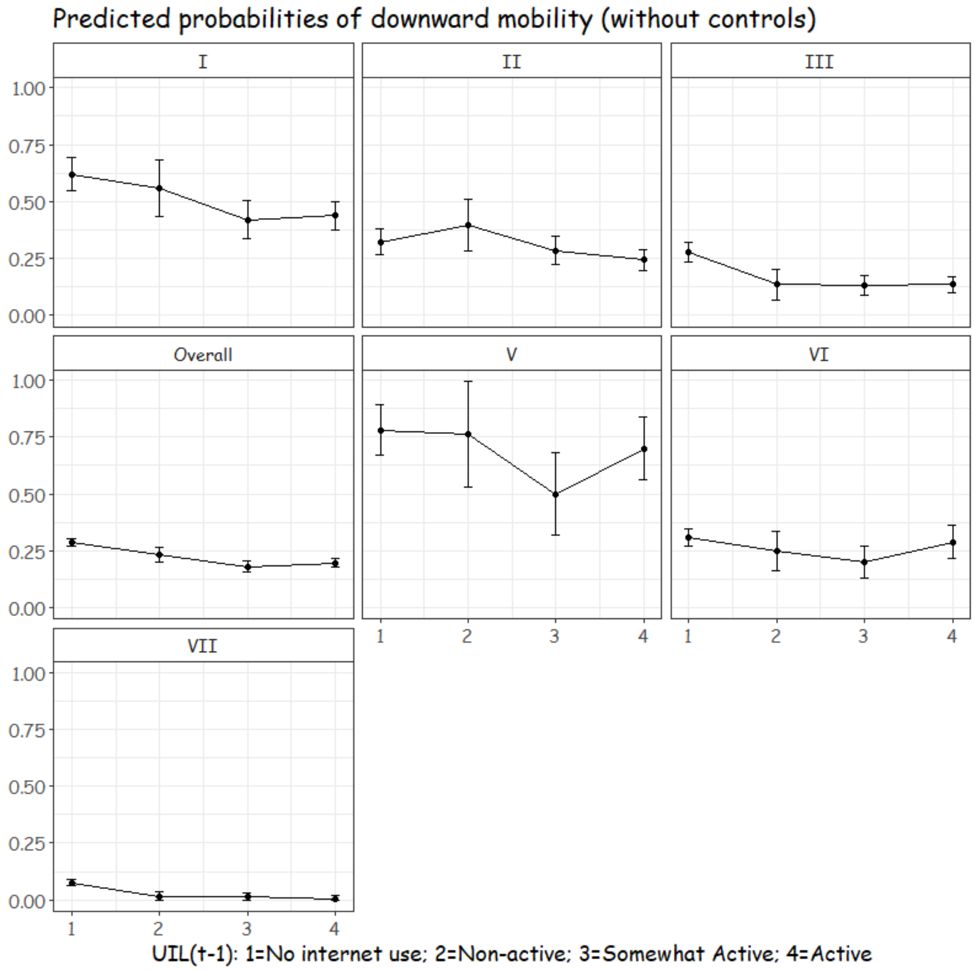

Figure 5.4. Average marginal effects of last wave UIL on downward mobility rate with 95% CIs from Model 5, grouped by last wave occupation. II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

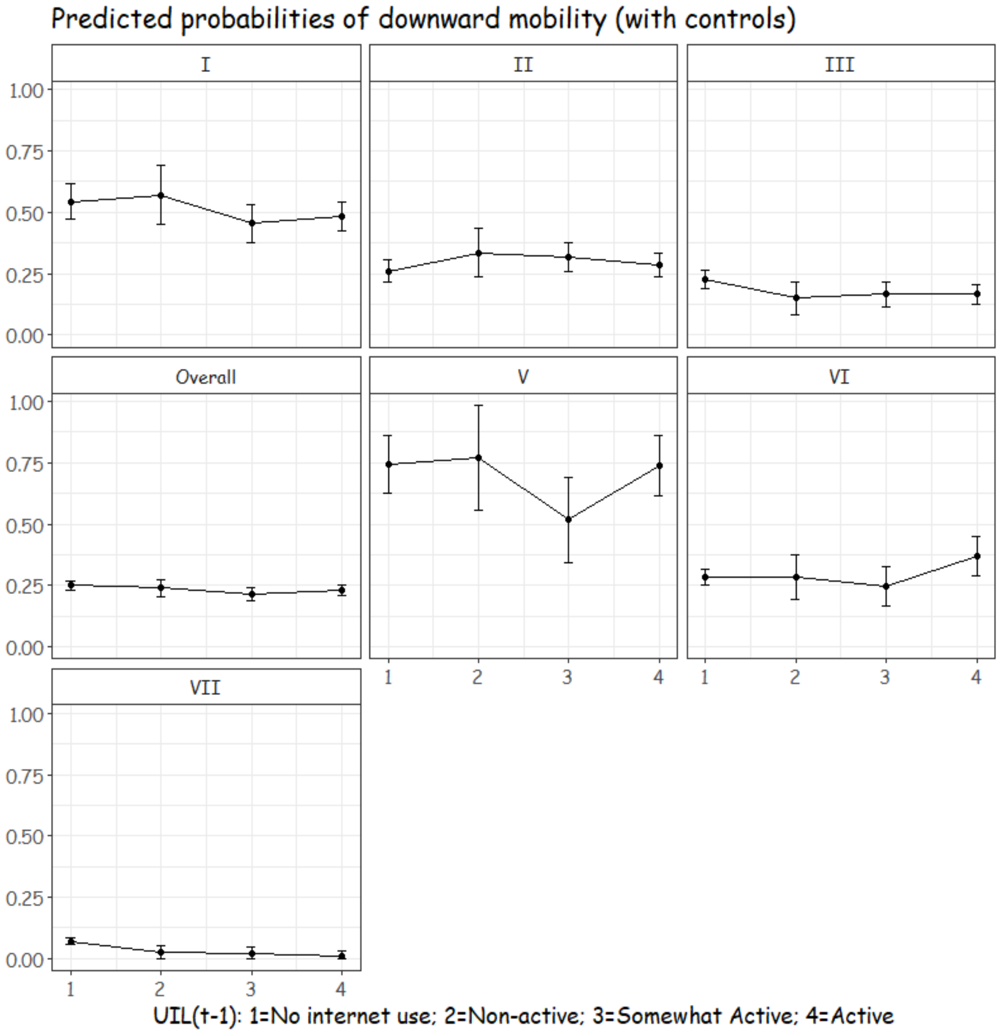

Figure 5.5. Average marginal effects of last wave UIL on downward mobility rate with 95% CIs from Model 6, grouped by last wave occupation. II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2010, 2014 and 2016

5.4.5. Prospect of upward mobility

This part of the analysis focuses on upward mobility. Table 5.3 shows that 21.98% of cases experienced upward mobility within 2010-2014 and 22.72% of cases experienced upward mobility within 2014-2016. The analysis ran mixed-effects binary logistic regression model with a binary variable *upward mobility* (1=Yes, 0=No) being used as the response. The sample did not contain the observations of those who started from higher professional and managerial groups, as it is meaningless to study the highest occupational class' upward mobility. Firstly, the results of mixed-effects logistic regression models on upward mobility rate (Model 1 to Model 4) are shown in Table 5.7. For Model 5 and 6 which contain a '*UIL* X *Occupation'* interaction term, I present the predicted probabilities instead (Figure 5.6 and 5.7).

Model 1 only includes *last wave UIL* as the main predictor, and with *year* and *last wave occupation* as the controls. The reference group was the 2014 result for the semi-unskilled manual background workers who had no internet use at that time. For them, the odds of having upward mobility ($P_{upward}/1-P_{upward}$) was estimated to be 0.459, regardless of the magnitude of mobility, as indicated by the constant term. The odds show a high rate of experiencing upward mobility (nearly one third, $P_{upward}=0.459/1+0.459$), but this is mainly due to the fact that the reference subjects (i.e., semi-unskilled manual workers) had been classified as the lowest level occupational group. When holding other variables constant, with growing activeness of UIL at the last time point, the odds of having upward mobility were even higher ($OR_{not\ active} = 1.537$, $p < 0.01$; $OR_{somewhat\ active} = 1.737$, $p < 0.001$; $OR_{active} = 2.204$, $p < 0.001$). And all levels of UIL have a significant difference (at the 99% level) compared to no internet use. Therefore, from Model 1 we can tell that there is a general relationship between the activeness of UIL and a higher chance of experiencing upward mobility. So, *H1c is supported.*

Table 5.7. Mixed-effects logistic regression models on upward mobility rate (odds ratios and standard errors)

		(1)	(2)	(3)	(4)
		Model 1 (UIL)	Model 2 (UIL+Edu)	Model 3 (Full)	Model 4 (Full+Edu change)
Last wave UIL (Ref: No internet use)					
	Not active	1.537**	1.285	1.198	1.199
		(0.223)	(0.197)	(0.182)	(0.182)
	Somewhat active	1.737***	1.350*	1.202	1.196
		(0.211)	(0.175)	(0.158)	(0.156)
	Active	2.204***	1.673***	1.515***	1.505***
		(0.254)	(0.204)	(0.187)	(0.185)
Formal educational background (Ref: Low)					
	Medium		1.630***	1.571***	1.565***
			(0.198)	(0.187)	(0.185)
	High		3.517***	3.185***	3.233***
			(0.633)	(0.566)	(0.574)
Higher level credential (Ref: No)					
	Yes				1.764* (0.448)
Constant		0.459***	0.320***	0.366***	0.315***
		(0.039)	(0.041)	(0.195)	(0.169)
Controls		a	a	b	b
Observations		4,799	4,799	4,799	4,799
Individuals		3,634	3,634	3,634	3,634
Wald Chi-square		119.9	126.7	152	154.8
df		8	10	23	24
Prob > chi2		0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

a: year, last wave occupation; b: year, last wave occupation, age, age-squared, gender, *hukou*, ethnicity, last wave industry, last wave sector; The sample excluded those started in higher managerial and professional group, as they were already the highest class; Coefficients of controlled variables presented in Table F3;

Source: CFPS adult 2010, 2014 and 2016

Model 2 further controls for the effect of formal educational background, with the purpose of examining the role of UIL on upward mobility rates independent from the effect of workers' educational background. The reference is the 2014 results for those who were from the semi-unskilled manual background in 2010, had no more than primary school educational background, and had no internet use at that time. The constant term shows that the odds of having upward mobility was estimated to be 0.320. Indeed, consistent with the literature discussed above, workers' educational backgrounds strongly impacted on their prospect of further career progression. Especially when compared to those with low-level educational background, those who had finished higher education were 3.5 times more likely to experience upward mobility. However, even after considering one's formal educational background, which might be a rough indication of their scarce skill levels in the beginning, further learning activities with the use of the internet still mattered. When the levels of educational background were similar, the difference between no internet use and not being active in UIL seems to be negligible. However, compared to no internet use, being somewhat active in UIL ($OR_{\text{somewhat active}}$ =1.35, $p < 0.05$) and being active in UIL (OR_{active} = 1.673, $p < 0.001$) had a noticeably higher chance to experience upward mobility. Afterwards, Model 2 shows us that having some active engagement in UIL did relate to a subsequently higher chance of experiencing upward mobility, even after controlling for formal educational background, a proxy of workers' initial scarce skills in the beginning. Thus, *H2c has gained some evidence*.

Again, Model 3 adds more controls (*age*, *age-squared*, *gender*, *ethnicity*, *hukou type*, *last wave sector* and *industry*) that are possibly related to workers' occupational mobility to further verify the role of UIL. So, in Model 3, the reference is the observations in 2014 of those female *Han* ethnic RMWs, who were semi-unskilled manual workers in the state sector and manufacturing-related industry, with no higher than primary school level educational background and no internet use at the last wave. For those observations, the odds of having upward mobility was estimated to be 0.66. In terms of UIL, the coefficients of non-active and somewhat active UIL are not significant, and the odds ratios (to no internet use) are also small. However, active UIL was estimated to increase the odds of having upward mobility by 50% as compared to no internet use, and the coefficient was significant at the 99.9% level. So, even after controlling for more factors that might be related to upward mobility prospects, active UIL is still found to be related to a higher chance of achieving upward mobility. Therefore, *H3c has gained some evidence*. Additionally, Model 3 also shows that workers from the non-state sector were more likely to experience upward mobility (see Table F3 in Appendix F).

Next, Model 4 further controls for the change of the level of credentials, which can give some implications for the nature of the role of learning activities. Whilst individuals' educational backgrounds were strongly relevant to their chances of getting upward mobility, compared to those who had no qualification level increase at the later wave, gaining a higher-level qualification led to 76% higher odds of achieving upward mobility. Yet, regardless of whether getting a higher-level credential or not, compared to no internet use, being active in UIL ($Or_{active} = 1.501$, $p < 0.001$) was still estimated to be related to a higher chance of having upward mobility, and the factor was statistically significant at the 99.9% level. Thus, the result of Model 4 tells us that if learning activities really help increase upward mobility chances, it is not just about getting a higher-level credential. As such, *H4c is supported*.

Next, Model 5 includes a term of interaction between *last wave UIL* and *last wave occupation*, with the variable *year* as a control. The results are presented by predicted probabilities in Figure 5.6. On average (i.e., the overall graph), the probability of upward mobility rises with the growth of activeness in UIL. Moreover, two steep growing lines can be seen for the skilled and semi-unskilled manual background workers, meaning a strong association between UIL and chances of upward mobility for those manual background individuals. For the routine non-manual background workers, not using the internet is associated with a lower chance of upward mobility. However, among the routine non-manual background workers who used the internet, the activeness in UIL is not related to a continual growth of chances of achieving upward mobility. *H5c is partially supported*, since the UIL-mobility associations seem to be strong for manual background workers, but there is no strong positive association between UIL and upward mobility found for other groups.

At last, building on Model 5, Model 6 adds all other variables as controls. After controlling for other factors, we can see that the average UIL-upward-mobility association has become weaker (i.e., the slope has become flatter in the overall graph). However, for manual background individuals (i.e., VI and VII), a line showing a positive association between UIL and upward mobility can still be observed, although the error bars often overlap. For the semi-unskilled manual background workers, being active in UIL is estimated to have significantly higher chances of achieving upward mobility than those who did not even use the internet. *As such, H6c is partially supported by some weak evidence.*

In summary, the evidence suggests that in general, workers' activeness in UIL is associated with a higher chance to achieve upward mobility, regardless of workers' previous educational backgrounds, new credential gaining and some other factors. Specifically, the data supports a clearly positive UIL-upward mobility association among manual workers, but not among those from non-manual occupation background. Apart from the reason of being affected by the error due to a small number of upward mobility observations among those who started from higher occupational classes, based on the temporarily scarce theory, there is another possible explanation. In the context of 'information post-scarcity,' for those white-collar workers, UIL to reproduce scarce work skills could be a part of their routine labour. Thus, simply participation in UIL, in general, does not easily make one more distinctive among white-collar workers. However, it is not very likely that UIL has become a daily work-task for manual workers. Thus, it could be the case that the manual workers who engage in UIL could easily be distinctive (in work skills and professional knowledge) among the manual worker populations. That might explain why a clearer UIL-upward mobility association is observed for the manual workers.

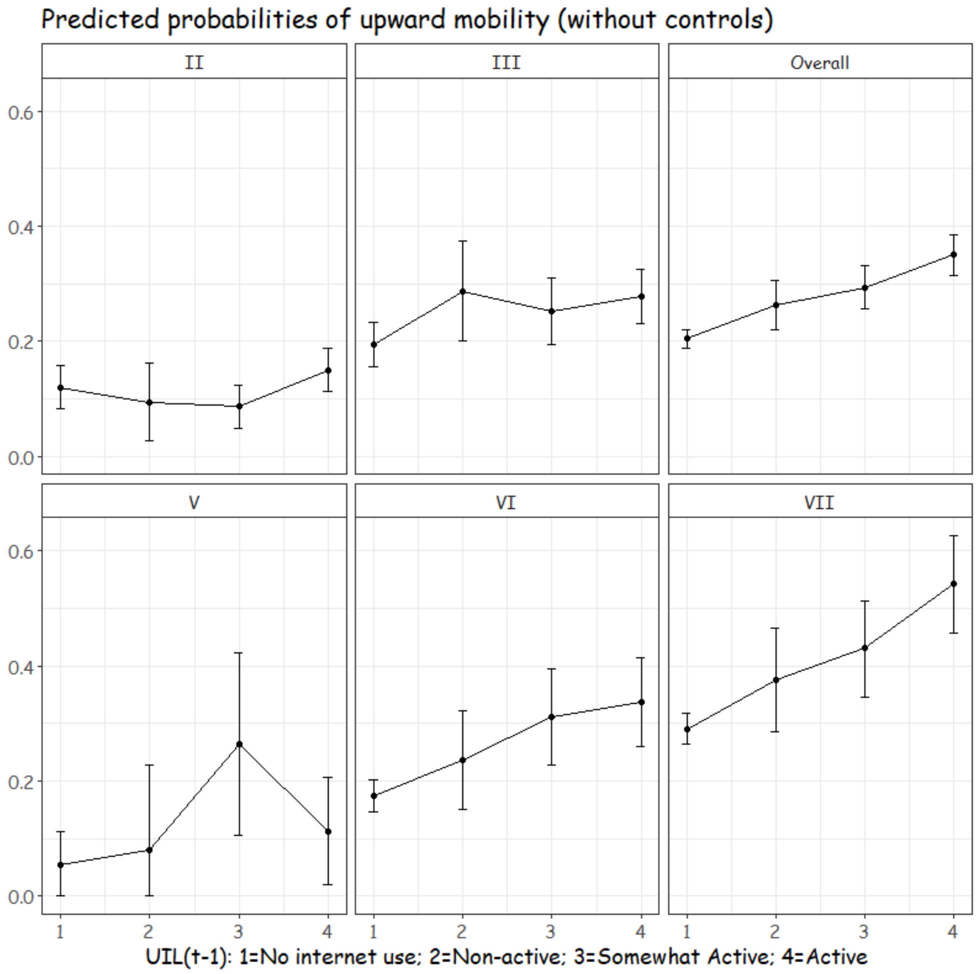

Figure 5.6. Average marginal effects of last wave UIL on upward mobility rate with 95% CIs from Model 5, grouped by last wave occupation. II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; CFPS adult 2010, 2014 and 2016

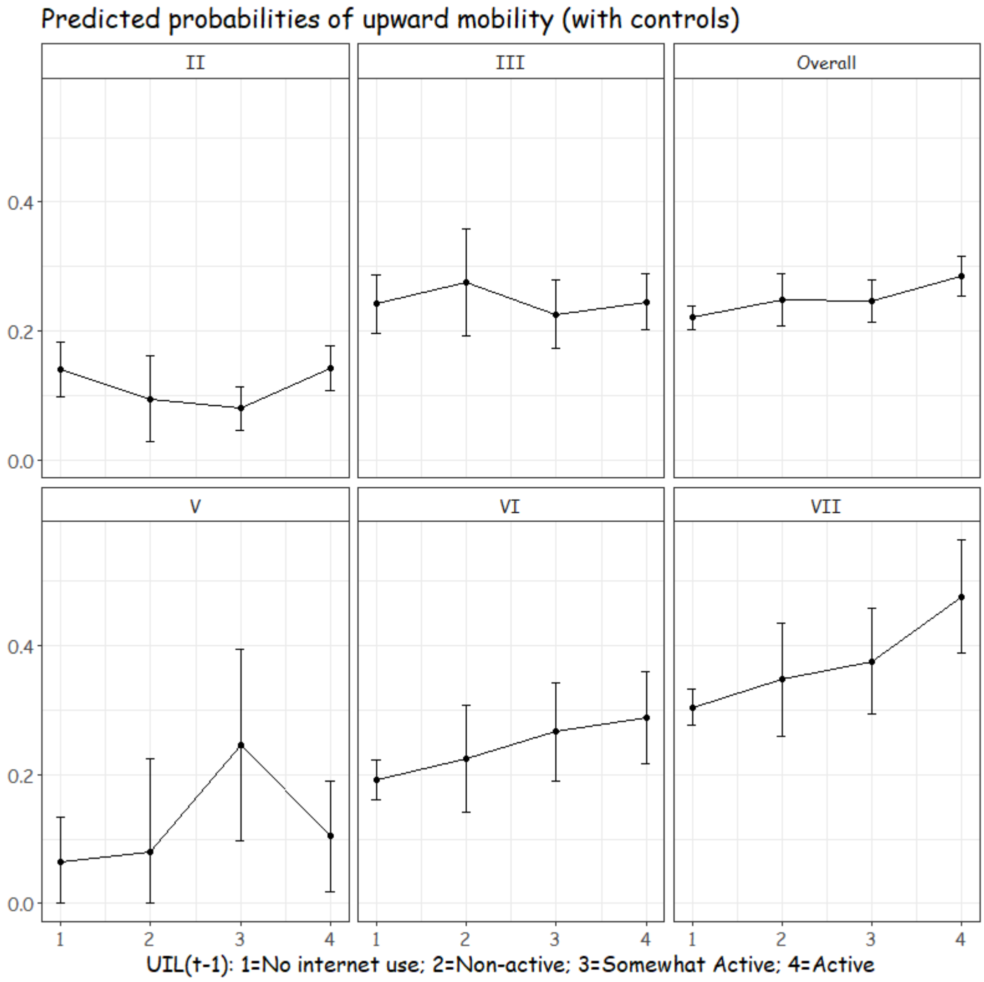

Figure 5.7. Average marginal effects of last wave UIL on upward mobility rate with 95% CIs from Model 6, grouped by last wave occupation. II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisors, VI=Skilled manual, VII=Semi-unskilled manual; CFPS adult 2010, 2014 and 2016

5.4.6. Summary

To sum up, the quantitative evidence has shown a general association between UIL and individuals' occupational mobility. In general, occupational change scores are associated with UIL at the aggregate level as well as across all occupational groups, although the associations have become weak after controlling for education-related factors, demographic factors, sector, and industry. The evidence for the link between UIL and downward mobility is very weak. The higher managerial and professional background individuals' downward mobility seems to be related to UIL. However, once controlling for the above-mentioned factors, the association has become weak. It could be the case that the maintenance of a managerial and professional role relies on other factors that are also related to participation in UIL (e.g., educational achievement, as will be shown in Chapter Seven). In terms of upward mobility, UIL seems to be more related to manual background workers' upward mobility. That might look counter-intuitive at first glance. However, it could be because that for manual workers, whose daily work tasks do not involve much learning and cognitive labour (especially the unskilled manual labourers), participation in UIL or other forms of learning can easily enable a person to be more distinctive in skills and professional knowledge among manual workers.

5.5. Making sense of the UIL-mobility link: the result of qualitative evidence

5.5.1. Analytical strategy

As introduced in Chapter Three, qualitative data from 24 semi-structured interviews is used to further scrutinise the explanatory power of the initially proposed preliminary theory (i.e., the temporarily scarce skills theory in this chapter) when attempting to make sense of the relationship between UIL and occupational mobility. To do that, participants' storytelling on their real-life labour market experiences are used to compare and question a typical storyline postulated from the temporarily scarce skills theory. Specifically, I chose to focus on the stories related to these two big themes: a) the prerequisites for mobility and b) the prerequisites for work skill development.

Firstly, regarding the prerequisites for mobility, the temporarily scarce skills theory argues that workers' occupational mobilities are due to a change in the scarcity of their work skills. Therefore, participants' stories of vertical occupational mobilities were used to compare this derived 'typical plot' from the temporarily scarce skills theory. To indicate vertical mobility, I let participants define whether they think the job position change could be seen as upward, horizontal or downward, according to the change of economic remuneration, the job title and the authority in workplaces. Compared to the EGP scheme used in quantitative analysis, participants' definitions discerned more 'micro-level' vertical mobility (e.g., a small promotion to be a team leader). After multiple rounds of iterative coding, the process identified four main domains of vertical mobility to discuss: *Downward mobility*, *The concern of downgrading*, *Internal upward mobility*, and *External upward mobility*. The analysis then looked at and compared how participants described the link between skill development and each type of mobility, and to explore other recurrent themes regarding the prerequisites of mobility.

Next, regarding the prerequisites for work skill development, the temporarily scarce skills theory argues that the production and reproduction of workers' scarce work skills comes from their labour of learning, and UIL has become one such effective learning practice. After reading through the texts multiple times and having been familiar with the participants' accounts, I found that it was helpful to group participants' learning activities by adopting Moore's (1989) interaction-based typology: *learner-instructor interaction*, *learner-learner interaction*, and *learner-content interaction*. After that, I elicited elements from participants' words on the effectiveness of each type of learning activities with the use of the internet, then to make a systematic comparison.

The analysis paid particular attention in discussing the inconsistencies in participants' accounts, and the discrepancies between participants' own storytelling and the typical 'learning-scarce skill - mobility' storyline derived from the temporarily scarce skills theory. The discussion then implicates some potential limitations of the temporarily scarce skills theory when making sense of the 'UIL-mobility' relationship.

5.5.2. The prerequisites for mobility

5.5.2.1. Downward mobility

Firstly, no participant attributed their actual downward mobility experience to any skill-related factor. Among all the participants, not one ever experienced downward mobility or losing their job within one workplace. All the downward mobility experiences were related to participants' *voluntary job-quitting* in former workplaces (N=5). Three participants explained that the downgrading was because of their failures to completely translate their previously appreciated skills into the new workplaces. R2, who once worked as a manual supervisor, claimed that he had no interest in continuing in a supervisor position in a manufacturing factory since he disliked the work-tasks of 'bossing people around.' As a result, he resigned and chose to work as an assembly line operator in a different workplace:

> '*I left that job [the supervisor position] a couple of months later […] I did not like that job because I did not like doing management or bossing people around. I do not mind undertaking a lot of hard work by myself, but I am not used to asking or even forcing other people to do their work. […] I quit my job and went to another factory to work as an operator again.'* (R2, Male, First job manual, 33)

Among all such discussions, the participants openly said that they left their previously advantaged work positions voluntarily. Thus, those episodes do not echo the temporarily scarce skills theory, but they also do not contradict the theory, since the theory does not aim to provide a mono-causal explanation about occupational mobility. Nevertheless, it reminds us of an important characteristic of downward mobility: unlike upward change, downward change should not always be seen as a misfortune. Individuals cannot choose to ‘go up’ by their free will, as they have to meet some objective criteria; however, individuals can choose to ‘move down’ by their own free will.

5.5.2.2. The concern of downgrading

Even though no participant had any incident of losing their advantaged work positions directly due to skill depreciation, there is a recurrent theme of *white-collar workers' concern* of job-loss or being downgraded with a link to skill and knowledge obsolescence, especially among those whose jobs were *professional roles*. The following excerpts exemplify this point:

> *‘In our industry [IT industry], things change very quickly. Just think, not long ago Nokia's Saipan system was a popular system, but now it is completely out of date and useless. Although things change very quickly, you could always be able to get access to the latest things online, keep updating your knowledge, you could still survive [....]'* (U1, Male, First job non-manual, 26)

> ‘*A lot of copywriters have been downgraded or lost their jobs in their late 30s. The job is a Qingchunfan (a profession for young people only) [...] older people will gradually be losing their abilities to generate innovative ideas when facing new demands in the market.*' (U5, Male, First job non-manual, 28)

> ‘*Also, later we had the "information explosion" with the popularity of the internet, not like in the past, we only read books and there were not that many books and newspapers to read. But when the information became more accessible, I felt that you were also forced to know more and update the latest knowledge. It was like whenever there is a new thing available online, you are supposed to know that because you are a*

financial officer […]. I think it has already become something essential for the profession […] something necessary for this job.' (R11, Female, First job non-manual, 38)

Nine non-manual occupation background participants perceived that the obsolescence of acquired skills is inevitable. Their perceptions on their acquired skills broadly echo ideas from the temporarily scarce skills theory that *knowledge and skills are only temporarily scarce* in a context where the demand for knowledge often refreshes whilst the learning resources are often available online. They clearly pointed out that the demand for skills changed swiftly within their own industries. And echoing the temporarily scarce skills theory, they had a similarly cautious estimation of the 'prices' of their acquired skills: the skills are somewhat valuable now, but only temporarily. For them, knowing the relevant information is often online, the constant labour of learning in order to update the latest in-demand knowledge and skills is seen as an effective measure to reduce any downgrading risk, which is consistent to the temporarily scarce skills theory.

However, there were some exceptions. For example, U9, who had been working in a state-owned textbook publisher, showed very little concern about the risk of downward mobility and job-loss. She held a belief that job-security is largely guaranteed by working in a state sector workplace (although our quantitative result does not support that, see Table F2 in Appendix F), as a legacy of the previous 'iron rice bowls' system,[20] even for the workers who were not active in updating their skills:

'*There are still some evaluations and you need to attend some training to upgrade yourself. However even though you did not upgrade yourself,*

[20] A system that ensures life-time job security, steady income and benefits, introduced after the establishment of the People's Republic of China in 1949 and cracked after the labour system reform. (e.g., see Leung, 1994, Fung, 2001)

they will not fire you. State-owned enterprises do not fire their staff very easily.' (U9, Female, First job non-manual, 30)

In addition, U4, who worked as a regional director in his family company, also mentioned that he was concerned about losing his privileged work position and he recognised the importance of updating professional skills and knowledge. However, it was not because he was worried about skill-depreciation in the workplace, but because without ensuring the work performance, and therefore the profitability of his family business, he did not feel his privileged position would be secure.

In contrast, among those who started from a manual background, none of them (0/10) showed any worry about their job security and skill obsolescence. Two relevant factors were brought up. First, all of them perceived the concern of skill-devaluation as irrelevant as the job required nearly 'zero skill.' Like the bracket name 'unskilled manual' suggests, participants who had worked in those positions said that those jobs '*require zero literacy or skill*' (R2, Male, First job manual, 33) and '*you just need to do what you have been told to do*' (R5, Male, First job manual, 27). From my perspective, it would be more appropriate to say that their current or previous jobs require very little *cultivated* work abilities (acquired from the labour of learning), but not like 'require no work skills at all' (i.e., the natural manual labour power should also be considered as a kind of work skill). In this sense, it is meaningless to discuss whether the cultivated skills will be obsolete and whether learning activities can secure a work position, if very little cultivated skill is required for that position. So even if they are facing a risk of job-loss, it would be irrelevant to that knowledge-sharing online challenges the scarcity of cultivated work skills. Second, although people often envisage a general trend of a) robots replacing the unskilled and low-skilled labour (e.g., *Oxford economics*, 2019; Chiacchio *et al*., 2018; Acemoglu and Restrepo, 2017) and 2) China's economy being less dependent on labour-intensive manufacturing (e.g. Butollo, 2014; Carter, 2018), at least 2 participants explicitly said they did not feel any sign of the reduction in the demand for unskilled manual workers especially in the manufacturing industry, as exemplified by R2's confident account:

> '*I saw so many spoiled single kids did not finish a good education so ended up working in manufacturing factories. They were being very lazy and inactive but never needed to worry about being sacked. Because the demand for manufacturing workers is so high! They [the factories] never have enough operators. Like I said, assembly line workers require nearly zero literacy. If you would like to work, you will get a job.*' (R2, Male, First job manual, 33)

Here, I have no interest (and am unable) to predict the future demand for manual workers in China, I simply want to point out that this optimistic view of the demand for manual labour leads to participants' lack of concern about the risk of losing manual job opportunities.

5.5.2.3. Internal upward mobility

Here, internal upward mobility refers to promotion experience in one workplace. 19 participants mentioned that they had the experience of internal upward mobility. Regarding types of internal upward mobility, three types of stories were mentioned by the participants. I have labelled them as: *performance-based stories (N=17)*, *nepotism stories (N=1)* and *seniority stories (N=1)*, which highlight the difference in promotion system across different workplaces. Among them, only the performance-based stories have something to do with the development of skills. Even among the performance-based stories, skill development is not always an essential element. Those stories have revealed a limitation of the temporarily scarce skills theory that it is only applicable under a highly 'skill-meritocratic' recruitment mechanism.

To begin with, the nepotism stories were related to two participants' experiences. While one participant (R5, Male, First job manual, 27) claimed that nepotism has created a 'ceiling' for his further upward mobility in his previous workplace, another participant (U4, Male, First job non-manual, 29) accounted that his personal 'promotion' experience within the family company was simply a part of the family arrangement. In the beginning, R5 (Male, First job manual, 27) was happy that he got promoted as a manual supervisor after a very short period of time at a small manual manufacturing factory. But later, he thought he had found a dark side of the small factory:

> '*But later I started to realise the problem of a small factory. You could only have a chance to be promoted as an upper-middle or middle-level staff. The high-level manager and professional positions have been reserved for the relatives [of the boss]. To the best, people like us who were recruited from job applications can only get a middle-level position like a supervisor. I felt hopeless so I left the place later.*' (R5, Male, First job manual, 27)

Perhaps U4 was like those 'relatives' in R5's story. U4, whose father owns a construction company, at first started to work as a project manager in his family's company. At that time, even though he was responsible for an investment failure of the project, he found that experience rewarding and still got promoted to be a regional director afterwards:

> '*It could be considered as a business failure [...] we lost around two million [yuan] in total. [...] it was not that problematic. It was an experience and a good lesson. If I had taken over the whole company at that time, what I had lost could have been the whole family business. But what I actually lost two years ago was just some money.*' (U4, Male, First

job non-manual, 29)

Regardless of whether company size really plays a role or not, here the most important thing is: the development of skill cannot be of any help when the positions are not opened to a skill-meritocratic competition. If nepotism or other similar kinds of closure mechanisms play a dominant role in the recruitment, the abundance of online information resources will not be helpful in any manner for individuals' career progression.

Next, a seniority story was told by U9 (Female, First job non-manual, 30) as a characteristic of the state sector workplace she worked in. With the help of her family, U9 firstly secured an administrative clerk's job in a state-owned textbook publisher. After six years, she got a promotion and became a senior level administrative clerk. Although the title had changed and the salary had risen, she reported that her work-tasks had not changed one bit, as she said:

> '*the promotion was like a change of title rather than the substance*. *I still do the same kind of work task every day*' (Female, First job non-manual, 30).

As for the reason for promotion, she mentioned the seniority promotion system in her workplace and claimed that was a common feature for most state sector workplaces:

> '*It is just your seniority. In a state-owned enterprise, as long as you have worked for a long period of time, do not make big mistakes, and have been responsible, you will have a chance to get promotion due to the restructuring.*' (U9, Female, First job non-manual, 30)

We cannot rely on her words to assume whether or not seniority is still a common feature within the state sector. Not only did the 1990s see the diversification of the forms of ownership within a context of the free-market economic reform, the state sector has also started its own labour system reform in many aspects, including moving toward a more performance-based promotion system, driven by the pursuit of productivity (e.g., Howard, 1991; Leung, 1994; Fung, 2001). However, U9's words can show that some of the 'iron rice bowl' legacy still exists in a few state-owned workplaces. In relation to the temporarily scarce skills theory, in a workplace where seniority is the primary determinant of one's chance of upward mobility, skill development will not impact one's chances of increasing internal upward job mobility. Thus, in some unchanged workplaces in the state sector, the residue of the seniority legacy can affect the degree of the effectiveness of skill development upon upward mobility chances. Thus, the temporarily scarce skills theory would not be a good theory for a context in which seniority is the dominant promotion system.

Finally, when accounting for internal mobility, performance-based stories recur most. Among the 19 participants who had experienced internal upward mobility, 17 of them believed that their own promotions were a result of the recognition of their abilities to bring a greater work output for the workplaces. However, one may not have to further develop productive work skills and professional knowledge to achieve greater performance and work output. For example, it could just be due to workers' extended working hours or extra effort, as discussed by U6 and U7:

> *'I took my first job very seriously and I worked very hard […] I think my hard-working paid off because I got a promotion and salary rise in the end. But the promotion had nothing to do with the development of knowledge in finance, it was all only about my hard-working. The 'knowledge payoff' things only existed for a professional role, but not an administrative role.*' (U6, Female, First job non-manual, 26)

‘*I think it is both mental and manual labour, because it requires you to work over-time very often, unless you have very good resources like I have mentioned. There are two kinds of people that could make a good career progression in investment banks: people who would like to work extremely hard and people who have a very good social network with rich people or money sources*.’ (U7, Male, First job non-manual, 29)

Their words provide a good reminder that in order to achieve a good work performance, one does not have to develop some more ‘advanced skills’. As can been seen, U7’s account also demonstrates another example: the use of social networks. U7 used to be a sales manager at an investment bank. He claimed that if a worker has a good relationship with rich clients, that person can achieve the goal of good work performance (i.e., attract investment) much more easily:

‘*Because you know in financial investment if you have a good relationship with the rich people and are able to persuade them to put money in your investment project, you will have good work performance very easily and get a promotion more quickly.*’ (U7, Male, First job non-manual, 29)

Certainly, the development of work skills is a very common approach to boost a worker’s performance. All those 17 participants said the development or enhancement of their work skills was the main reason why they had improved their work performance. And echoing the temporarily scarce work skills theory, participants’ stories pointed out that to gain promotion opportunity, it is not simply about individuals’ work skill improvement, but also about making certain that they have a better work capability than other workers within the workplace, given that other workers’ skills might also be improving. However, the ‘constant competition’ within one workplace is different from the competition within a whole labour market. For the former, a worker usually only needs to compete with a sub-group of the whole labour force, and the degree of the fierceness of the competition might deviate from the average fierceness level. I could use R5’s example to illustrate:

> ‘*It [the promotion] was mainly because I worked in a small factory at that time, where the competition was less fierce. In the beginning, I worked in many big factories and we were quite aware that it takes at least four to five years to have a chance to be recruited into the management team.*’ (R5, Male, First job manual, 27)

Clearly, R5’s experience only exemplifies the positive scenario of the ‘sub-group competition,’ as he worked in a less competitive workplace. In the real world, presumably, opposite stories also exist (i.e., working in an extremely competitive workplace).

However, compared to participants’ accounts, the temporarily scarce skills theory lacks a discussion of how workers’ skill development was discerned. In summary, participants mentioned three elements that were related to the identification of workers’ work skills development: a good record of previous work performance, additional certificates (especially for the professional roles) and line managers’ judgements. In some workplaces, the former two elements were written into the promotion policies as part of the indicators of workers’ work capabilities. In addition, all of those skill-development upward mobility stories mentioned an example in which their newly developed work-capabilities were noticed and appreciated by their line manager or employer, who had the power to recommend or decide to put the candidate forward for promotion. The following story is an example:

‘*I think I worked hard and learnt well. I spent some extra time working and trying to learn more. This was appreciated by my supervisor, so he assigned me to work on some important lines, which provided me with a good chance to learn some precious things. Later, I was promoted as a supervisor assistant.*’ (U3, Male, First job non-manual, 22)

At first glance, this account seems to only highlight that the supervisor’s judgement is simply a part of the mechanical process which discerns workers’ skill development. However, the following two accounts might be able to reveal some further complexities of the supervisor’s judgement:

‘*We [her employer and she] are quite close as we talk to each other very frequently. We worked in the same company previously when he was my also superior and later I joined his start-up. I love to talk to him whenever I have any difficulties with work or even my personal troubles. Maybe because we have always had good communication, he knows me well and trusts me more.*’ (R10, Female, First job non-manual, 29)

‘*I had a good performance, which was noticed by my boss and line manager. They trusted me so gave me a chance at promotion [...] My line manager left the factory. You know he appreciated me a lot, but the other managers did not. Managers were in a competitive relationship and they formed different cliques. Managers from other cliques would not appreciate me as they did not trust me, a person from a rival clique. So I left right after my line manager left*’ (R5, Male, First job manual, 27)

Clearly, a line manager or employer is never an ‘unbiased skill detection machine.’ Both R10 and R5’s stories revealed that the interpersonal relationship with the line manager or employer might affect their ‘professional judgement’ on who will be the best candidate for a promotion opportunity with the name of 'most capable workers'. Within the context of internal upward mobility, where the opportunity of upgrading to an economically advantaged employment situation is monopolized by a handful of powerful decision makers (i.e., the line managers, employers), workers do not always have the freedom to progress. Consequently, they might try to impress their line managers or employers in order to earn 'the recognition of work skills.' This critical element is neglected by the temporarily scarce skills theory.

5.5.2.4. External upward mobility

Here, external upward mobility refers to upwardly occupational mobility outside one's previous workplaces. Whilst 19 participants had experience of internal upward mobility, only six participants had seven episodes of external upward mobility. Two kinds of external upward mobility stories were reported. First, three participants job-hopped to a new workplace as employees but still remained in the same industry, which I call *a job-hopping story*. Moreover, four participants used their savings to start their own business and to take over a higher managerial role in their new companies, which I called *an entrepreneurship story*. For those who stayed as employees after moving to a new workplace, by comparison, the stories of horizontal mobility and downward mobility had the events of cross-industrial movement (i.e., participants moved to a new workplace in a different industry). As we discussed in *5.5.2.1 Downward mobility*, completely translating one's previously appreciated work skills into a new workplace might be difficult. And it might be even harder for occupational mobility into a different industry. Thus, even though there is no evidence to confirm it, it is reasonable to hypothesize that the upward mobility to a different industry is usually harder than the upward mobility within the same industry.

All the *job-hopping stories* told are also *performance-based stories*, the stories that participants entered a new advantaged work-position in a new workplace as they managed to convince the recruitment team that their prospective labour would bring an excellent work performance to the workplaces. Theoretically speaking, when facing some *non-skill-related* barriers to upward mobility within one workplace, like a lack of promotion vacancies, nepotism, and seniority system, job-hopping to a new workplace could be a way to bypass those immobility barriers. For example, R5 (Male, First job manual, 27), who was not satisfied with his previous workplace's reservation of the high-level positions for the employers' relatives, quit the job and tried to start his career again in a new workplace.

However, job-hopping still does not bypass a key issue that also occurs in the context of internal mobility. That is, how can one ensure that the developed skills can be recognised and appreciated by the decision-makers (i.e., the recruitment team)? In the context of internal mobility, where workers can have a long-time interaction with their line managers or employers, the line managers or employers do have a lot more information to screen workers' work skills and productivity, although their judgements might be biased or 'miscalculated'. In terms of external mobility, one participant mentioned that job-hopping is not just about letting the more capable workers have a place to go, it is also about *how to impress the interviewers*. For example, U1 had a belief that perhaps the communication and presentation during the interview were as important as acquiring the essential skills:

> '*I will say it [the work skills] accounted for part of the reason [of successfully getting the job]. Firstly, I needed to meet the person specifications. They needed someone who had those skills for the role and I got those skills from my daily working and learning activities. […] So actively updating professional skills is essential. Another part of it, I will say, was because of the 'soft skills' of good communication or presentation during the interview […] Compared to other engineers, I am more active in communication and that might be related to my personality.*' (U1, Male, First job non-manual, 26)

In short, this part of the analysis has revealed two major issues of the temporarily scarce skills theory. First, the temporarily scarce skills theory is only applicable in an ideal context where the recruitment is completely opened and ‘skill-meritocratic.’ Whilst in reality, that does not always occur, especially in the context of internal promotion. In addition, the temporarily scarce skills theory presupposes workers’ developed work skills can always be accurately discerned. However, this somewhat naive assumption has been challenged by participants’ narratives sketching the complexity of the interaction between workers and their line managers or employers. In the real-world, in order to achieve upward mobility in a skill-meritocratic selection, not only should workers develop their work skills, they also need to be skilful to signal the employers, or interviewers that they really have got the required work skills necessary to perform that job or necessary for promotion.

5.5.3. The prerequisites for skill acquisition

Based on participants’ accounts, the mentioned activities related to workers’ skill development can be broadly classified in a way set out in Figure 5.8. Firstly, depending on whether or not the primary aim of a kind of activity is to develop certain kinds of capabilities or understandings that are related to approaching work tasks, activities can be divided into learning (e.g., attending a course) and non-learning activities (e.g., work practice). Based on Moore’s (1989) interaction-based learning activities typology, the learning activities can be broadly divided into three types: learner-content interaction (e.g., learning from reading a paper), learner-instructor interaction (e.g., attending a training course with an expert’s instruction) and learner-learner interaction (e.g., learning from communication with peers).

For the non-learning activities, 14 participants mentioned that the work experience was critical for their work skill development. They sketched the process like in Adam Smith's (1977) ‘pin factory specialization story,’ where for the same work task, the more repeated works they had practised, the more familiar they had become with the process, the more skilful they became, and therefore more productive. Whilst recognising the importance of one's work experience on work skill development, as it is not largely relevant to our discussion about the relation between UIL and skill acquisition, I will not expand the discussion about the non-learning activities. The following three sections will present and discuss participants' accounts on each type of learning activities.

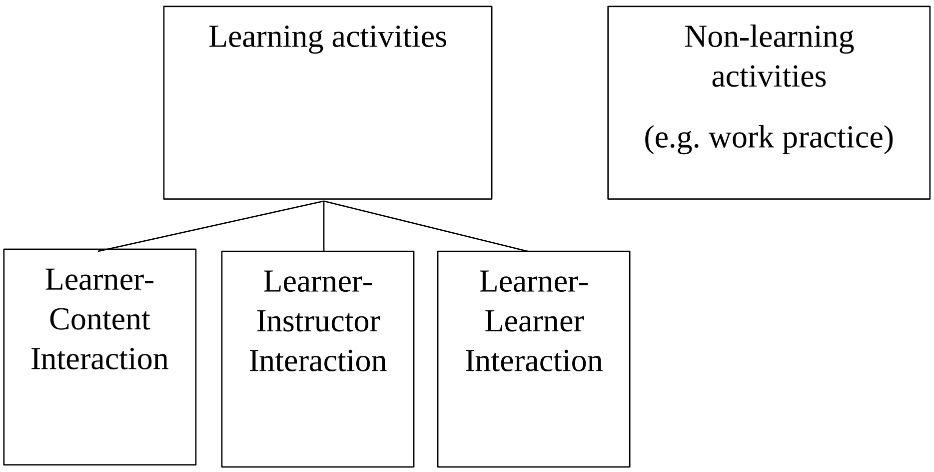

Figure 5. 8 Sources of skill development based on participants' accounts

5.5.3.1. Learner-instructor interaction

Five participants had the experience of participating in learner-instructor interaction activities during their working lives, although none of the activities actually took place online. Among participants' learning stories, the above-mentioned learner-instructor interaction activities were: official on-the-job training in the workplace, professionals' private tutoring, signing up for external training courses, and formal education for a further degree.

The key emergent theme of learner-instructor interaction is *effectiveness*. In general, for those who had tried multiple types of learning activities, they believed that the learning activities with an instructor's tutoring were the most effective practice, in comparison with other types of learning practice. This echoes Moore's (1989) remarks that learner-instructor interaction is ‘regarded […] as highly desirable by many learners’ (p.2). Firstly, all the mentioned learner-instructor interaction practices were delivered in a structural and educational manner. Two participants’ learner-instructor interaction activities were even accompanied with a final assessment (e.g., degree/certificate-oriented formal education), which was regarded by them as being effective in ensuring a systematic understanding of the relevant knowledge and the successful work skill-development. Secondly, compared to interaction with non-experts and simply content, all five participants who had learner-instructor interaction experience believed that the frequent interactions with an expert (e.g., an instructor’s step-by-step tutoring) was more effective in helping learners successfully develop knowledge and skills in a short period of time, as shown by the remark on the comparison made by U3:

> ‘*Learning things from online sources completely depends on your own. A tutor will keep trying to explain things to you if you fail to follow. No one will be there to help you when you are searching information online.*’
> (U3, Male, First job manual, 22)

Nevertheless, learner-instructor interaction does not seem to be largely empowered by the use of the internet. Those five participants’ personal experiences of learner-instructor interaction took place in a physical context without the use of the internet. Of course, that does not mean that this type of learning activity could not go online. However, the key question is: does going online massively transform the acquisition of learning opportunities? As discussed above, the most prominent advantage of the learner-instructor interaction seems to be the availability of a human expert’s involvement, regardless of whatever ways one communicates with the expert. The use of the internet does not make an instructor’s service less scarce, higher quality, or better in other ways. Although our participants believed that this form of learning was the most effective way to acquire professional knowledge and to develop work skills, they also regarded this type of practice as the most difficult to access resources. U5's words below exemplify this point:

> '*You either need to pay them [the experts] for providing training or work with or for them to get their help in exchange.*' (U5, Male, First job non-manual, 28)

5.5.3.2. Learner-learner interaction

All participants mentioned episodes of learning skills and knowledge from their peers or colleagues, although only two participants talked about their experiences of online learner-learner interaction. The learner-learner interaction activities mentioned by participants were: asking colleagues questions, observing colleagues' work practices, and peer discussions in online group chats. The former two situations were often related to a spontaneous demand for some know-hows to directly deal with some practical work tasks within the workplaces. But those learning practices were also not highly relevant to the use of the internet, as the interactions happened when workers were working in the physical workplace and the use of the internet did not seem to be an essential tool for their communication.

Two white-collar participants introduced their stories of updating new professional knowledge from their professional peers in online chat rooms. Peer discussions in online group chats refer to workers who actively found and joined online groups (usually on an instant messaging application) made of professional peers, and engaged in discussions with group members in order to learn professional knowledge and help one another. Those two participants believed that being engaged in online chat groups was key to keeping them *'up-to-date.'* According to them, the engagement in the chat groups was perceived as an essential means to keep up with new information, such as the latest development within the industry and any newly in-demand knowledge/skills beyond the scope of what they could get from their work colleagues. They believed through group members' mutual help they could stay ‘qualified’ in the labour market. For example, R10, who worked in online marketing, showed her gratitude for the help from the chatroom members:

> ‘*I joined some chat groups consisting of online marketing professionals [...] Because Amazon changes its policies and settings very often, like it changes the algorithm of its searching engine and rating and the ranking system frequently [...], we often update the latest news and discuss how to improve our marketing strategy. And I learned a lot from other people's expertise and I appreciated their prompt updates about some of the latest changes and their knowledge sharing, which helped me overcome a lot of challenges for my work.*’ (R10, Female, First job non-manual, 29)

The way of mutual help was beyond simply sharing content with the group, as people also offered help through constant communication like answering each other’s questions based on their own understandings. In this case, the use of the internet served the material basis for this type of many-to-many instant communication. Through the use of the internet, the scale and the scope of mutual help went beyond an inter-colleague level peer interaction, which was restricted to a small-scale face-to-face communication in physical workplaces. Yet, it is worth noting that those two white-collar participants preferred to sketch this kind of online peer discussion as a ‘safety-net,’ which protects them from being obsolete, rather than helping them become more ‘outstanding.’

5.5.3.3. Learner-content interaction

Among all types of learning activities, learner-content interaction occurred most frequently in participants’ working lives, and it was most relevant to the use of the internet. All participants have experience of learner-content interaction. Some recurrent learner-content interaction practices were: browsing websites in general (e.g., search engines, official websites of an institution, online forums, social media), reading other text-based materials (e.g., books, articles, blog posts, workplace documents), listening to audio-based materials (e.g., broadcast, audiobooks, an audio-recording of a lecture) and watching video-based materials (e.g., a video-recording of a presentation or a lecture, educational animation videos).

Participants from manual and non-manual occupational backgrounds had completely different opinions on the importance of learner-content interaction with the use of the internet for the development of their work skills. All participants from manual occupational backgrounds perceived the engagement with online information content as generally useless for the maintenance of their work skills for their daily work tasks. Especially, as discussed in *5.5.2.1 Downward mobility*, some manual jobs required very little literacy and *cultivated skills*. So, for them, the interaction with online information content seemed irrelevant to the required work capability of machine operation or other manual work tasks. However, R4, the only participant who had the experience of upward mobility from a junior assembly line operator to a technician in manufacturing, perceived that the utilization of online information content was essential for his acquisition of professional knowledge in engineering, which was required for his current work position (see his account below). Like other participants who were once manual operators, he acknowledged the irrelevance of the interaction with online information content to some simple machine-operation work tasks. However, a technician position required someone to have professional knowledge in industrial production. To acquire professional knowledge, he did a lot of self-learning activities by interacting with the information content he searched for online. He saw a 'paradox' within the environment of the manufacturing factory. Whilst a more skilled position did require a good body of knowledge, the environment generally tended to reduce the manual workers into a 'mindless machine,' without providing them additional training opportunities. Thus, promotion opportunities seem to rely on the awareness and active action of self-learning. And the utilization of free online information content might just be a convenient means for his self-learning. That echoes our quantitative findings that the probabilities of upward mobility were strongly associated with UIL among individuals with semi-unskilled manual background.

> '*I started to do more self-learning by searching information online and actively raised some complex questions in order to have an advanced understanding […] Mostly I searched for information related to the products we are producing and the production process. I could not find anything related to some practical issues like machine operation, but I learned a lot about some general theoretical knowledge about production and engineering, and more information about the products […] So in the factory we are only taught how to use the machine, but we are not taught what it is for, why are we doing it, and what exactly we are producing. We are just like a machine and just do what we have been told to do. If you do not try to learn things by yourself, no one will teach you what is going on […] that [searching information online] was very helpful for my experience of being promoted to be a technician, as they required a technician to have a good body of professional knowledge about the industrial production.*' (R4, Male, First job manual, 30)

In contrast, the narratives from those who worked in white-collar occupations were completely different. They claimed that self-learning activities with the use of online information content were necessary but not largely effective for maintaining the required work skill level.

Firstly, nine out of 14 white-collar background participants expressed that self-learning is necessary, as the demands for knowledge and work skills change very often. As we discussed in *5.2.2.2. The concern of downgrading*, they perceived the inevitability of 'skill obsolescence' and self-learning as a measure to keep producing the up-to-date in-demand work skills. Moreover, two participants even said that nowadays the boundary between learning and working was blurring, as learning had often become a part of the official work tasks, which made learning even more ‘necessary’:

‘[…] 30% of my daily time I use the internet for learning purposes […] but it [learning] is more like a daily work task for the IT professionals […] when I received my client’s demand I firstly needed to look online for some available cases and study the technical frameworks behind them […].’ (U1, Male, First job non-manual, 26)

‘Researcher: Recently, do you use the internet for any learning purposes?

U6: Yes, I do it like every day. This is a part of my job as a researcher […] studying things in finance and different industries and then writing reports.’ (U6, Female, First job non-manual, 26)

Secondly, when facing the demand for skill development, the interaction with online information resources was seen as necessary for all 14 white-collar background participants, as they thought the use of the internet was the fastest, most convenient, and an affordable way to acquire abundant and useful content for self-learning:

'It does not make you to be more competitive, but you just cannot stop updating the latest things from online sources.' (U5, Male, first job non-manual, 28)

'Can you imagine doing anything without using the internet, especially when you want to know something or learn something? Staying old-fashioned and going to the library to read books or newspapers? Possibly, but it’s too slow. I am the kind of person who has the experience

of learning in the old ways, back to the days when I was still at school, every time I had a simple question I went to the library to search for a book to read. Sometimes I spent a whole day there, gave myself a'headache,' but still could not find an answer. Nowadays? It does not take you more than one second to search for an answer online now.' (R3, Male, First job non-manual, 34)

To clarify, by saying necessary, participants did not mean that the use of the internet was a necessary condition to acquire information content for learning, as both R3's words and our common knowledge tell us that is not the case. What R3 meant here was that when facing fierce competitions in the labour market, *they could not afford to learn something too slowly* and so they could not bypass the use of the internet as well as the interaction with the online content.

Furthermore, it was not largely effective, in the sense that self-directed learning by interactions with the internet content could not guarantee one's successful knowledge and skill development to a large degree, compared to the learning practice by communication with another human being, especially an expert instructor. This point was explicitly expressed by nine out of fourteen white-collar background participants. According to those participants, the main issue was that the content could not provide them instant feedback to help them 'move forward' when they were stuck at certain points. Thus, they felt that self-learning with the use of information content partly depends on ones' personal abilities and accumulated knowledge. Thus, the effectiveness of learning depends on how knowledgeable one has already been. This point will be further discussed in Chapter Seven when we discuss inequalities in participation in online learner-content interaction. One might argue that if we really have abundant information resources online, the issue could probably be mitigated as one might just need to find additional information content to help them figure out the points at which they are stuck. However, even if one could infinitely search for additional information, instant feedback from an instructor still looks more effective, since feedback is tailored for one's personal need and one does not need to spend much time and effort searching for the information themselves.

To summarise, in order to acquire the work skills to achieve a good outcome of occupational mobility, the effectiveness of three types of learning practices and the relevance of the use of the internet is discussed. In general, learner-instructor interaction activities are seen as the most effective practice for developing one's professional knowledge and skills, although the use of the internet does not seem to be largely relevant to this kind of learning practice. Online learner-learner interaction activities are perceived as an effective means in helping workers acquire up-to-date information and support for updating knowledge and professional skills from other professional peer sharing. The use of the internet enables workers' learner-learner interaction to go beyond an inter-colleague level. The internet is largely relevant to learner-content interaction in the contemporary world. In order to learn knowledge and develop skills quickly, the use of the internet is seen as somewhat necessary. However, the interaction with online information resources does not always guarantee one's successful skill development. As told by participants, without someone else's feedback and support, the effectiveness of self-learning depends on how much one had already known.

5.5.4. Summary

To sum up, this part of the analysis uses qualitative evidence drawn from 24 semi-structured interviews to further scrutinise the explanatory power of the proposed temporarily scarce skills theory and to enrich the understanding of the relationship between UIL and occupational mobility in the contemporary labour market. Although, to a large degree, participants' career stories do not contradict the temporarily scarce skills theory, the qualitative findings have revealed some limitations of the temporarily scarce skills theory. The most salient one is that the temporarily scarce skills theory only makes sense in a context where the recruitment of a work position is opened and purely 'skill-meritocratic.' In such contexts, workers are appreciated as their more productive labour power is thought to be able to bring good work performance. In addition, in a real-life situation, the signalling and screening of workers' skills without using indicators like a qualification are rife with complexity, mixing up elements like interpersonal communication abilities, line managers' personal biases, etc. And it is possible that a) the lack of absolutely 'skill-meritocratic' selection and b) the difficulties of signalling and screening workers' outcome from UIL (i.e., actual skills rather than certificates) all contribute to the overall weak association between UIL and occupational mobility, as presented by the quantitative findings.

In addition, the qualitative findings show that for skill-development, learner-instructor interaction is the most effective learning practice, although this practice is not fundamentally dependent upon whether or not one is using the internet. In contrast, whilst the use of the internet has become an essential tool for workers' learner-content interaction nowadays, the effectiveness of learner-content interaction is dependent on learners' accumulated knowledge and personal abilities. In *5.4.4 The risk of downward mobility*, the quantitative findings show that for higher professional and managerial background individuals, there is an overall 'UIL-downward mobility' association, but the association becomes almost negligible after adding controls like one's educational background. It seems the qualitative findings are able to offer a possible explanation. On the one hand, UIL, especially the learner-content interaction, is found to be strongly associated with white-collar professional workers' daily tasks, echoing the observed overall association between UIL and downward mobility. On the other hand, if the effectiveness of learner-content interaction is largely reliant on one's accumulated knowledge, it seems that simply being engaged in learning is not sufficient enough to help one successfully develop scarce work skills, echoing the observed, almost negligible, association between UIL and downward mobility after adding for controls like educational background.

5.6. Concluding remarks

This chapter sets out to build knowledge to answer the first research question: *to what extent is UIL related to individuals' occupational mobility?*, which is the foundational question needing to be addressed before discussing UIL's mitigation effect on unequal mobilities between RMWs and URWs. After reviewing and reflecting on the known theories on addressing the 'learning-mobility' relationship, this chapter first proposes a preliminary theory, *the temporarily scarce skills theory*. The theory is built upon Erik Olin Wright's (1997, pp. 18-19) scarce skills account, which can be summarised as: among the wage workers who sell their labour power for economic remuneration in an exploitative employment relationship, those who possess scarce work skills have better control over their labour and can enjoy a relatively better economic remuneration. Wright (Ibid.) regarded the obstacles to formal education opportunities as an important mechanism to preserve the scarcity of some work skills. However, if information resources online are becoming abundant, the inaccessibility to learning resources is being challenged. Regarding this tension, the temporarily scarce skills theory argues that the scarce status of work skills can no longer be seen as stable. Skills might face a risk of being depreciated and devalued. For workers, the labour of learning with the use of the internet can help someone develop and reproduce scarce skills in an efficient manner, which is also a way to gain and secure an advantaged employment situation (i.e., increase upward mobility chances and reduce downward mobility risks).

The temporarily scarce skills theory predicts a positive association between UIL and occupational mobility in general. To examine the validity of this claim, quantitative data is used. Drawing on data from CFPS, the results of mixed-effects models indicated that, in general, UIL is associated with a higher occupational change score and a higher chance of upward mobility. However, UIL is only found to be weakly associated with the reduction of downward mobility risk. Those who were active in UIL had a significantly higher occupational change score and a higher upward mobility rate (especially amongst manual background workers) than those who did not even have the use of the internet. This echoes and provides evidence to support the earlier literature on claiming that it is not just about having access to the internet, but more importantly, the ways of internet use that affects individuals' economic welfare (e.g., Hargittai, and Hinnant, 2008). Overall, we can say that the quantitative evidence has shown a not so strong, but definitely not ignorable, association between UIL and occupational mobility.

After confirming this general 'UIL-mobility' association, I used qualitative evidence drawn from 24 semi-structured interviews to further scrutinize the explanatory power of the temporarily scarce skills theory. To do this, I adopted a narrative analysis approach to compare participants' own accounts of their career experiences and the typical 'UIL-skill-mobility' storyline derived from the temporarily scarce skills theory. Three marked issues of the temporarily scarce skills theory were highlighted: first, the temporarily scarce skills theory is not applicable in a context where an open and 'skill-meritocratic' selection is not the dominant mechanism; second, the temporarily scarce skills theory presupposes that workers' developed skills can be accurately detected, which undermines the complexities of the screening and signalling of workers' skills in the real-world situation; and third, UIL seems to be most relevant to learner-content interaction, a kind of self-learning activity whose effectiveness relies heavily on learners' accumulated knowledge (the third point will be further discussed in Chapter Seven).

Although the temporarily scarce skills theory is applicable in a more 'skill-meritocratic' context, given the general 'UIL-mobility' and 'formal education-mobility' correlation is found in the quantitative evidence, it is reasonable to assume that 'skill-meritocracy' still characterises a marked feature of China's urban labour market, which gives some credits to the applicability of the temporarily scarce skills theory. This is consistent with our discussion on the market-oriented labour market reform in China in

Chapter Two.

Although 1) the temporarily scarce skills theory postulates a negative 'UIL-downward mobility' association and 2) the qualitative evidence had shown white-collar professional workers' concern on skill-obsolescence and the risk of downgrading, our quantitative evidence did not confirm this phenomenon with strong evidence. Despite that the limitation of the secondary data's measurement validity is always a possible reason, I speculate that two other factors might be related. First, the real-world employment situation might not be as precarious as sketched out by the temporarily scarce skills theory. The precariousness would only manifest in a purely free-market for 'buying and selling labour power.' However, it is not likely that any existing labour market in the world (including China's) only follows a free-market logic without any labour protection policies and regulations. Second, it is possible that the reproduction of scarce work skills is not solely related to UIL, but also to other sources that the study fails to include in the statistical models like non-internet-based learning activities and work experience.

If UIL is mostly relevant to learner-content interaction, and the effectiveness of this type of self-learning activity largely depends on one's accumulated knowledge, then this confounding effect should be highlighted. Does the 'UIL-mobility' association purely reflect the effect of UIL on work skill development, or is it confounded by some elements like 'only the skilful and knowledgeable people can learn things effectively from online information'? There is a similar dilemma in other educational studies, as Zhou (2019) argues that robust empirical evidence for the relatively high social mobility among college graduates is not clear enough to distinguish the 'selectivity' (i.e., do colleges simply select the most talented from the disadvantaged background) and 'educational' effect of college. The control of individuals' formal educational backgrounds in our quantitative analysis does help reduce this confounding bias to some degree, but it is still not able to eliminate it.

Chapter Six: More returns for the disadvantaged diligent?

6.1. Introduction

The preceding chapter analysed the overall relationship between UIL and occupational mobility in China's urban labour market. It is noteworthy that although UIL seems to be related to a good outcome of occupational mobility, the association does not look strong and may confound with other factors. For manual workers, UIL is associated with a higher chance of upward mobility. While the white-collar background participants mentioned that UIL, especially in the form of learner-content interaction, has become routine labour to constantly reskill themselves to meet the latest demand in the labour market, the negative association between UIL and downward mobility is not found to be salient in the quantitative findings.

After examining the general role of UIL in occupational mobility in the contemporary labour market, this chapter attempts to directly analyse the potential of UIL in mitigating the unequal occupational mobility. In particular, this chapter looks at one key aspect of the evaluation – the variation of the effect of UIL across RMWs and URWs; and therefore seeks to answer our second research question: *when having similar participation in UIL, do RMWs benefit more from UIL when it comes to occupational mobility?* If new learning opportunities are more effective in helping disadvantaged populations' career mobility, then it might provide an opportunity to narrow the gap in mobility between the disadvantaged and the advantaged, in this case, RMWs and URWs.

This chapter starts by reviewing the existing literature on the variation of the effect of learning on individuals' labour market outcomes across different social groups. To answer the research question, and drawing upon the empirical and theoretical knowledge, the next section develops a preliminary theory called *the diligence dependence theory*. This theory envisages a more crucial role of extra effort of learning on occupational mobility for disadvantaged populations, although it simply reflects disadvantaged background people's deprived situations. Subsequently, the study uses both quantitative and qualitative evidence to examine the validity of the developed account of the diligence dependence theory. The quantitative analysis provides robust results for comparison on the extent to which a) a greater UIL-mobility association for RMWs and b) a declining RMW-URW gap along with being more active in UIL exists as general phenomena. The analysis is followed by further examining the interpretation of the diligence dependence theory when making sense of the heterogeneity of the UIL-mobility association, by using qualitative evidence from the interview data.

6.2. Studies on 'differential dividend' to learning

To my knowledge, no previous study has researched relative occupational returns to UIL. However, there is a large body of useful literature that concerns the variation in the labour market outcome to the availability of learning opportunities by social background. This section gives a comprehensive review of previous studies on the difference in labour market return to learning. I begin by presenting and evaluating key empirical evidence that compares occupation and earnings returns to formal educational background, life-long learning, and internet use between disadvantaged and advantaged populations. The second part moves on to a theoretical discussion. It reviews and compares the existing theoretical knowledge that seeks to make sense of the relative labour market returns to learning.

6.2.1. Relevant empirical evidence

Many empirical investigations have been done to compare the labour market rewards to formal education, life-long learning, and internet use between the disadvantaged and advantaged groups. Most findings seem to suggest that the effect of learning on career success is greater for the disadvantaged group.

Most empirical findings are from the inquiries that focus on the role of formal educational achievement (especially higher education) in occupational attainment. In Blau and Duncan's (1967, p. 431) status attainment study, they famously claimed that the association between status origin and destination status has been intervened by education in industrialised societies, since highly industrialised societies cannot any longer afford the waste of human resources a rigid class society entails. However, landmark studies by Hout (1984, 1988) show that this pattern varied across workers from different educational backgrounds in American society. The association between status origin and destination status was weaker among the well-educated populations, especially among the male college graduates, whose status attainments had absolutely no association with their status origins (Ibid.). Later, Goldthorpe's (2003) intergenerational class mobility study found a similar pattern in Britain. In most cases, there was a three-way association between a person's class origin (O), educational attainment (E) and class destination (D) (see Figure 6.1). In addition to the traditional interpretation such as what Hout (1988) offered that a weaker O-D association could be found among the highly educated personnel, Goldthorpe (2003) offered an alternative way to narrate the observation: educational achievement is less related to class destination for the advantaged populations, which he thought had better captured the class society nature of Britain. Based on a similar technique (i.e., loglinear modelling), the later comparative class mobility studies also found that this interaction effect existed in many European countries (e.g., Vallet, 2004; Breen and Luijx, 2004; Breen and Jonsson, 2005; Pfeffer and Hertel, 2015). In particular, the association between class origin and class destination was found to be insignificant among the college graduates in France, Sweden and Germany (Breen and Luijx, 2004; Breen, 2019), consistent to the earlier days' status attainment studies by Hout. Furthermore, Beller and Hout's (2006a) investigation on the cross-national difference in the effect of social and educational policy indirectly echoes this thread. According to their findings, the effect of education expansion policy on weakening the O-D association was greater in corporatist and liberal welfare states than in socialist and social democratic regimes, where occupational attainment is less dependent on social origins (Ibid.).

Moreover, some studies have also investigated the relative earnings returns to educational achievement. Dale and Kruger (2002) found that in the US, selective college graduates did not earn more than those who attended non-selective colleges with seemingly comparable ability (e.g., SAT score), except for those who were originally from low-income families since attending a selective college could allow them to earn more. As a response to the contingency of the measurement used (Bjorklund and Jantti 2000; Beller and Hout, 2006b; Erikson and Goldthorpe, 2008), Torche (2011) provided a comprehensive examination by looking at the variation in both class, status, individual earnings, and total family income returns to education across different social groups. The study further confirmed that BA degree holders' class, status, individual earnings, and total family income were independent of their social backgrounds, whereas less-educated workers' socio-economic success was still associated with their social origins (Ibid.). In addition, both Chetty et al. (2017) and Zhou (2019) show that the highest intergenerational income mobility rate existed at highly selective colleges in the US (e.g., Ivy League universities), which is due to the high rate of intergenerational change for the students from low-income families.

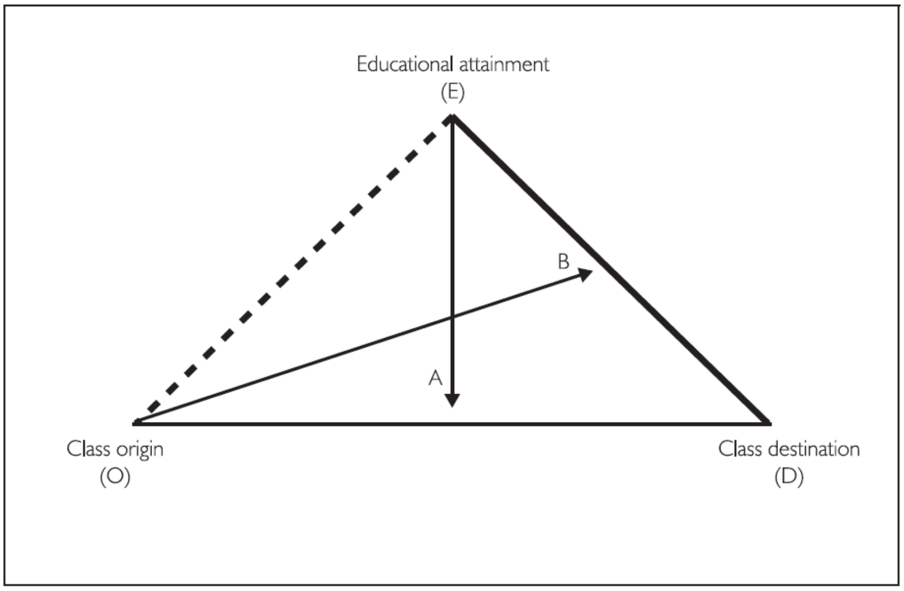

Figure 6.1 The OED triangulation and the interaction effects. Source: (Goldthorpe, 2003)

In particular, among those studies mentioned, a few works did a very good job in attempting to reduce the confounding effects, which allows the evidence to implicate a greater labour market return to learning opportunities for the disadvantaged people, rather than to conflate with other elements (e.g., educational institutions select the most competitive individuals for labour market success from disadvantaged backgrounds). For instance, in Zhou's (2019) inquiry, after controlling for a range of pre-college individual characteristics that were related to parental income and individual earnings, the higher intergenerational income mobility observation disappeared among the non-selective college graduates, but still existed among the graduates who attended the selective universities in American society. Furthermore, Maurin and McNally (2008) did a study that has some similar controls to a 'natural experiment' design. After the May 1968 events in France, the thresholds for passing the exam had been lower down for the cohort who attended the movements at that time, and so there was a higher proportion of college students who chose to pursue a higher-level college education among that cohort (Ibid.). The result shows that the effect of every extra year of higher education on wage return was much greater for that 'less-selective' cohort than for the other studied cohorts (Ibid.).

Some findings first appear to dispute the 'premium effect' of education for disadvantaged background individuals, but they are actually not contradictory to the mainstream empirical results after careful scrutiny. Firstly, Gary Becker (1993, pp. 187-195) claimed that his study demonstrated a greater earnings return to higher education for the white, urban, and male Americans, namely the advantaged populations. He explained that it was mainly due to advantaged populations' greater cost on higher education (Ibid.). For instance, white students usually went to universities with higher tuition fees (Ibid.). Secondly, Torche (2011) found a 'U-shape' trend of the strength of association between class origin and destination along with the growth of educational level in the US. The association between class origin and destination was lowest at BA level as BA degree holder's labour market outcomes were completely independent of their parental resources (Ibid.). However, the association grew again among advanced degree holders,' which Torche (2011) explained that the post-graduate study is more specialised and 'horizontally stratified' (p.799) as students from high-income families would choose to study the subjects that would allow them to get a high earnings job. However, both of these studies are different from a context that aims to compare the effectiveness of one kind of learning opportunity for different groups of people. In both Becker's (e.g., Black and White Americans went to different kinds of colleges) and Torche's studies (e.g., individuals from advantaged and disadvantaged backgrounds studied different postgraduate programmes), they claimed that advantaged and disadvantaged populations actually accessed different kinds of learning resources.

To the best of my knowledge, there is only one study that researches the relative labour market returns to lifelong learning between individuals from different social backgrounds. In that study, Bukodi (2017) investigated the possibility of the 'compensatory effect' of adult learning after full-time education for disadvantaged background workers' occupational mobility in Britain. However, she failed to find any evidence to indicate that the effect of academic and vocational learning programs on occupational attainment vary across social groups.

Next, there is some scattered evidence indirectly suggesting that internet use or ICT adoption was more strongly related to disadvantaged populations' economic returns, regardless of the actual mechanism. Qiang and Rossotto (2009) showed that broadband access was more powerfully associated with developing countries and regions' GDP growths than the growths in high-income countries. Atasoy (2013) found that broadband availability was related to employment rate growth more in rural areas than in urban areas in the US between 1999 and 2007. Whilst ICTs are often thought to help reduce the poverty rate, an investigation in East Africa (May et al., 2011) shows that the ICTs-poverty reduction association was even stronger among the poorest households. Nonetheless, all these empirical findings are only useful in an indirect manner for our study, since it is not clear whether the internet and ICT were used for any learning purposes, and to what extent the GDP growth in Qiang and Rossotto's (2009) findings and poverty reduction in May et al.'s (2011) research were related to individuals' labour market returns.

Although Wu (2019) remarked that there is very little research investigating the three-way association between social origin, education, and class destination in the context of China, a few empirical studies are actually able to provide some weak indications on the relative returns to learning in China. One earlier study conducted by Wu and Treiman (2007) on *hukou*-related comparative intergenerational social mobility suggests that educational achievement matters more for rural origin men's occupational mobility than for the urban counterparts. Drawing on a 1996 national probability sample of adult men ages 20–55, the study shows that rural but non-agricultural occupation origin men were actually very vulnerable to downgrading to an agricultural job (the lowest level strata in their class scheme), and their educational background was associated with a much lower risk of downward mobility and a higher chance of succeeding in career enhancement. In addition, Fu and Ren's (2010) inquiry shows that the income return to tertiary education was greater for rural migrants than rural non-migrants, and was least effective for urban residents.

6.2.2. Some theoretical explanations

The preceding discussion suggests that, in general, the relationship between learning opportunities and occupational mobility is more likely to be stronger among disadvantaged populations. Despite the abundance of empirical evidence, both Torche (2011, p. 798) and Zhou (2019, p. 461) comment that the theoretical interpretations of its underlying mechanisms are scarce and underdeveloped. Nonetheless, in this part, I present and discuss some existing theoretical accounts that attempt to make sense of the observed heterogeneity of the return to learning.

Universalism

Regarding the high social mobility among college students, Hout (1988) explained that it was due to the difference in the degree of universalism among different status professions. Originating from Parsons' (1951, pp. 58-67; pp. 101-102) modification of Weber's principle of 'progressive rationalism,' universalism, in the context of status attainment study, refers to a meritocratic selection process that a rational allocation of people to a position according to their actual abilities and achievement should be based on some objective criteria (e.g., education), rather than their ascribed status (e.g., family background) (Blau and Duncan, 1967, p. 429). The selection of the higher status positions, which is said to contain a more important role for the functioning of a society, cannot take the risk of losing the most capable personnel by accepting any elements of inheritance and discrimination (Blau and Duncan, 1967, p. 430; Hout, 1988). However, that might not be the case for the selection of a lower status position, since the waste of human resources at the lower strata does not contribute to a serious result of inefficiency for the society. Hout (1988) argued that the jobs that college graduates look for are usually higher status and skilled, whose recruitments are more universalistic characterised by meritocratic selection. On the contrary, less-educated people look for relatively low status and low-skilled jobs, which could tolerate a larger degree of capability mismatch.

The signalling effect

Regarding the weaker association between social origin and class destination at higher levels of education, Breen (2010) speculates that it might be because a formal certificate itself has the powerful effect to *signal* to employers one's potential work skills. Thus, for the well-educated, they do not need other resources to signal to employers that the job seekers are equipped with the required skills. For those who do not have a certificate but are competent to perform work tasks for a position, they might rely on their social networks to help them find suitable jobs, which could partly explain the stronger association between social origin and class destination.

Organisational bureaucracy

This account was provided by Torche (2011) and has many similarities to the universalism theory. However, whilst universalism theory assumes that differences in the degree of meritocratic selection vary across different status jobs, organisational bureaucracy theory believes that the meritocracy difference resides between work organisations but not positions. The basic idea is that well-educated and skilled individuals (e.g., college graduates) are more likely to seek professional jobs and those jobs are usually within work organisations with a well-developed bureaucratic system (Torche, 2011). When recruiting workers, bureaucratic organisations have a smaller degree of subjectivity in personal bias and attempt to find the role-specific candidate with the potential to maximize work performance. As a result, bureaucratic organisations seek to eliminate discrimination against ascriptive characteristics like family background, race, and gender (Bielby, 2000; Reskin, 2000; Elvira and Graham, 2002; Baron et al., 2007).

Deprivation and reliance

Regarding the three-way interaction between social origin, learning and class destination, whilst the above accounts seek to explain why the well-educated individuals' labour market outcomes are less relevant to their social origin, Brand and Xie (2010) and Goldthorpe (2003) seek to explain why labour market returns to learning is greater for individuals with disadvantaged backgrounds. For them, the key is actually that individuals from disadvantaged backgrounds are deprived of other kinds of resources (e.g., social networks, family support) for occupational attainment, making the association between labour market outcomes and accessing learning opportunities more salient. Interpreting a greater association between college attainment and earnings return for the disadvantaged in the US, Brand and Xie (2010) explain that those who were born with rich resources (e.g., economic, cultural, social, institutional) could utilise their resources to achieve career success more easily, rather than solely rely on their educational achievement. In contrast, those who are deprived of resources could only rely on educational achievement to help them achieve career success. Similarly, Goldthorpe (2003) offers an *alternative interpretation* on the three-way interaction between social origin, educational attainment, and class destination in Britain:

> '*Children from less advantaged backgrounds have little that can help them to 'get ahead' other than education [...] But children from more advantaged backgrounds, if their educational attainments are only modest, are still likely to have other resources available to them that can help them maintain their class positions – including economic resources, but also socio-cultural resources [...].*' (p.238)

In short, both of them suggest that the relatively greater effect for the disadvantaged group simply reflects their lack of alternative resources for socio-economic success.

Discussion

Table 6.1 summarises the key features of those four theoretical interpretations. Although all four accounts attempt to make sense of an observation of the three-way association between one's social origin, learning, and the labour market outcome, they interpret the pattern from different perspectives. As highlighted in Table 6.1, *universalism*, *the signalling effect*, and *organisational bureaucracy* seek to explain why well-educated populations' career achievements are less linked to their social origins, whilst *the deprivation and reliance account* attempts to explain why disadvantaged people could benefit more from the same kind of resource.

Table 6.1. Summary of the main features of the provided four explanatory accounts

	Perspective	**Mechanism that contributes to the difference**
Universalism	Seek to explain the difference in the association between social origin and labour market outcome, across achievements in learning	Different levels of universalism for different work positions' recruitment
The signalling effect		Those who have a qualification can signal their work skills more easily
Organisational bureaucracy		High-status jobs' workplaces have a well-developed bureaucratic system
Deprivation and reliance	Seek to explain the difference in the association between learning and labour market outcome, across social origins	To achieve career success, advantaged groups have various kinds of resources, whereas disadvantaged groups have little but their own learning

Organisational bureaucracy theory assumes that the organisations of advantaged occupations have a better developed bureaucratic system. This assumption is premised on two things: 1) disadvantaged and advantaged occupations are segregated into different organisations and 2) advantaged occupations' organisations have a relatively well-developed bureaucratic system. If the first premise holds, the second premise may hold. However, the occupational segregation premise is not convincing. As work organisations are often characterised by hierarchy, any such organisation will have both high- and low-level positions.

In addition, it is hard to believe that the signalling effect can explain the whole story on the variation in the association between social origin and class destination. The signalling effect account implies that more mismatches happen when a powerful signalling tool, like a qualification certificate, is lacking. However, those who have good social network resources would not experience mismatch that frequently. Thus, the variation in the origin-destination association has been reduced to simply an outcome of miscommunication, that the skilful individuals without a tool like a qualification certificate fail to signal their actual work skills to the potential employers, when they also do not contain social network resources. This account neglects the fact that social network resources shape labour market outcomes in a variety of ways like heterogenous job information acquisition (e.g., Granovetter, 1974), advantaged groups' opportunity hoarding (e.g., Tilly, 1998), network-based resources and power borrowing (e.g., Lin, 1999), and reciprocal social exchange between those who hold resources (e.g., Molm, Collett, and Schaefer, 2007).

It could be the case that the well-educated often look for professional positions, and the recruitment for professional positions is more 'meritocratic,' as suggested by the universalism approach. However, the claim that more meritocratic selection operates among the higher positions is still not sufficient enough to explain why disadvantaged individuals' labour market outcomes are associated with their participation in learning activities to a greater extent. The elements within the deprivation and reliance claim actually captures the most crucial reason for the heterogeneity in the economic returns: the greater relevance of learning to disadvantaged populations' occupational mobility simply reflects their deprivation of other kinds of resources, regardless of the organisational and occupational difference in the extent of meritocracy in recruitment, and the signalling effect of a qualification. Although the empirical results often say 'the effect is greater' for the disadvantaged, it is not in a literal sense that the effect of certain learning opportunities is greater for anyone, but only means that they are more reliant on those learning opportunities to achieve certain labour market outcomes compared to those who are already in advantaged positions. Presumably, disadvantaged populations have a stronger reliance on learning to achieve occupational mobility, as they lack other kinds of resources.

6.3. The diligence dependence theory

This section develops a preliminary theory that combines the elements from the *deprivation and reliance claim* and the *temporarily scarce skills theory* from Chapter Five to envisage and interpret the role of UIL for disadvantaged and advantaged groups' occupational mobility. I call this theory *the diligence dependence theory*. The word *dependence* refers to the situation that disadvantaged background individuals are more reliant on learning and skill-development to secure occupational outcomes since they are deprived of other kinds of resources, as highlighted in the deprivation and reliance claim. The word *diligence* refers to workers' constant effort of learning to produce up-to-date labour power and to cope with skill obsolescence, as highlighted in the temporarily scarce skills theory in Chapter Five.

The wisdom of the diligence dependence theory implies that due to the deprivation of multiple kinds of resources, disadvantaged background individuals would be more reliant on UIL and further work-skills development to achieve good occupational mobility than the advantaged. First, individuals from disadvantaged social backgrounds like RMWs are more reliant on means like UIL to catch up with the 'skill and knowledge gap.' As advantaged background workers like URWs might have received a good education, training, and other cultural resources more easily due to the abundance of educational resources and opportunities in urban areas, they might have acquired the required work skills and professional knowledge more easily than the workers from disadvantaged backgrounds. In this sense, for URWs, further learning by the means of UIL might be auxiliary, but less essential. However, workers who did not enjoy those educational and cultural resources before might need to spend more time and effort on learning to further develop their work skills and knowledge to 'catch up.' For them, a further effort of learning like UIL might be more essential rather than additional. Second, advantaged background individuals' occupational mobilities might be less skill-dependent, as their non-skill-related resources (e.g., family business, social networks) can also help them achieve good occupational mobility more easily. Thus, for those who have no UIL activities, advantaged populations like URWs would still have much better career prospects than the disadvantaged RMWs in this case. Since learning means like UIL is more critical for the disadvantaged's career development, when holding other conditions constant, with the growth of activeness in UIL, the gap between disadvantaged and advantaged individuals will decrease. This pattern is illustrated in Figure 6.1. In Figure 6.1, the horizontal axis measures a group's activeness in learning (e.g., length of time spent on online learning per week), and the vertical axis measures the average outcome of occupational mobility (e.g., probability of upward mobility). The diligence dependence theory expects that for those from advantaged backgrounds, even without engaging in learning, they always have a better outcome of occupational mobility. Whilst the gap between the disadvantaged and the advantaged is very small when actively engaging in learning, those two groups would have a larger gap in the outcome of occupational mobility when not actively engaging in learning.

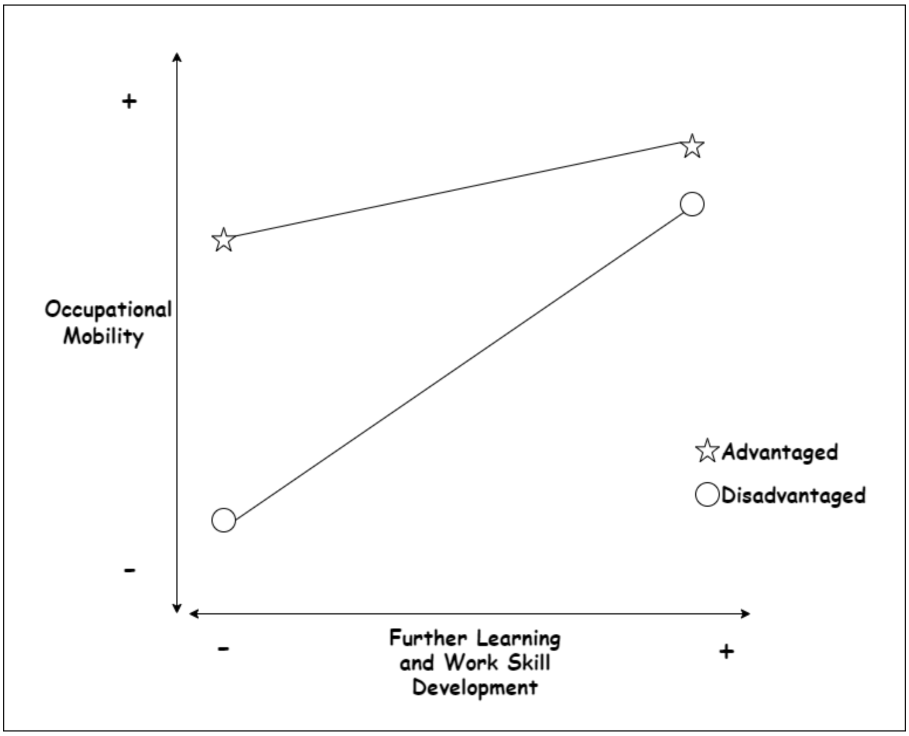

Figure 6.1. Different growth trajectories

However, UIL is not a once and for all achievement, like getting a qualification certificate from formal education before the labour market entry.

As discussed in the temporarily scarce skills theory, UIL is more like a form of on-going labour that exists throughout workers' working lives in this information age (Livingstone and Sawchuck, 2004). The temporarily scarce skills theory informs us that the scarcity of work skills affects one's occupational attainment, although the scarce status of skills is not stable. In order to secure their desired career prospects, particularly if their occupational attainment is more skill-reliant, UIL might have to become a form of routine labour to keep reproducing the scarce skills. However, for those whose occupational attainment is less skill-dependent and who are more likely to have advantaged social backgrounds, the resources they rely on might be less subject to obsolescence (e.g., monetary resources, social networks, family inheritance). These workers would not need to constantly perform that extra labour of learning to 'fight against' skill obsolescence and devaluation in order to secure their occupational attainment.

In this situation, some diligent learners from disadvantaged backgrounds manage to narrow the gap between them and their advantaged counterparts. Disadvantaged background workers' extra effort of learning in the form of UIL reduces their disadvantages in the labour market. However, the 'victory' of a few disadvantaged individuals' occupational achievement through their own effort of learning actually reflects that there is a lack of structural-level measures to reduce the gap between disadvantaged and advantaged background individuals. Indeed, the possibility of UIL has to be premised on the availability of abundant and accessible learning resources online. However, the abundance of online information resources does not automatically empower disadvantaged populations in occupational mobility, as it has to rely on the workers' own effort of learning, which is actually a hidden form of labour in the contemporary world (Livingstone and Sawchuck, 2004), in order to achieve the goal of scarce skills development and reproduction.

6.4. A three-way association? The result of quantitative evidence

6.4.1. Analytical strategy

This section uses quantitative data to make a robust comparison on the 'UIL-mobility' association between RMWs and URWs. If the diligence dependence theory is valid, two derived empirical patterns should be observed. First, whilst UIL is associated with workers' occupational mobilities, that association should be stronger among RMW populations, compared to URWs. I call this pattern *differential returns*. Second, along with the growth of activeness in UIL, the gap in occupational mobility between RMWs and URWs should be reduced gradually. I call this pattern *gap-narrowing*. Empirically, both of these expectations can be examined by studying the interaction effect of *hukou* type and UIL activeness on occupational mobility, two faces of the same coin of the interaction effect. This part of the analysis used the same data, sample, and measurement that are used in Chapter Five. So likewise, I used a scale value of occupational mobility (called *occupational change score* below), and two binary variables, *downward mobility* and *upward mobility*, to operationalize multiple aspects of occupational mobility. The modelling techniques are also the same, but I further added an interaction term (UIL $_{t-1}$ x *hukou*) into the mixed-effects models.

I begin by assuming that in general the gross association between UIL and occupational mobility is contingent on one's *hukou* type. Meanwhile, we should also expect that the gap in occupational mobility has been narrowed, along with the growth of activeness in UIL:

> ***H1.*** *In general, the gross UIL-Occupational change score (H1a), UIL-Downward mobility (H1b) and UIL-Upward mobility (H1c) associations are stronger among RMWs. Along with the growth of activeness in UIL, the RMW-URW differences in average occupational change score (H1d), downward mobility rate (H1e) and upward mobility rate (H1f) decrease.*

Both the gross UIL-mobility (e.g., well-educated workers are more likely to have UIL and to achieve a good occupational change) and *hukou*-mobility (e.g., urban background workers are more likely to be well-educated) associations contain some confounding elements, among which education plays a prominent role. To reduce the confounding bias to some degree, I added the controls of educational achievement, some other demographic characteristics (age, gender, ethnicity), industry, and sector, and expect that the different returns and gap narrowing observations still persist:

> ***H2.*** *After controlling for educational achievement, other demographic characteristics (age, gender, ethnicity), industry, and sector, the UIL-Occupational change score (H2a), UIL-Downward mobility (H2b) and UIL-Upward mobility (H2c) associations are still stronger among RMWs. The RMW-URW differences in average occupational change score (H2d), downward mobility rate (H2e), and upward mobility rate (H2f) decrease, along with the growth of activeness in UIL.*

As said, since the analysis used exactly the same data, sample, measures, and modelling techniques in Chapter Five, I would not introduce them again in this section. To test the hypotheses, there are two steps of modellings. To test H1, the first model (Model 1: UIL x *hukou*) contains fixed-effect components of an interaction term of *last wave UIL* and *hukou type* and independent terms of *year* and *last wave occupation*, as well as an individual-specific random intercept. To test H2, based on the first model, the second model (Model 2: UIL x *hukou* + controls) further adds the following terms: *educational background*, *higher credential gaining*, *gender*, *ethnicity*, *age*, *age-squared*, *last wave industry*, *last wave sector*.

I adopted suggestions from Mustillo et al. (2018, p.1282) and Mize (2019) that one should move beyond simply looking at the model coefficients when investigating a possibly non-linear interaction effect. Specifically, Mize (2019) recommended that in addition to the model coefficients of the interaction terms, one should also plot the predictions to determine the nature of the interaction and carry out a second difference analysis[21] on the equality of two marginal effects. To gain a better insight into interaction, Berry, Golder, and Milton (2012) recommend that the best practice is to examine two sides of the interaction effect. Particularly, in the context of this study, the implications from both sides of the interaction effect (i.e., different effects of UIL for RMWs and URWs; different effects of *hukou* type across UIL activeness level) are equally crucial to address our research question, so I carry out second difference tests on both sides. The tests are done by comparing the 95% confidence intervals of the average marginal effects by a third variable, by using *margins* command and the user written package *SPlot13* in Stata environment (Long and Freese, 2014). When doing the second difference analysis to compare *the changes of RMW-URW gap in occupational mobility*, I simply compare the predicted 95% confidence intervals of the RMW-URW differences in occupational mobility across different UIL activeness levels. Regarding *the variation of the UIL-mobility associations between RMWs and URWs*, I compare the second differences in two ways. The first, which I call *different returns compared with internet non-use*, compares the RMW-URW differences in the outcomes due to changes from *no internet use* to each level of activeness in UIL. The second way, which I call *different gradational change*s, compares the RMW-URW differences due to the changes from a less active level UIL to a more active level UIL.

6.4.2. Occupational change score

I begin the analysis by looking at the results of linear mixed-effects models

[21] The first difference refers to the difference in the outcome by one explanatory variable (e.g., different occupational outcome between RMW and URW). The second difference is the difference in the association between two variables by another explanatory variable (e.g., the variation of RMW-URW gap in occupational attainment by UIL).

on the scale outcome of occupational mobility, *occupational change score*. Model coefficients are reported in Table 6.2.

Firstly, model 1 contains an interaction term $UIL_{(t-1)}$ x *Hukou*, and controls for the occupational category at the last wave and year. The reference observation is the average occupational change in 2014 of the rural and professional and managerial background individuals who did not have any internet use in 2010. The constant term is -1.95, indicating an average 1.95 degree of downward mobility. But that estimation is exaggerated due to the skewness of the distribution of the scale indicator of mobility for the higher managerial and professional background individuals. Urban background individuals who did not use the internet (Non-agricultural=0.317, $p< 0.001$) had a better occupational change compared to their rural migrant peers. Among RMWs, compared to those who did not even use the internet at the last time point, last wave UIL was also related to gradually better occupational changes (Non-active= 0.261, $p< 0.05$; Somewhat active = 0.437, $p< 0.001$; Active=0.663, $p< 0.001$). Among URWs, the Non-Active UIL to No internet use (Non-agricultural x Non-active=0.031, $p>=0.1$) and Somewhat active UIL to No internet use (Non-agricultural x Somewhat active=0.021, $p>=0.1$) differences were similar to the RMW groups. However, the difference between no internet use and active UIL was significantly stronger among RMW groups (Non-agricultural x Active=-0.208, $p< 0.05$), compared to URWs.

Table 6.2. Linear mixed models on occupational change score (coefficients and standard errors)

	(1) Model 1 (UIL x *Hukou*)	(2) Model 2 (UIL x *Hukou* +Full controls)
Last wave UIL (Ref: No internet use)		
Non-active	0.261*	0.144
	(0.107)	(0.106)
Somewhat active	0.437***	0.204*
	(0.083)	(0.085)
Active	0.663***	0.382***
	(0.076)	(0.078)
Hukou type (Ref: Agricultural)		
Non-agricultural	0.317***	0.189***
	(0.046)	(0.047)
Interaction		
Non-agricultural x Non-active	0.031	-0.017
	(0.127)	(0.123)
Non-agricultural x Somewhat active	0.021	0.007
	(0.099)	(0.097)
Non-agricultural x Active	-0.208*	-0.194*
	(0.088)	(0.087)
Constant	-1.951***	-2.332***
	(0.060)	(0.225)
Controls	a	b
Observations	5,466	5,466
Individuals	3,992	3,992
R-square	0.2093	0.254

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
a: year, last wave occupation; b: year, last wave occupation, educational background, higher level credential, age, age^2, gender, *hukou*, ethnicity, last wave industry, last wave sector; Coefficients of controlled variables presented in Table F4;
Source: CFPS adult 2010, 2014 and 2016

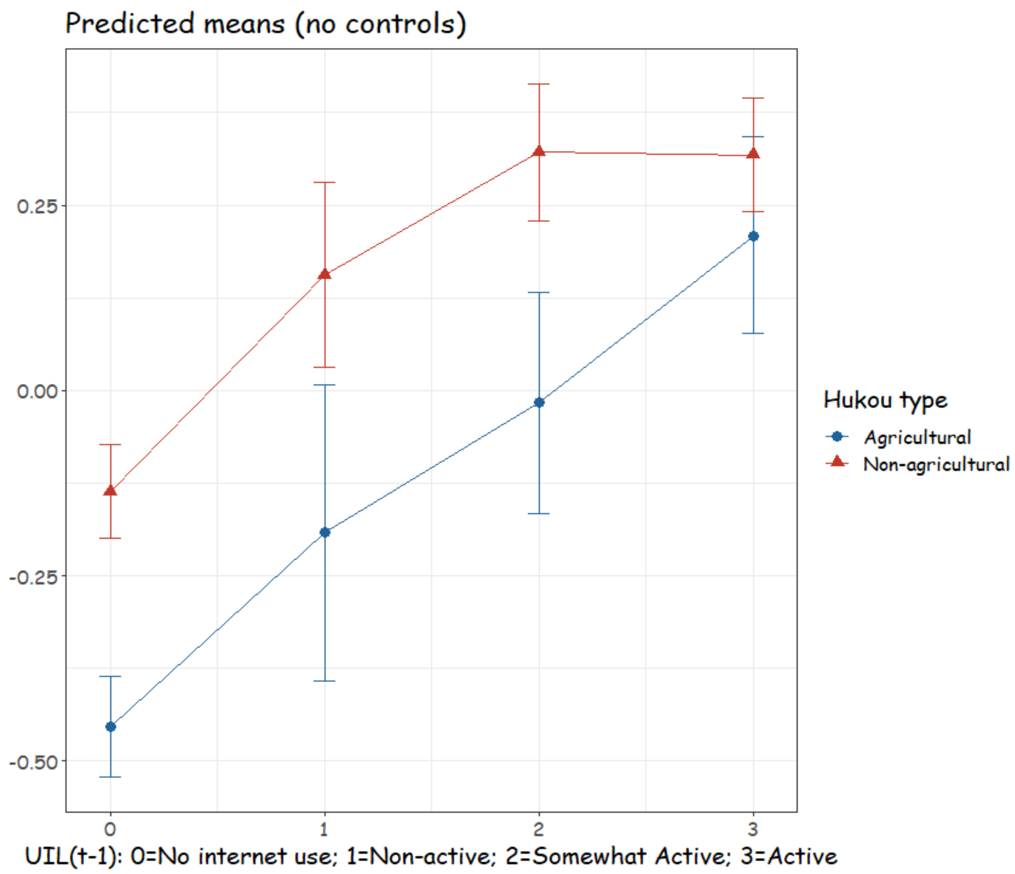

Figure 6.2 Average marginal effects of last wave UIL x Hukou type on occupational change score (the scale indicator) with 95% CIs from Model 1. Source: CFPS adult 2010, 2014 and 2016

To better illustrate the interactive relationship, Figure 6.2 plots the predicted means of occupational change score with the 95% confidence intervals, grouped by level of activeness of last wave UIL and *hukou* type. As we can see, both the RMW and URW groups' lines show an overall growing trend along with the growth of activeness in UIL. The slopes of both lines are similar in the beginning. However, URW's predicted mean stops rising after somewhat active UIL, whereas the RMW group's predicted mean continues growing. In other words, the RMW group only has a faster growth rate than URWs when reaching the most active level of UIL. Seeing the pattern from another angle, whilst URWs always have a larger predicted mean value compared to RMWs, the RMW-URW mean difference reaches the smallest and becomes non-significant among those who were most active in UIL.

Next, Model 2 adds further controls of educational achievement, demographic characteristics, last wave industry, and last wave sector. For RMWs, even after adding those controls, UIL was still associated with a linear growth in occupational change value (Non-active= 0.144, $p>0.1$; Somewhat active = 0.204, $p< 0.05$; Active=0.382, $p< 0.001$). And compared to the RMWs who had no internet use, no internet use URWs had a significantly better outcome in occupational change (Non-agricultural=0.189, $p< 0.001$). Similar to the findings in Model 1, compared to no internet use, the effects of *non-active* and *somewhat active UIL* on occupational change are very similar across RMWs to URWs, but the effect of being active in UIL is weaker for the URW group (Non-agricultural x Active= -0.194, $p< 0.05$).

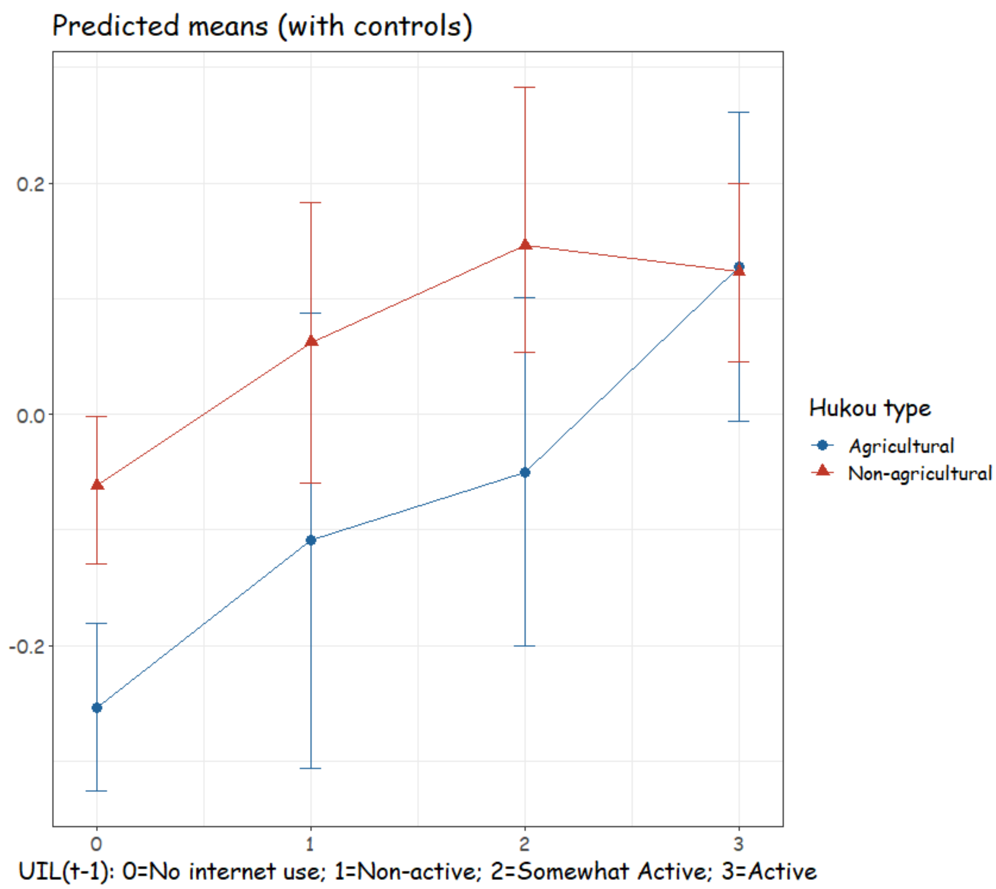

Figure 6.3 Average marginal effects of last wave UIL x *Hukou* type on occupational change score (the scale indicator) with 95% CIs from Model 2. Source: CFPS adult 2010, 2014 and 2016

Figure 6.3 plots the predicted means of occupational change score by UIL activeness at last wave and *hukou* type. At first glance, the pattern looks similar to Figure 6.2, except for that among those who had the most active UIL, the RMW group's predicted mean is even slightly higher than the URW group's, yet the difference is very small. The differences between *somewhat active UIL* and *active UIL* in occupational change vary by *hukou* type. For RMWs, the change from *somewhat active UIL* to *active UIL* is related to an improvement in occupational change, but despite that, the difference is not significant at the 95% confidence level. For URWs, active UIL's occupational change is even slightly worse than somewhat active UIL's, although the difference is very tiny and statistically insignificant.

In comparison, the different returns and gap narrowing observations look slightly more apparent in Model 2, where some confounding variables have been controlled. This actually makes sense, since the confounding bias could actually conceal the interaction effect. For instance, RMWs being active in UIL were more likely to be the well-educated RMWs. But since well-educated individuals would not benefit more from learning than the less educated, that may lead to an under-estimation of the relative UIL return to occupational change for RMWs.

The next step addresses the second difference test. Firstly, Figure 6.4 shows the mean differences in occupational change score compared to no internet use, grouped by *hukou* type. This is used to examine the *different returns compared with internet non-use*. Compared with no internet use, all levels of UIL activeness across both RMWs and URWs from the results of Model 1 and 2 have a significantly larger predicted mean in occupational change (all figures larger than zero). The RMW-URW difference in the effects of *non-active* and *somewhat active* UIL (compared to no internet use) is negligible. Compared to no internet use, the effect of *active UIL* is relatively strong for RMWs. Yet, since the 95% confidence intervals overlap, we do not have strong evidence to support the RMW-URW difference in the effect of active UIL on occupational change compared to no internet use.

Next, I further scrutinized the *different gradational change*s, the differences in the changes of predicted means from a less active to a more active UIL level. Figure 6.5 shows the pairwise comparisons on predicted means with the 95% confidence intervals between a more active level UIL and a less active level UIL grouped by *hukou* type, based on the results from Model 1 and 2. Both graphs in Figure 6.5 show a negligible RMW-URW difference in the first two pairs of gradational changes (non-active UIL vs no internet use; somewhat active UIL vs. non-active UIL). However, RMWs and URWs differed in the last pair of gradual change (active UIL vs somewhat active UIL). In the last pair of comparison, the mean differences for RMWs were consistently higher than 0.15, indicating an improvement in occupational change along with the growth of activeness in UIL. In contrast, the figures for URWs were around zero, meaning no noticeable improvement. This further indicates a possible RMW-URW difference in the effect of active UIL on occupational change. However, the confidence intervals overlap, again meaning that the evidence is not strong.

Finally, we scrutinized the changes of the RMW-URW gap in occupational change by UIL activeness level. Figure 6.6 plots the predicted RMW-URW mean differences in occupational change with the 95% confidence intervals by UIL activeness level, based on Model 1's and 2's estimations. For both graphs in Figure 6.6, the gap between RMWs and URWs remained very similar from no internet use to somewhat active UIL. When having active UIL, the RMW-URW gap reduced a lot and was even around 0 in the second graph. However, as the error bars also overlap, there is a lack of strong evidence to support the gap narrowing effect of UIL in the working populations in urban China.

To sum up, when using a scale indicator *occupational change score* to measure occupational mobility, the mixed-effects linear models show some signs of ‘greater UIL effect for RMWs’ and ‘RMW-URW gap narrowing,’ but only when reaching the most active level of UIL. Although both Models 1 and 2 show statistically significant coefficients of the interaction term *Non-agricultural* x *Active*, the second difference tests fail to provide strong evidence to support the generalisability of either a) a variation of UIL effect on occupational change or b) a reducing RMW-URW gap along with growing activeness in UIL, as the 95% confidence intervals overlapped. *As such, we can conclude that we do not have very strong evidence to support H1a, H1d, H2a, and H2d*.

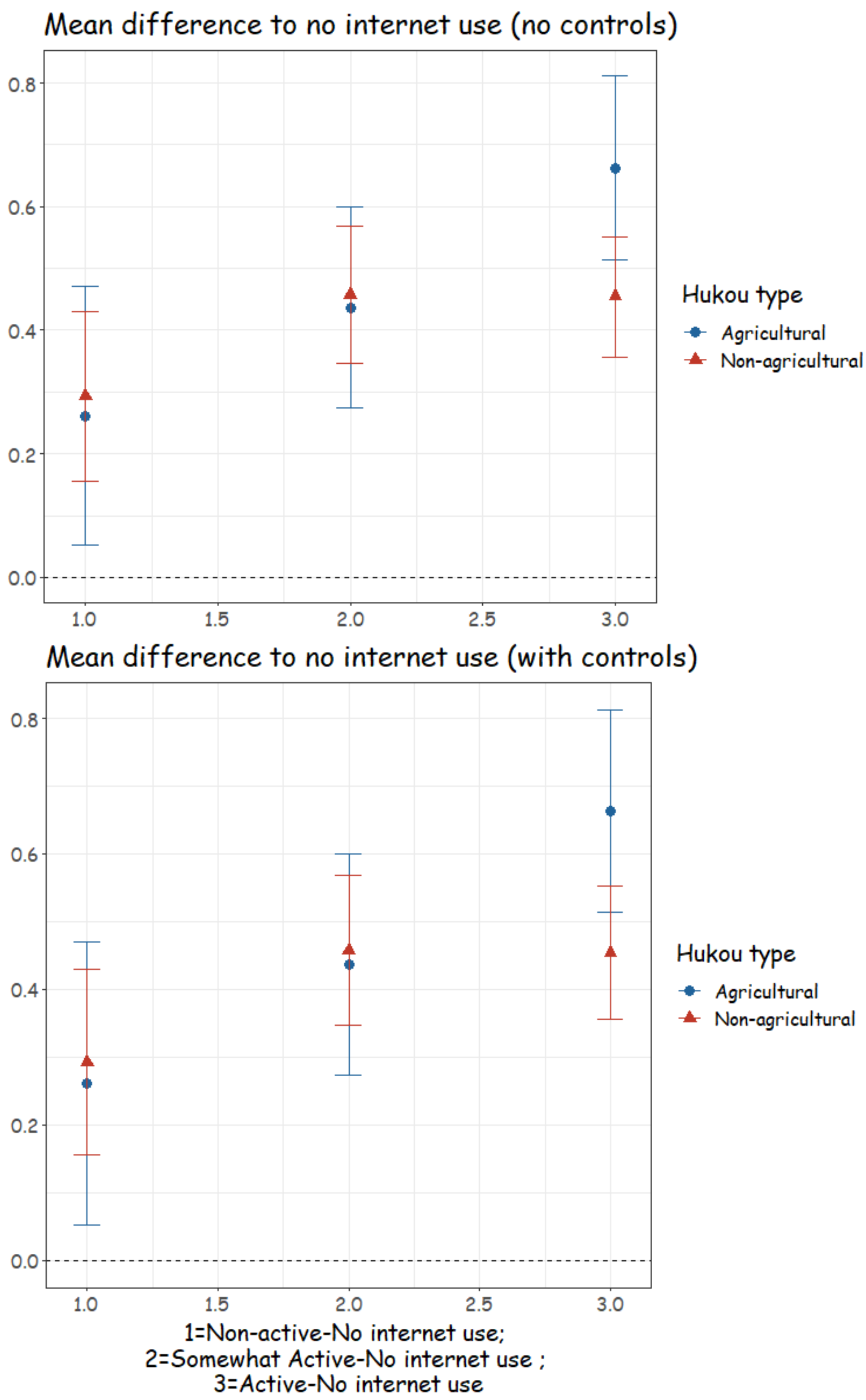

Figure 6.4 Mean differences in occupational change compared to no internet use by level of activeness in UIL and Hukou type

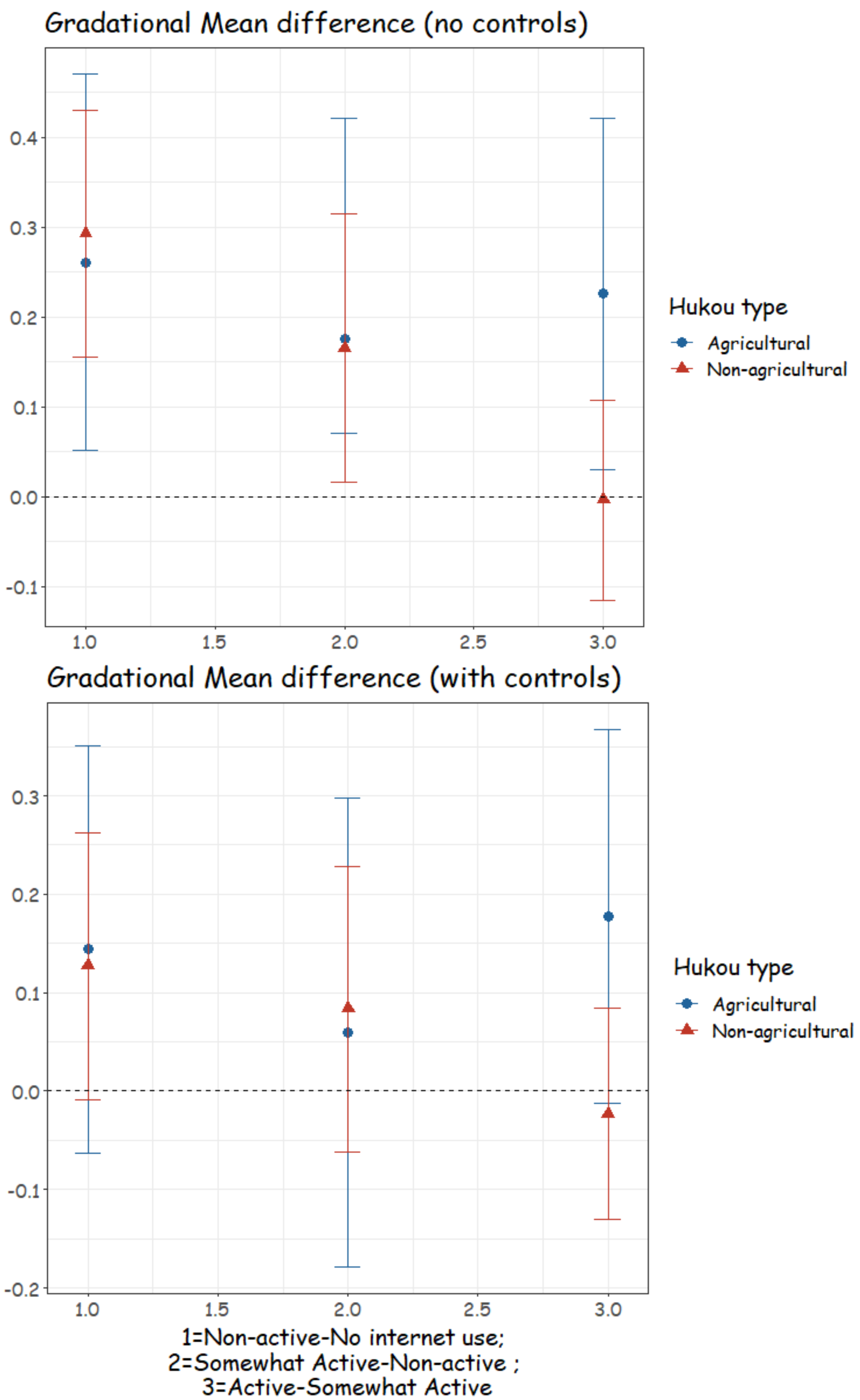

Figure 6.5 Gradational Mean differences in occupational change by level of activeness in UIL and Hukou type

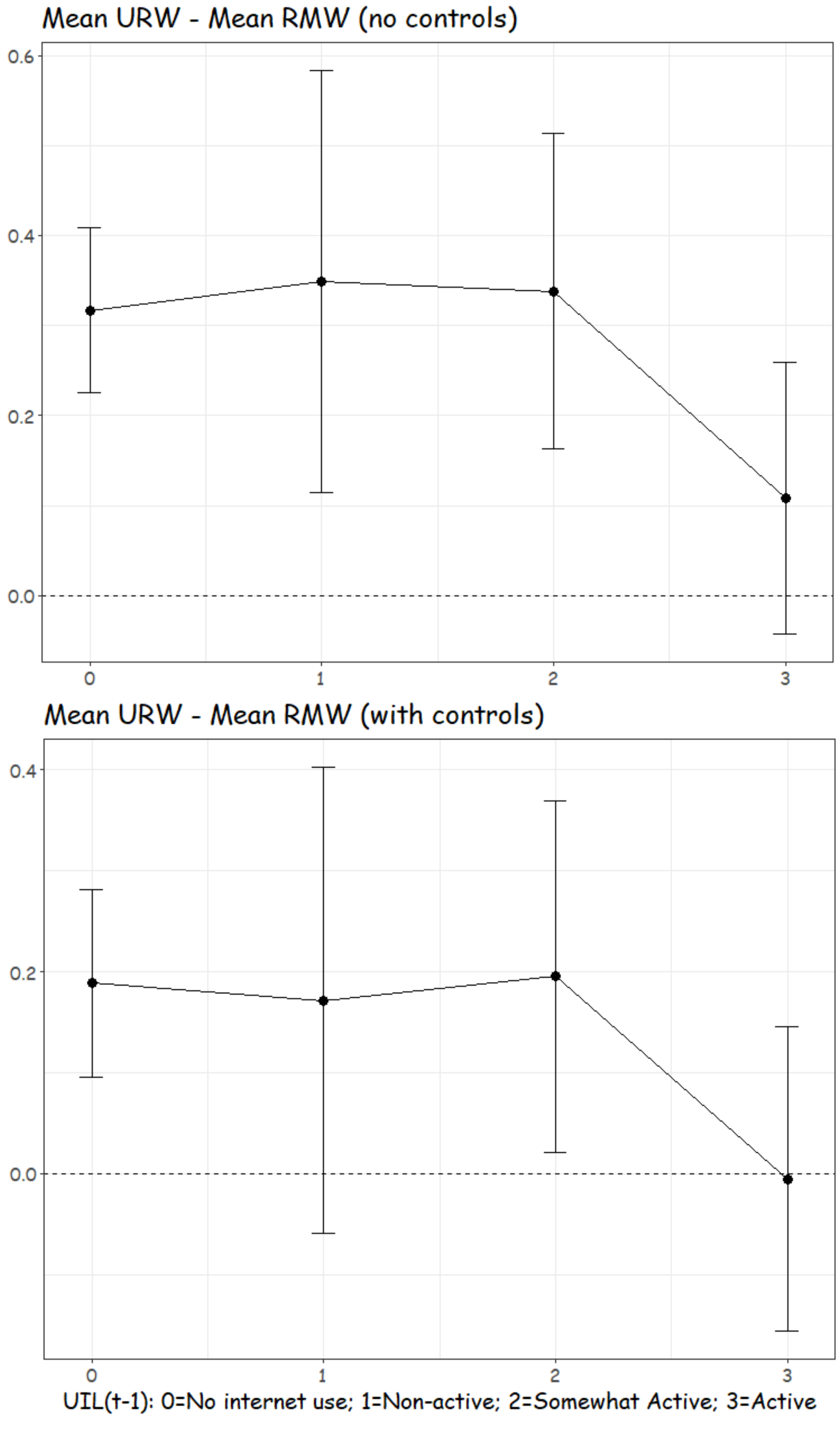

Figure 6.6 RMW-URW gap in predicted mean of occupational change by UIL activeness level

6.4.3. The risk of downward mobility

In this section, I specifically focused on the effect on downward mobility risk. Table 6.3 reports the coefficients of mixed-effects logistic regression models on downward mobility rates.

Model 1 only includes the interaction effect of *last wave UIL* and *hukou* type, and independent terms *year* and *last wave occupation*. For the reference group (rural background, higher managerial and professional background, and no internet use), the probability of downward mobility in 2014 was as high as 73% (Odds=2.830, $p < 0.001$). For RMWs, the activeness of UIL was linked to a reduction of downward mobility rate in a linear trend ($OR_{\text{non active}} = 0.698$, $p > 0.1$; $OR_{\text{somewhat active}} = 0.478$, $p < 0.001$; $OR_{\text{somewhat active}} = 0.362$, $p < 0.001$). Among those who did not use the internet, RMWs were two times more likely to experience downward mobility than URWs ($OR_{\text{Non-agricultural}} = 0.457$, $p < 0.001$). For URWs, compared to no internet use, the functions of *non-active* ($OR_{\text{Non-agricultural x Non-active}} = 1.072$, $p > 0.1$) and *somewhat active UIL* ($OR_{\text{Non-agricultural x Somewhat active}} = 1.065$, $p > 0.1$) on reducing downward mobility rates look almost the same to the functions among RMWs. However, RMWs and URWs differ in the gross effect of active UIL on reducing downward mobility rates. The gross effect of active UIL on downward mobility risk reduction was much stronger among RMWs ($OR_{\text{Non-agricultural x Active}} = 1.733$, $p < 0.05$).

Based on Model 1, I plotted the predicted probabilities of downward mobility (see Figure 6.7) to illustrate the interactive function of UIL and *hukou* type. Both RMWs and URWs had a somewhat negative relationship line between UIL and downward mobility rates. Those two lines look horizontal in the beginning, but go to completely different directions in the end. Whilst the RMW group's predicted downward mobility rate continued reducing when reaching active UIL, the downward mobility rate for URWs rose back. In the beginning, RMWs had a higher downward mobility rate and the gap between these two groups persisted almost the same before reaching active UIL. However, when reaching active UIL, the downward mobility rate for URWs was lower than the RMW’s, although the difference was not statistically significant.

Table 6.3 Mixed-effects logistic regression models on downward mobility rate

(odds ratios and standard errors)

	(1)	(2)
	Model 1 (UIL x Hukou)	Model 2 (UIL x Hukou +Full controls)
Last wave UIL (Ref: No internet use)		
Non-active	0.698	0.769
	(0.183)	(0.221)
Somewhat active	0.478***	0.670+
	(0.102)	(0.158)
Active	0.362***	0.534**
	(0.073)	(0.118)
Hukou type (Ref: Agricultural)		
Non-agricultural	0.457***	0.548***
	(0.059)	(0.078)
Interaction		
Non-agricultural x Non-active	1.072	1.315
	(0.341)	(0.452)
Non-agricultural x Somewhat active	1.065	1.167
	(0.268)	(0.318)
Non-agricultural x Active	1.733*	1.924**
	(0.389)	(0.473)
Constant	2.830***	10.027***
	(0.467)	(6.319)
Controls	a	b
Observations	5,466	5,466
Individuals	3,992	3,992
Wald Chi-square	219.7	203
df	13	29
Prob > chi2	0	0

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
a: year, last wave occupation; b: year, last wave occupation, educational background, higher level credential, age, age^2, gender, *hukou*, ethnicity, last wave industry, last wave sector; Coefficients of controlled variables presented in Table F5;
Source: CFPS adult 2010, 2014 and 2016

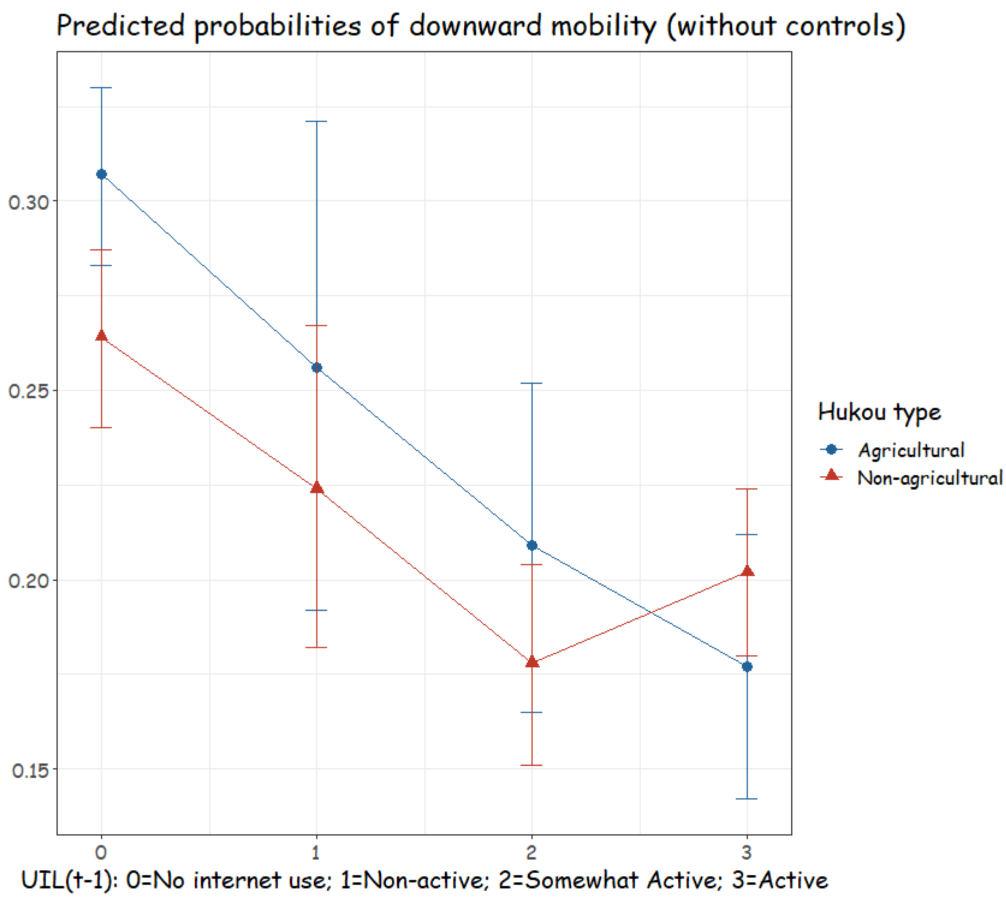

Figure 6.7 Average marginal effects of last wave UIL x Hukou type on downward mobility rate with 95% CIs from Model 1. Source: CFPS adult 2010, 2014 and 2016

Next, Model 2 added controls of educational achievement, other demographic characteristics, and last wave's industry and sector. The result looks almost the same to the result in Model 1: for RMWs, the relationship between last wave UIL and downward mobility rates was still negative and linear ($OR_{non\ active}$ =0.769, p >0.1; $OR_{somewhat\ active}$ =0.670, $p < 0.1$; $OR_{somewhat\ active}$ =0.534, $p < 0.01$); for the no internet use, having a non-agricultural *hukou* type was still linked to a much smaller risk of downward mobility ($OR_{Non\text{-}agricultural}$ =0.548, $p < 0.001$); and the function of active UIL on reducing downward mobility rate was much stronger among RMWs ($OR_{Non\text{-}agricultural\ x\ Active}$ =1.924, $p < 0.05$).

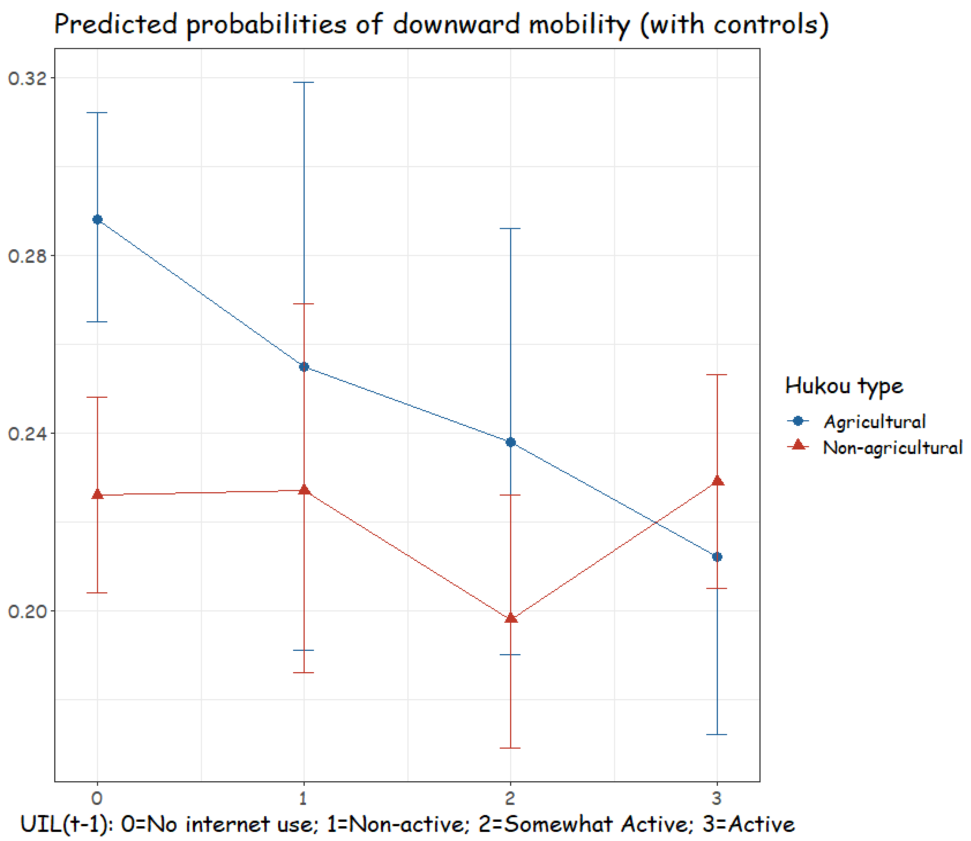

Figure 6.8 Average marginal effects of last wave UIL x Hukou type on downward mobility rate with 95% CIs from Model 2. Source: CFPS adult 2010, 2014 and 2016

Based on Model 2, Figure 6.8 plotted the predicted rates of downward mobilities grouped by UIL activeness and *hukou* type. Compared to Figure 6.7 (based on Model 1's prediction), Figure 6.8 shows a different pattern on the association between UIL and downward mobility for URWs. Whilst there was an overall negative association between UIL and downward mobility for URWs in Figure 6.7, after adding controls, the UIL-downward mobility association disappeared in Figure 6.8 (shown by the fluctuating red line). For those having no internet use, the predicted probabilities on downward movement were significantly different at the 95% confidence level between RMWs and URWs. When having no internet use, RMWs had a high risk of downward mobility, whereas downward mobility rate for URWs was low. For RMWs, there was still a negative association between UIL and downward mobility. Active UIL's downgrading rate was significantly lower than no internet use's rate for the RMW group. Thus, Model 2's result gives a clear indication that whilst URWs always had a relatively low risk of downward mobility, the RMW group's downward mobility risk reduced and became similar to the URW group's when the activeness in UIL grew.

Next, I used three second different tests to further scrutinise the reliability of the differences in the UIL effect on downward mobility, and the changing RMW-URW gap along with the change in UIL.

Figure 6.9 shows the comparison in downward mobility rates between *no internet use* and *different levels of activeness in UIL*, grouped by *hukou* type. Based on Model 1's prediction, the first graph shows that the magnitudes of difference between active UIL and no internet use on downward mobility rates were significantly different between RMWs and URWs at the 95% confidence level. As shown by the second graph, after adding controls, Model 2 did not indicate a statistically significant RMW-URW difference in the effect of active UIL (compared to no internet use) on downward mobility, although the error bars only overlapped to a very small degree.

Next, Figure 6.10 shows the comparison of the *gradational difference* in downward mobility rates by UIL and *hukou* type. The results from both graphs were similar in the way that in the beginning, the differences in the gradational change of downward mobility rate by UIL activeness were very small between RMWs and URWs. When reaching active UIL, the RMW group's figure was still under 0, meaning a predicted lower downward mobility rate compared to somewhat active UIL. However, the URW group's figure was slightly higher than 0, when having active UIL. Nonetheless, as the 95% confidence intervals overlapped, the evidence was not strong enough to infer the greater active UIL effect for RMWs on reducing downward mobility risk at the population level.

Finally, I looked at the change of the RMW-URW gap in downward mobility rate by UIL, which is shown in Figure 6.11. Based on the estimation from Model 1, the first graph in Figure 6.11 shows that the RMW-URW difference in downward mobility rate shrank when the activeness in UIL grew. At the level of *no internet use, non-active UIL,* and *somewhat active UIL*, RMWs still had a lower risk of downward mobility significant at the 95% confidence level (figures were significantly smaller than 0). At the *active UIL* level, the difference was no longer statistically significant. In particular, the RMW-URW gaps (in downward mobility rate) at *no internet use* and *active UIL* levels were significantly different at the 95% confidence level. Even after adding controls, the pattern in the second graph based on Model 2's result was almost the same. First, there was a general association between UIL activeness and the reduction of RMW-URW gap in downward mobility rate. In addition, compared to the RMW-URW gap at the *no internet use* level, the RMW-URW gap in downward mobility rate at the *active UIL* level was much smaller and the difference was significant at the 95% confidence level.

To sum up, results from the mixed-effects logistic regression models on downward mobility show a significant interaction effect of UIL and *hukou* type on downward mobility risk reduction. The effect of UIL on reducing the RMW group's downward mobility rate was noticeable, whereas the URW group's mobility did not seem to be subject to the change of UIL as their downward mobility rates were always low. However, I have not gained very strong evidence to show the different UIL effects on the change of downward mobility between RMWs and URWs, as the second difference test fails to show the significant different UIL effect. However, the second difference test results do show that the RMW-URW gap in downward mobility rate reduced significantly when the level of activeness in UIL rose. *Thus, H1e and H2e are supported by some strong evidence.*

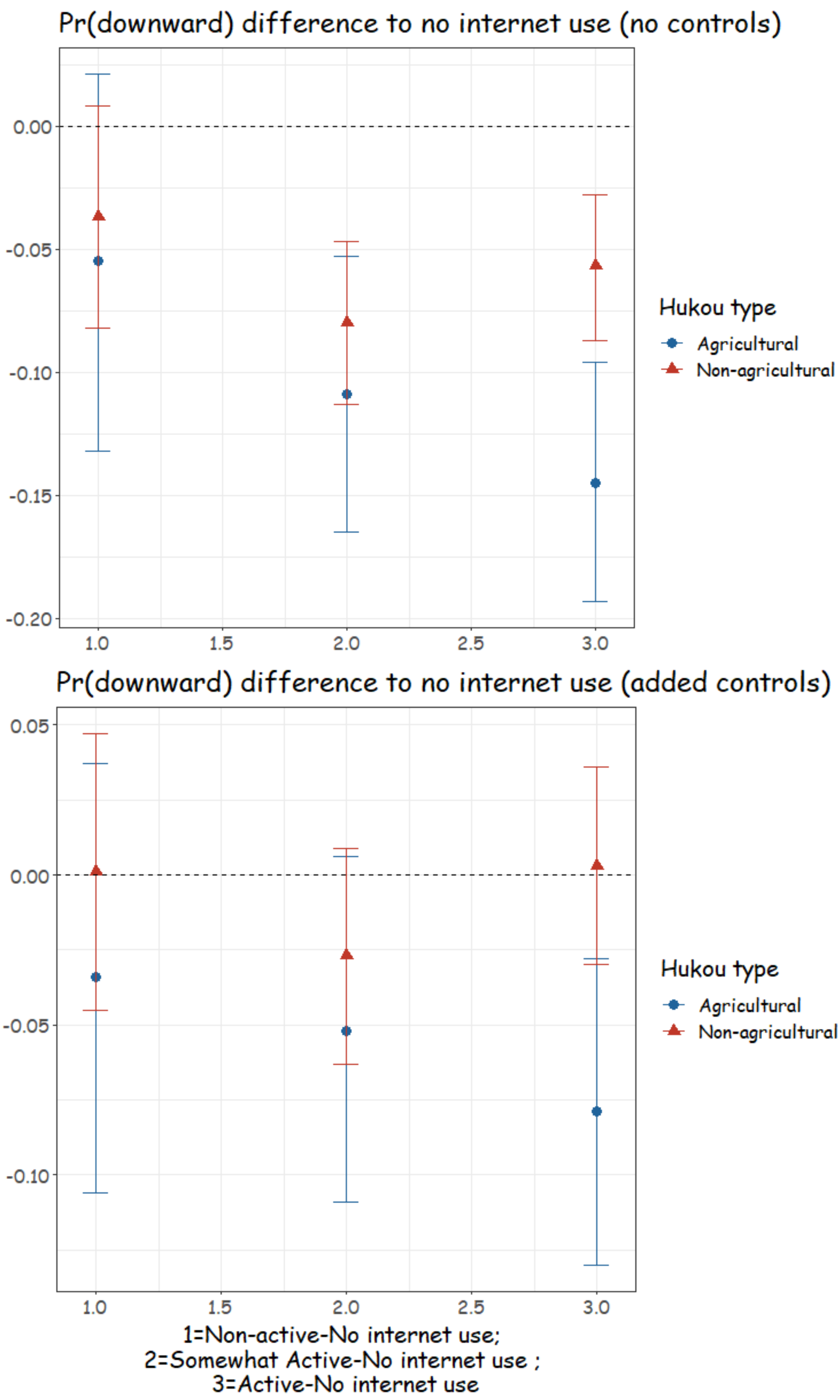

Figure 6.9 Downward mobility rates compared to no internet use by level of activeness in UIL and *Hukou* type

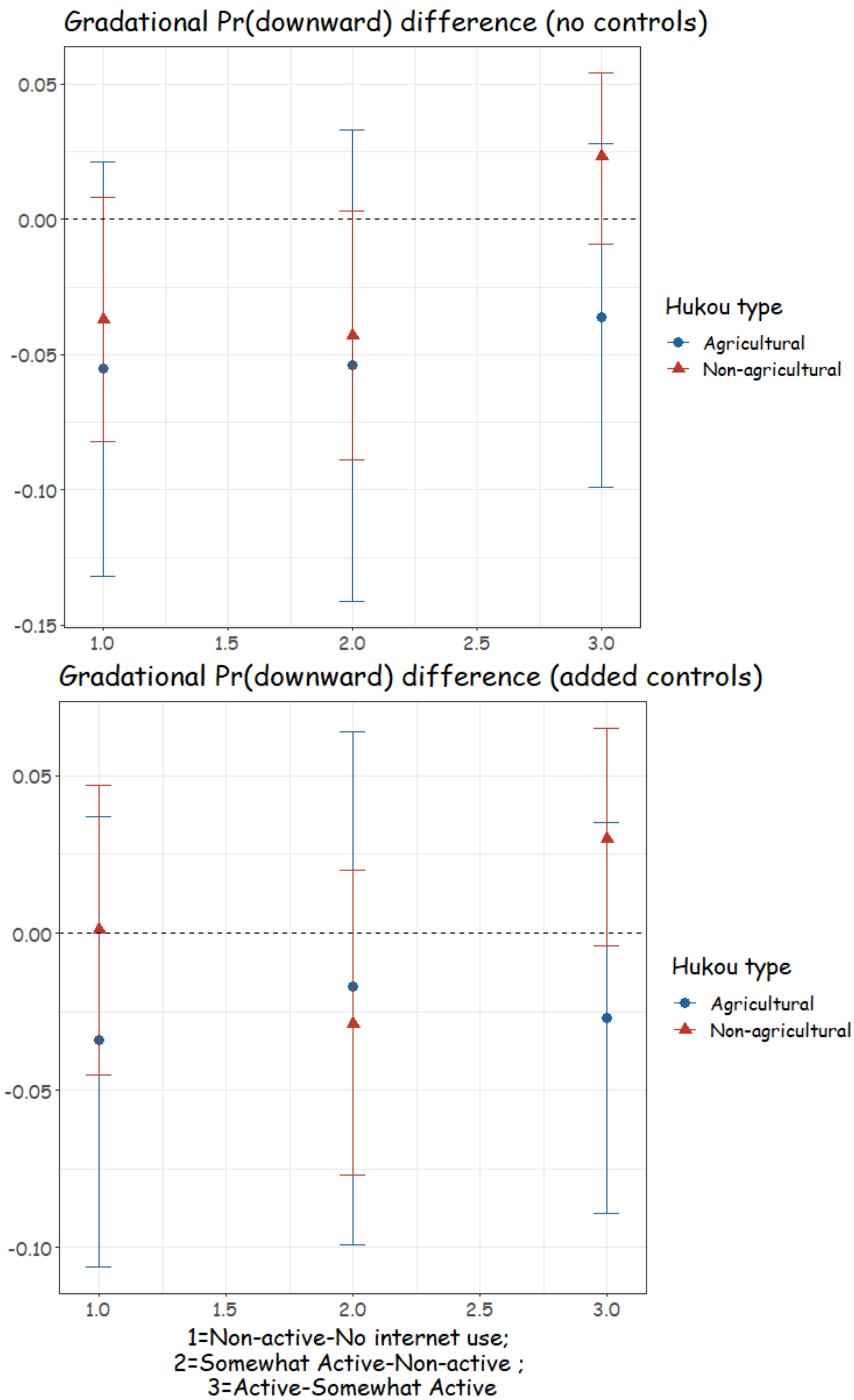

Figure 6.10 Gradational differences in downward mobility by level of activeness in UIL and *Hukou* type

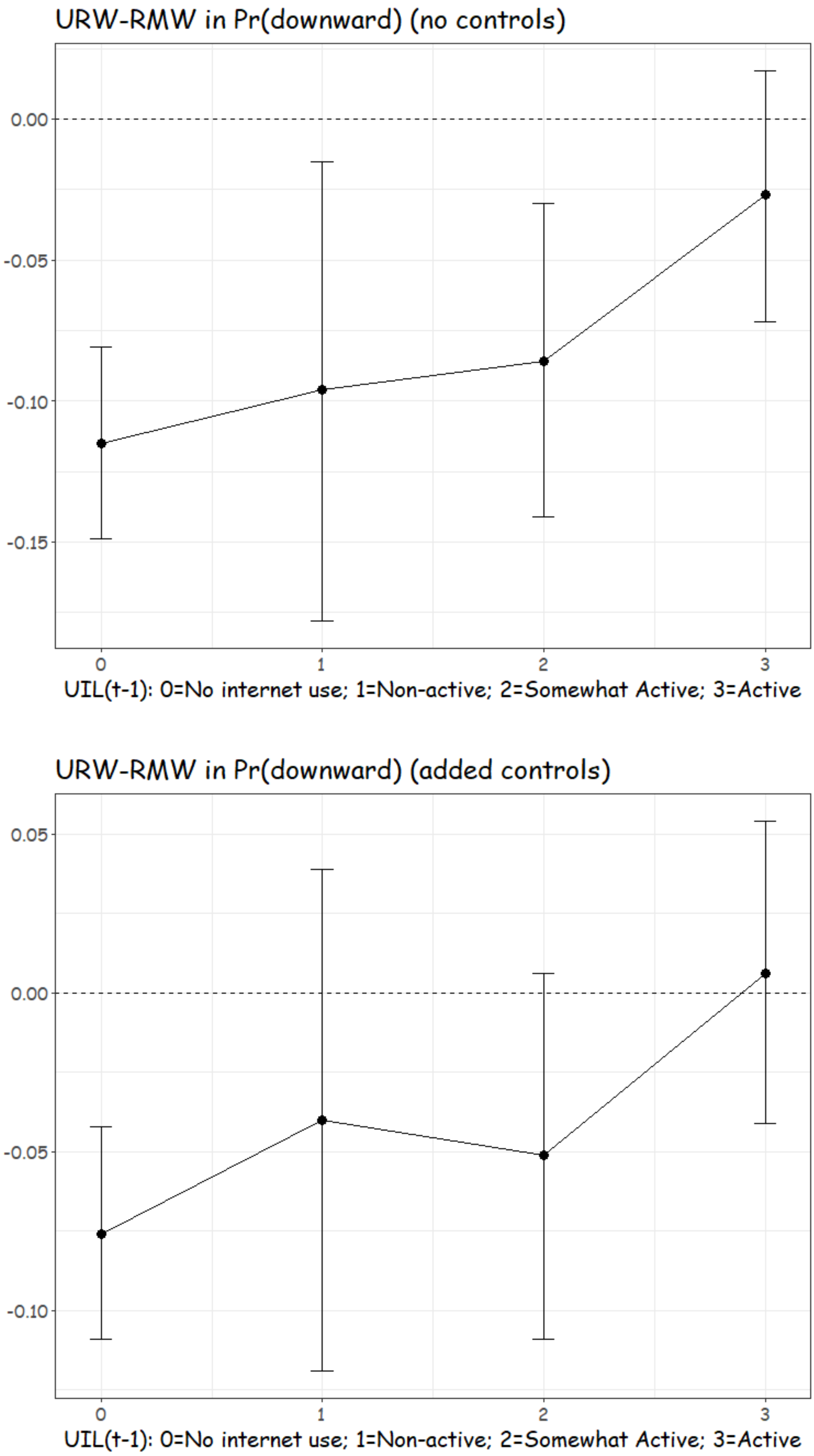

Figure 6.11 RMW-URW gap in downward mobility rate by UIL activeness level

6.4.4. Prospect of upward mobility

Table 6.4 shows the outcome of a mixed-effects logistic regression model on upward mobility. Since there is no point to study the highest occupational class' upward mobility, both models dropped cases whose original occupations were in the higher managerial and professional category. Model 1 only contains a 'UIL x *hukou* type' interaction term, *year*, and *last wave UIL* as the covariates. For RMWs, UIL was positively related to upward mobility rate ($OR_{\text{non active}} = 1.613$, $p < 0.1$; $OR_{\text{somewhat active}} = 1.932$, $p < 0.01$; $OR_{\text{active}} = 2.510$, $p < 0.001$). For those who did not use the internet, URWs might have a slightly higher upward mobility rate ($OR_{\text{Non-agricultural}} = 1.224$, $p < 0.1$), although the coefficient was only significant at the 90% confidence level. However, as shown in Table 6.4, the interaction term did not show that the correlations between UIL and upward mobility vary significantly across RMWs and URWs ($OR_{\text{Non-agricultural x Non-active}} = 0.891$, $p > 0.1$; $OR_{\text{Non-agricultural x Somewhat active}} = 0.825$, $p > 0.1$; $OR_{\text{Non-agricultural x Active}} = 0.805$, $p > 0.1$).

Based on Model 1's estimation, Figure 6.12 plotted predicted probabilities of upward mobility, grouped by UIL activeness level at the last wave and *hukou* type. At first glance, these two lines' slopes look a bit different in the beginning (especially from *no internet use* to *non-active UIL*), with the slopes of RMWs being slightly steeper. However, from *somewhat active* to *active UIL*, the slopes of both lines look almost identical. URWs did not appear to be more advantaged in upward mobility when having no internet use. And even when the differences were not estimated to be statistically significant at the 95% level, the RMW group's predicted upward mobility rate exceeded the URW group's rate and the gap kept expanding with growth in UIL activeness.

Next, Model 2 added controls of educational achievement, additional demographic information, original industry, and sector. As shown in Table

6.4, for RMWs, active UIL (OR_{active} =1.754, $p < 0.01$) was associated with a higher chance of achieving upward mobility compared to not having internet use at the last wave. It is noteworthy that among those who did not use the internet, URWs did not show a marked advantage in upward occupational mobility ($OR_{Non\text{-}agricultural} = 1.158$, $p > 0.1$). There might be some small variations in the effect of UIL on upward progression between RMWs and URWs. That being said, the coefficients were not statistically significant ($OR_{Non\text{-}agricultural \times Non\text{-}active} = 0.872$, $p > 0.1$; $OR_{Non\text{-}agricultural \times Somewhat\ active} = 0.790$, $p > 0.1$; $OR_{Non\text{-}agricultural \times Active} = 0.798$, $p > 0.1$).

Table 6.4 Mixed-effects logistic regression models on upward mobility rate

(reporting odds ratios and standard errors)

	(1) Model 1 (UIL x Hukou)	(2) Model 2 (UIL x Hukou +Full controls)
Last wave UIL (Ref: No internet use)		
Non-active	1.613+	1.309
	(0.419)	(0.348)
Somewhat active	1.932**	1.398
	(0.391)	(0.298)
Active	2.510***	1.754**
	(0.476)	(0.350)
Hukou type (Ref: Agricultural)		
Non-agricultural	1.224+	1.158
	(0.135)	(0.134)
Interaction		
Non-agricultural x Non-active	0.891	0.872
	(0.277)	(0.273)
Non-agricultural x Somewhat active	0.825	0.790
	(0.200)	(0.195)
Non-agricultural x Active	0.805	0.798
	(0.173)	(0.176)
Constant	0.412***	0.279*
	(0.044)	(0.152)
Controls	a	b
Observations	4,799	4,799
Individuals	3,634	3,634
Wald Chi-square	118.9	155.6
df	12	28
Prob > chi2	0	0

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1
a: year, last wave occupation; b: year, last wave occupation, educational background, higher level credential, age, age^2, gender, *hukou*, ethnicity, last wave industry, last wave sector; Coefficients of controlled variables presented in Table F5;
Source: CFPS adult 2010, 2014 and 2016

Figure 6.13 plotted predicted probabilities of upward mobility grouped by UIL activeness level and *hukou* type, based on the estimations of Model 2. At first sight, the graph looks similar to the graph in Figure 6.12, except for a slightly larger RMW-URW gap when there was no internet use. In addition, compared to no internet use, the changes from *no internet use* to *non-active UIL* and from *non-active* to *somewhat active UIL* were linked to a greater increase of the upward mobility rate among RMWs rather than URWs. However, the change from *somewhat active* to *active UIL* seems to be identical in terms of its relevance to the upward mobility rate changes. The trend began from RMWs having a slightly lower upgrading chance when there was no internet, to the RMW group's upward mobility rate being higher than URWs when they were both active in UIL, although no statistically significant difference was found.

Next, I carried out the second difference tests. Figure 6.14 plotted the upward mobility rate differences between *no internet use* and *other levels of activeness in UIL*, grouped by *hukou* type. Despite that the UIL-led mobility changes (compared to no internet use) were always greater for RMWs, the difference (in UIL-related upward mobility change) was not statistically significant at the 95% confidence level. Figure 6.14 further presented the result of the comparison in UIL-led gradational change in upward mobility rate by *hukou*. Both graphs in Figure 6.15 shows that the effects of gradational UIL change on upward mobility rate were almost similar between RMWs and URWs. Last but not least, the gap narrowing observation was also scrutinised, with the result being shown in Figure 6.16. The first graph in Figure 6.16 shows that the estimated points were from 0.025 to very close to 0, indicating a narrowing gap between RMWs and URWs in upward mobility rates when the activeness of UIL increased. Nevertheless, all points' confidence intervals overlapped, indicating that the changes of the RMW-URW gap in upward mobility rates were not estimated to be statistically significant. The second was also similar, although the estimated points were slightly below 0 when reaching somewhat-active and active UIL, meaning the RMW group's upward mobility rates overtook. That said, the RMW-URW gap was not found to have any statistically significant change.

Thus, when researching upward mobility, this section did not find good evidence to support that the effect of UIL was greater for the RMW group's upward mobility and the RMW-URW gap in upward mobility had been greatly reduced when being active in UIL. *Thus, no evidence for both H1c, H1f, H2c and H2f has gained.* However, also because that when both RMWs and URWs had no internet use, there was no serious issue of inequality in upward mobility, we do not need to further discuss whether UIL has narrowed the gap between the two groups.

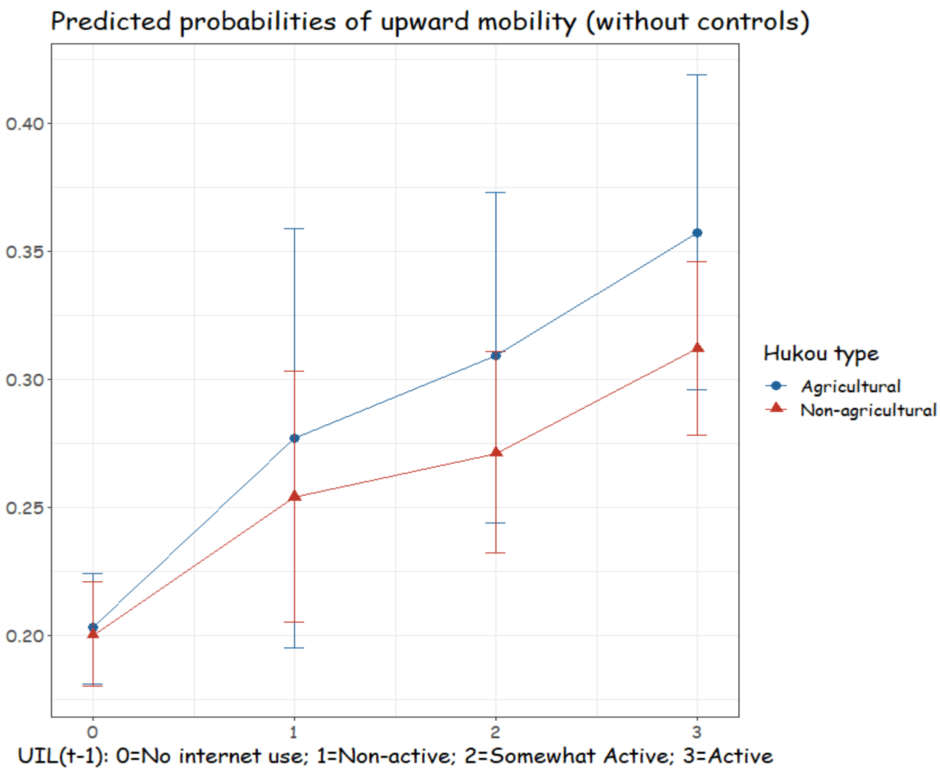

Figure 6.12 Average marginal effects of last wave UIL x Hukou type on upward mobility rate with 95% CIs from Model 1. Source: CFPS adult 2010, 2014 and 2016

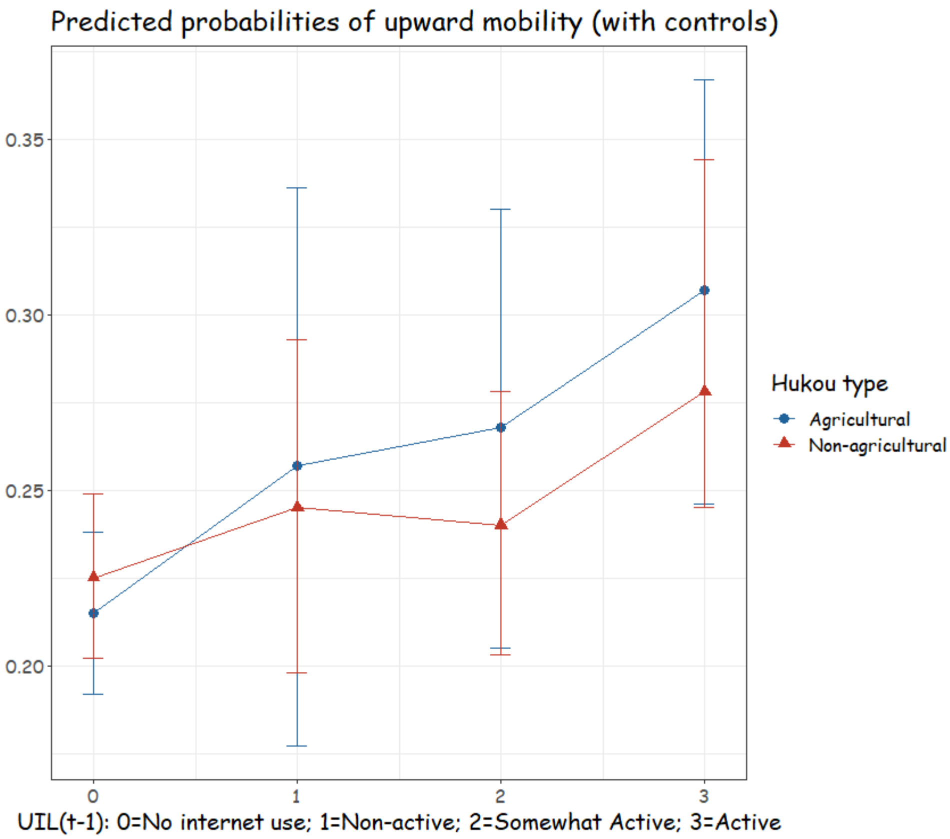

Figure 6.13 Average marginal effects of last wave UIL x Hukou type on upward mobility rate with 95% CIs from Model 1. Source: CFPS adult 2010, 2014 and 2016

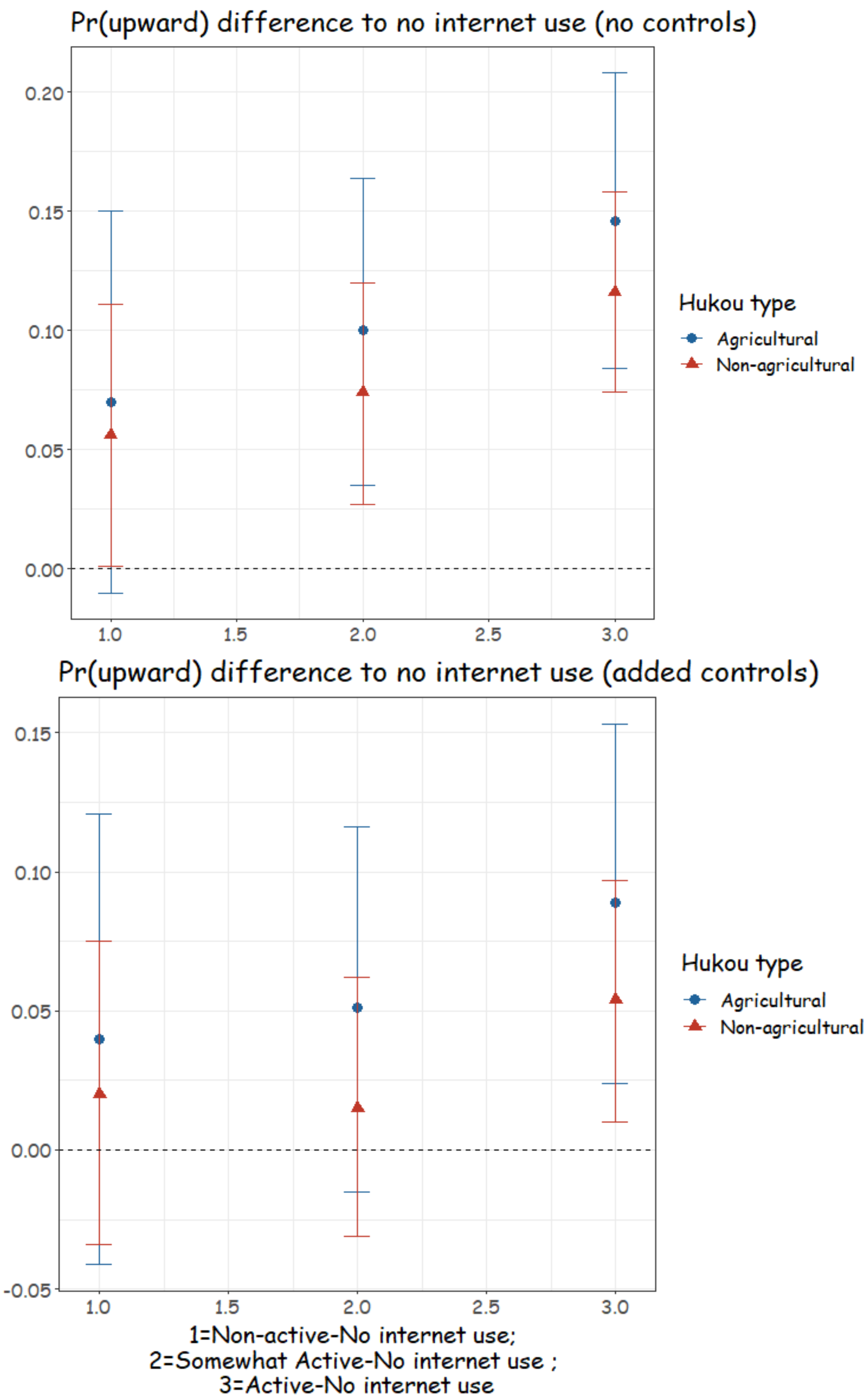

Figure 6.14 Upward mobility rates compared to no internet use by level of activeness in UIL and *Hukou* type

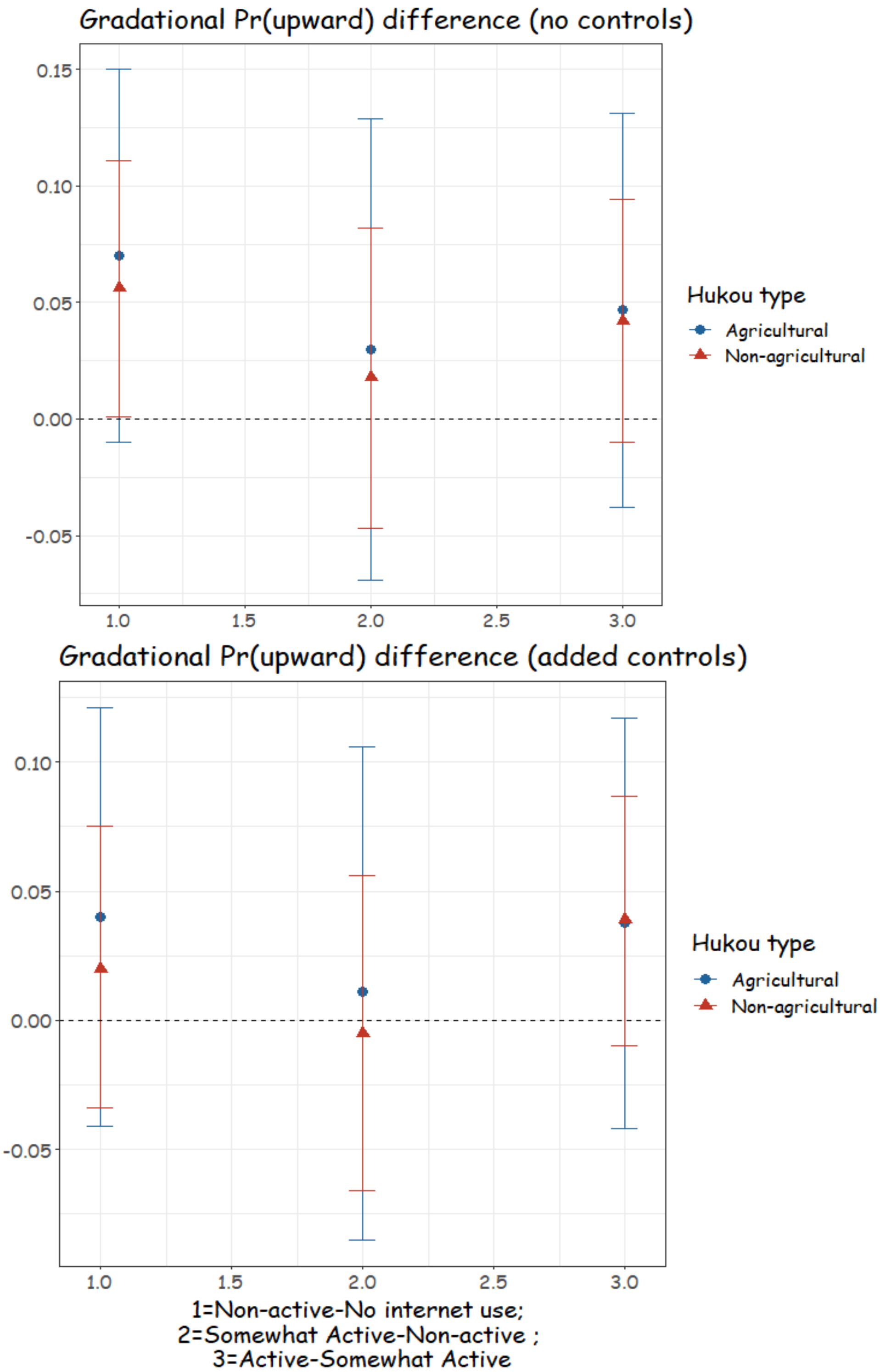

Figure 6.15. Gradational changes in upward mobility rate by level of activeness in UIL and *Hukou* type

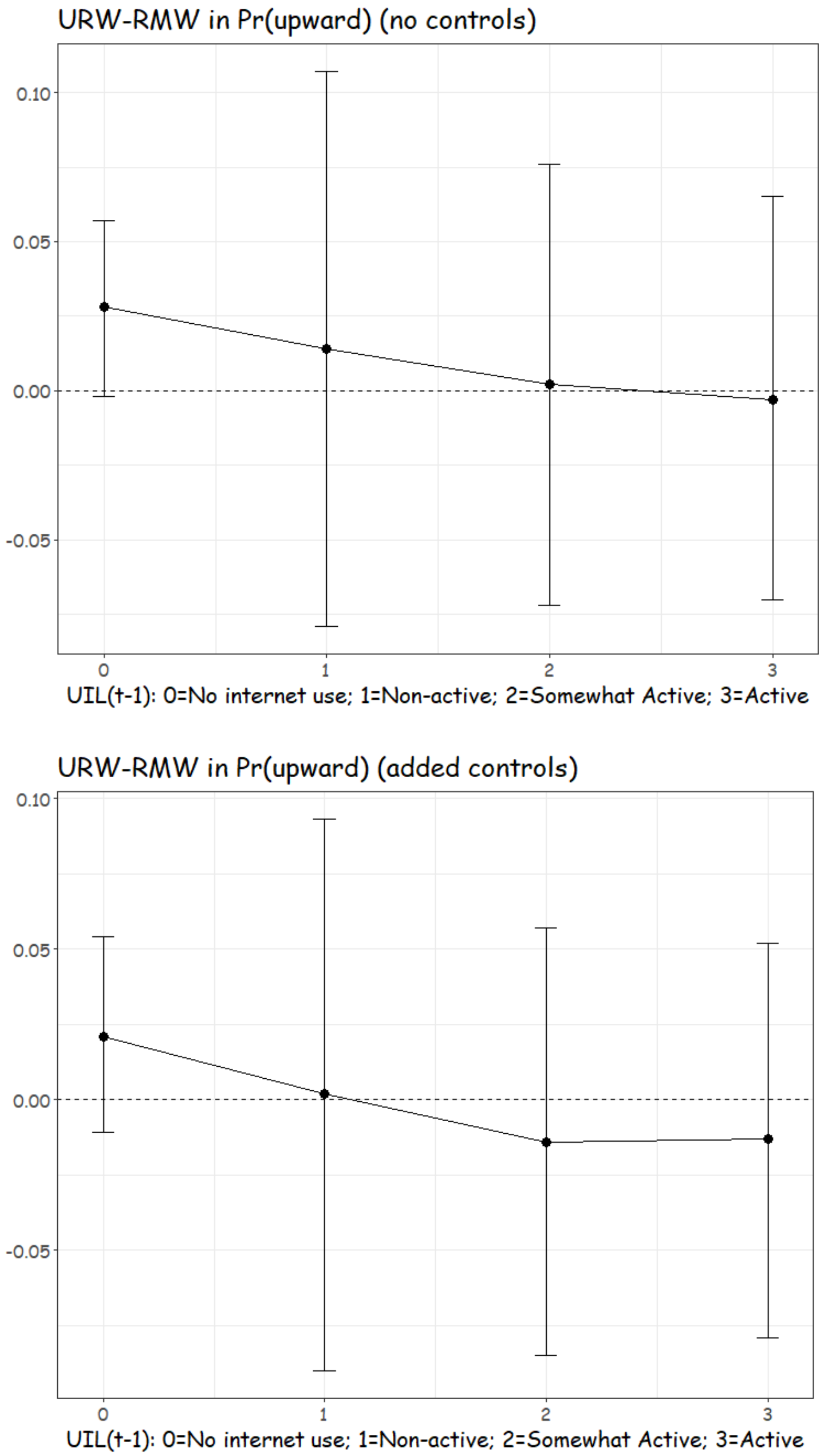

Figure 6.16. RMW-URW gap in upward mobility rate by UIL activeness level

6.4.5. Summary

To sum up, the quantitative analyses attempted to find some evidence of the patterns of 1) a greater UIL effect for the RMW group's occupational mobility and 2) a narrowing RMW-URW gap in occupational mobility when UIL activeness level increases – two expected observable connections derived from the diligence dependence theory. Firstly, the results of linear mixed models show weak evidence to support that active UIL was probably more helpful for the RMW group's occupational change, and able to reduce the gap between RMWs and URWs. When breaking down into considering downward and upward mobility respectively (regardless of the magnitude of mobility), the results show heterogeneity of the effect of UIL on downward mobility but not upward mobility. After controlling for some possibly confounding factors (i.e., educational background, demographic factors, sector, industry), the URW group's downward mobility did not seem to be very subject to the variation of UIL. In contrast, RMWs had a considerably higher downgrading trend when not using the internet or not having a high level of activeness in UIL. The gap in the risk of downward mobility between RMWs and URWs was significantly reduced when having active UIL. Interestingly, after considering UIL and other possible mobility-related attributes in the statistical models, URWs did not show a significantly higher upward mobility rate than RMWs. The association between UIL and upward mobility was also not found to be stronger for RMWs. The bivariate analyses from Chapter Four also show that the URW group did not have a tremendously higher upward mobility rate than RMWs. The URW group's advantage in occupational mobility might not be featured by a much better career progression, but by their lower risk of downward mobility – a 'glass floor' for URWs in cities.

6.5. Making sense of differential trajectories: the result of qualitative evidence

6.5.1. Analytical strategy

To refine the interpretation of the underlying mechanisms of the observed heterogeneity of the ‘UIL-mobility’ association between RMWs and URWs, qualitative analysis is carried out to further examine the explanation of the diligence dependence theory. To do that, I used participants’ accounts of their own career experience, as well as their perceptions on the ‘RMW-URW’ differences with regard to labour market performance from the interview data. The latter, participants’ perception on the general RMW-URW difference in occupational mobility, was drawn from an explorative question in the interview that asked for participants’ views on the role of *hukou* type for succeeding in career advancement and reducing the risk of downward movement. In turns out that some participants came up with a common perception that to achieve a good outcome of occupational mobility, URWs have the strength of being ‘knowledgeable’ (five RMWs and three URW participants) whilst RMWs have the merit of being hard-working (four RMW and three URW participants) (see 6.5.3). These two common perceptions, as a way of making sense of career mobility for RMWs and URWs, provide good material to compare the explanation provided by the diligence dependence theory, as will be discussed later.

Specifically, three important elements of the diligence dependence theory have been further examined. The first is the non-skill-related advantage for job attainment among the advantaged group, in this case, URWs. To examine this point, I explore the conditions for acquiring the non-skill-related advantage based on participants’ storytelling of their working lives. Second, I further examined the assumption that URWs have the strengths in skills and professional knowledge. For this part, participants’ shared perception of ‘knowledgeable URWs’ was explored. And lastly, participants’ shared perceptions of ‘hard-working RMWs’ provide good material for further examining the idea from the diligence dependence’ theory that the hard work of RMWs could close up the gap between them and urban background workers. Again, the analysis highlights and discusses the discrepancies between participants’ accounts and the diligence dependence theory’s explanation, which reveals some issues of the diligence dependence theory and further enriches our understandings of the effect of UIL, and learning in general, on labour market outcomes for RMWs and URWs.

6.5.2. The difference in non-skill-related advantage

As mentioned in Chapter Five, apart from work skill improvement through learning activities to boost work performance, a few participants also rely on non-skill-related resources to help them achieve occupational success. Non-skill-related resources might boost workers' work performance (e.g., existing social networks can help one achieve a good sales performance), but they can also bypass a performance-based mechanism when helping people achieve a good labour market outcome. For those whose occupational mobility is less skill-dependant, some might be less subject to the risk of skill devaluation and obsolescence, and therefore they do not need to perform the constant labour of learning to secure scarce skills. Those non-skill-related resource beneficiaries were all non-agricultural *hukou* holders. However, even among those who hold a non-agricultural *hukou* type, having those resources was not common, and might be related to highly privileged social backgrounds.

As introduced in the last chapter, U9, a clerk in a state-owned textbook publisher, did not voice any concern about the risk of downward movement due to skill devaluation and obsolescence, unlike other white-collar worker participants, since she believed that job-security can be guaranteed by working in a state sector workplace. When explaining her job acquisition, she admitted that her parents' social networks helped her get the job, but she believed that it was simply helping the qualified person get the right job:

> '*My family wanted me to work there and they had a connection with some people there […] Yes they [parents]did help me get the job but I also fit the criteria of the role actually*.' (U9, Female, first job non-manual, 30)

In addition to her parents' social network resources, it was also the 'less performance pressure' characteristic that led to her carefree attitude to skill devaluation and career stability. In her view, it was a common feature of the legacy of the 'iron rice bowl' policy within state sector workplaces:

> '*The stability can be guaranteed by working in a state-owned enterprise because even though the salary is not higher than other workplaces, there is less pressure on work performance, less over-time working and more holidays for the employees [...] In a state*-owned enterprise, as long as you have worked for a long period of time, did not make big mistakes, and were responsible, you will have a chance to get promotion due to the restructuring. There are still some evaluations and you will need to attend some training to upgrade yourself. However, even if you did not upgrade yourself, they will not fire you. State-owned enterprises do not fire staff very easily.' (U9, Female, first job non-manual, 30)

U9's narrative illustrates the way that she made sense of her own career mobility and cannot infer an overall picture of work in the state sector. Certainly, before China's economic reform, the 'iron rice bowl' and the seniority system were common characteristics in most state sector workplaces. The landscape of the state sector has changed since the reform, featuring more competition, profit-orientation, differentiated rewards to the employees, and lay-offs of unproductive workers (e.g., Naughton, 1997; Xie and Wu, 2008; Wu, 2019). However, the dramatic change within the state sector does not imply that the differences between the state and non-state sectors have completely disappeared. Bian et al. (2006) claims that even though marketization is definitely the historical trend, during the transitional period, some state sector workplaces still had maintained more pre-reform era characteristics, for example, no linkage between resource-distribution and performance. Besides, internal differentiation also exists within the state sector. For instance, large state-owned enterprises and public institutions still benefit from direct financial subsidy and policy support, which help ensure their workers' employment security and good economic remuneration (Ibid.). This indicates that although a performance-oriented reform is certainly the long-term trend, at least a few privileged employment opportunities have not been wiped out and will continue to exist within the state sector for a foreseeable period.

Another key issue concerns who has better access to those privileged employment opportunities. U9 only briefly mentioned that her parents' connections helped her get the job in her workplace, but she did not explain clearly the process in detail. On the one hand, at least in the past, state sector job acquisition was famously characterized by the use of relational resources or *Guanxi* (the Chinese expression of interpersonal connections) in urban China (e.g., Bian, 1994, 2018a, 2018b). However, on the other hand, the recruitment in the state sector is also known for its strict examination system that aims to select the best candidate meritocratically, and an extremely low success rate of the job application (e.g., Jarrett and Huihan, 2009). If a person could bypass the strict selection system and get a privileged position in the workplace by simply using their social network resources, presumably those network resources might refer to the connection with those who hold the most authority and power in the organisation, like a cadre rather than a junior-level clerk position. However, that kind of extremely precious social network resource does not seem to be related simply to *hukou* status but rather seems to be related to a highly privileged social background. Simply being a non-agricultural resident does not grant the privilege of knowing and having a good relationship with a cadre or a senior officer in the state sector organisations.

Again, not being skill-dependent does not mean one's occupational mobility is not based on work performance. For example, U7 noted that one's career development in an investment bank is highly dependent on one's performance in attracting investment to support financial projects. In such a context, workers who had a social network with tycoons or successful business owners due to their family backgrounds could easily achieve a good work performance. In this case, the boundary between work capability and non-skilled related factors is actually blurring, but it is definitely less related to the textbook professional knowledge in finance and learning activities. In the workplaces where U7 had worked, all those who had social networks with wealthy investors were from urban areas, but not all urban background workers, including U7 himself, have the privilege of knowing tycoons in the city.

In the end, U4's situation shows a more complex picture. U4 worked as a regional director in his family company, and his occupational attainment was purely because he is the 'heir' of his family business 'empire.' However, he was concerned about losing his privileged work position and he recognised the importance of updating professional skills and knowledge, since, over the longer term, his job and socioeconomic security relies on a good work performance and the profitability of the family business.

Indeed, among our participants, those whose occupational mobilities are less work skill-dependent are all from an urban background. Comparing resources like social networks to work skills, work skills' value might be less stable in this age since the scarcity of skills is often challenged. However, it is noteworthy that even though those non-skill-related resources (e.g., the social networks that could allow one to attain a privileged work position or to easily attract investment from tycoons, or a lucrative family enterprise) are generally held by people from urban backgrounds, it is also not common for most urban background people to enjoy those extremely precious resources that could offset the continual learning and work skill development to secure the socio-economic advantage. For instance, the urban background white-collar participants who did not have the mentioned non-skill-related resources also showed the same concern of skill devaluation and took measures like UIL to keep updating their work skills to meet the latest demand.

6.5.3. Perception of two trajectories: the knowledgeable URWs and the hard-working RMWs

Interestingly, when being asked about their perceptions of the occupational mobilities of RMWs and URWs, rural and urban background participants related two common themes: URWs have the strength of being 'knowledgeable' and RMWs have the strength of being 'hard-working.' This is normal when the method of data collection allows some space for inter-participants discussion (e.g., focus group, group interviews) since the interaction will lead participants to produce accounts with a high degree of homogeneity (Bryman, 2012, p. 520). However, this study conducted semi-structural interviews individually with no space for interaction among the participants. Also, most participants did not know each other. Certainly, the similarity in their perceptions across both RMWs and URWs does not automatically render validity to their accounts. However, that might indicate that both RMWs and URWs have observed similar phenomena, and for some reason, they chose to make sense of those observed phenomena in a similar way.

Although participants perceived that RMWs and URWs have different characteristics in occupational mobilities, interestingly, no participant believed that one group is essentially doing better than the other. In other words, inequality of occupational mobility was not perceived by any of our participants. What they perceived is that RMWs and URWs have different assets in order to achieve a good outcome of occupational mobility. Among our 15 rural background and nine urban background participants, five RMWs and three URWs explicitly said URWs had the advantage of being more 'knowledgeable,' four RMWs and three URWs perceived that RMWs are more 'hard-working,' whilst no one said anything opposing those two points, as exemplified by the following examples:

‘*Well, they [urban residents] have their advantages but we [rural migrants] also have our own strengths. The urban residents have seen a lot of things and therefore know more things. However, we [rural migrants] have our own strengths […] the rural people are forced to develop a fighting spirit and would like to work very hard to change their life.*’ (R12, Male, First job non-manual, 35)

‘I think we can say that we [urban residents] have better knowledge than them [rural migrants], and can learn new things more quickly, but they work much harder they us.’ (U7, Male, First job non-manual, 29)

6.5.4. The knowledgeable urbaners or the urbaners’ knowledge?

Surprisingly, both RMW and URW participants described that urban residents have the advantage of being more ‘knowledgeable,’ when accounting for the RMW-URW differences in occupational mobility. Those who mentioned URWs being knowledgeable believed that URW people’s advanced knowledge could lead to career success more easily. However, what does ‘knowledgeable,’ really mean? Are their views of URWs being knowledgeable akin to the idea from the diligence dependence theory that there is a knowledge and work skills gap between disadvantaged and advantaged populations, which allows the advantaged group to achieve good occupational mobility?

Occasionally, the word ‘knowledgeable’ has included elements like URWs having achieved better educational attainment (mentioned by two participants). However, in other cases, participants did not mean the outcome of one’s educational achievement when saying ‘urban people know more.’ Participants said ‘urban people know more’ to refer to a specific kind of ‘professional knowledge’ that is related to work tasks in their industries or workplaces. And for URW people’s advantage in the acquisition of the mentioned professional knowledge, participants regarded it as almost independent of one's educational background, but it is related to one's experience of growing up in a modernised urban environment:

'*The urbaners have seen a lot of things and therefore know more things. In the profession of IT, they had access to computers and the internet much earlier than us. So naturally, they had more experience and advantage in the beginning.*' (R12, Male, First job non-manual, 35)

'*Our colleagues who grew up in urban areas, especially those who grew up in Shenzhen, know a lot and have seen a lot of things. For example, about the consumer products, like some fashionable products, then brand culture, they are very familiar with those products and know who are the relevant potential customers in some major big cities[…] For me, I did not know many different kinds of commodities before checking them online, and I did not know why those products can be so expensive before they told me.*' (R10, Female, First job non-manual, 29)

'*People who are from rural areas did not have a chance to see a lot of things so they are less knowledgeable. In our industry [advertisement], what we need is a person who has accumulated rich knowledge [about trendy things] in many areas. Like for example, Haidilao [a famous hotpot restaurant chain] opened in Guangzhou long ago, but it took a long time to have a branch opened in some less developed cities, let alone rural areas. This is the gap*.' (U5, Male, First job non-manual, 28)

On the other hand, RMWs did not regard their experience of working in rural areas as obtaining any knowledge or work skills:

'*I had always been a farmer [before entering the urban labour market].*

> *There was no such thing called knowledge, skills, or learning*.' (R15 Male, First job manual, 60)

Furthermore, U3 believed that not only has the gap resided in the accumulation of knowledge, but also in the capability of learning more knowledge quickly, since people from urban backgrounds grew up in an environment where everyone could access new information technologies earlier:

> '*I think we can say that we [URWs] have better knowledge than them [RMW], and can learn new things more quickly […] we have better information searching skills so learn things much quicker. Compared to them, we grew up in an environment full of new technologies and we played with those new technologies earlier than them […]*' (U3, Male, First job manual, 22)

The diligence dependence theory does point out a gap in professional knowledge and skill between disadvantaged and advantaged populations. However, this preliminary account also contains some limitations in explaining the formation of the gap in professional knowledge and skills. To explain the gap, on the one hand, a theory needs to explain the difference in the sources of skill and knowledge acquisition. It turns out that the critical knowledge and work skills gap is not just from the difference in educational or training opportunities, but also from a lack of experience of living and growing up in a so-called modernised urban environment.

On the other hand, a theory also needs to address what has been recognised as professional knowledge and skills in a specific context and why. In the context of the urban labour market, the familiarity with the latest technologies, consumer products, popular brands, and restaurant franchises in cities were recognised as ‘expertise’ and were appreciated by employers and workplaces. On the other hand, practical know-how like farming, which rural background individuals learnt when growing up in a rural setting, received no recognition or appreciation in cities. People who used to farm were seen as ignorant, not only by their urban peers, but also by the rural migrants themselves. The concepts ‘knowledge’ and ‘skills’ in this context are urban-biased. Presumably, the ‘legitimate’ knowledge and skills (e.g., abilities to appreciate productions from popular brands) are crucial for the dominant economies in the urban areas (e.g., the mass production, wholesale, and marketing of consumer products; information technologies). And in return, it is the dominance of those economies that has legitimised some capabilities (e.g., knowledge about brands) as ‘skills’ that are particularly related to urban individuals’ everyday life rather than individuals’ participation in education or learning.

Therefore, the gap in knowledge and skill is not simply an issue of the deprivation of educational and learning opportunities, but also an issue of *whose knowledge and capacities are being recognised* as valuable labour power, an outcome of the exercise of symbolic power (Bourdieu, 2010). The definition of ‘work skills’ is urban-biased in the urban labour market. The familiarity with urban-based culture and lifestyles (e.g., knowledge of popular brands, consumer products, new technologies) can sometimes be appreciated as a kind of work skill in some workplaces in cities, and urban background individuals acquire those so-called ‘work skills’ by simply growing up in an urban setting. In contrast, in order to catch up, RMWs need to make the extra effort to learn about urban-based culture and lifestyles. Utilising the internet for learning such topics might just be one of the ways in which RMWs ‘catch up,’ thus acquiring that additional knowledge central to an urban-based worker’s life.

6.5.5. A hard-working spirit of RMWs? Or, only the hardworking RMWs survive?

Not a single participant expressed the view that RMWs are not doing as well as URWs in terms of labour market achievement, which is different from what previous empirical findings (e.g., Li, 2004) and our analysis has shown. Among the participants, four RMWs and three URWs mentioned that RMWs had a 'hardworking spirit,' and that a 'hardworking spirit' is a kind of strength for them to achieve a good outcome in occupational mobility.

For example, R12 perceived that in the IT industry, rural migrants work harder to mitigate their previous deficiency in IT-related knowledge and skills. As shown in the last section, he stated that those who grew up in an urban area accessed computers, the internet, and some of the latest digital technologies earlier than those who grew up in rural settings. When studying computer science in college, he could easily feel the gap between him and other colleagues from urban backgrounds, in terms of the familiarity with digital technologies. However, as he viewed the IT industry being highly meritocratic, that only one's professional IT skills mattered for career progression, he believed that in the long term those from rural backgrounds actually have the upper-hand in this industry because of their 'hard-working spirit.' To advance his knowledge and skills, he signed up for programming courses and kept updating his professional IT knowledge from online forums:

> '*I think I have chosen a right career path, because I started as an IT professional, and the career path for an IT professional massively counts on your professional IT skills more than any other things. For a person from a rural area and who knew no people in the city, this is a fair chance. I worked very hard because I was the first person in my family to study and work in a developed urban city and I cherished this opportunity a lot […] I signed up for some programming courses […], spent more time to look for some updates from the online IT professional forums to update myself on the latest knowledge. As I worked a lot more and harder [than*

his colleagues], I developed the most outstanding IT skills and work abilities among our cohort at the college, and had an even better career progression than my urban peers […] we [rural migrants] have our own strengths. People who are from rural areas and wanted to settle down in a city know that they could not move backwards but only forward. So, rural people are forced to develop a fighting spirit and would like to work very hard to change their lives.' (R12, Male, First job non-manual, 35)

Boosting work performance by an individual's hard work does not have to be through the approach of learning to close the 'knowledge gap' and therefore improve workers' productivity. It could also be done by simply extending the working hours, regardless of the productivity per working hour (although these two things are often correlated). Interestingly, U2 sketched a scene of 'reverse discrimination' against non-agricultural individuals when manufacturing factories were recruiting assembly line operators. Those unskilled manual jobs do not require much literacy or other forms of knowledge. U2 believed that the employers he met favoured rural migrants, since the employers also had the belief that 'rural background people work harder':

'*[…] the factories like people from underdeveloped rural areas more than those of us who grew up in an urban setting. They think urbaners would not work as hard as them [rural migrants].*' (U2, Male, First job manual, 33)

In the finance industry, U7 regarded his rural migrant colleagues' overtime working led to their career success. He explained that within an investment bank, one of the most important factors for career progression is the capability of bringing funding to support financial projects. And workers' previous performance of investment attraction was used as an indicator of their capabilities. To achieve a good performance, workers either need to work extremely hard or have a good social network that includes some tycoons. Although those who could do the latter were definitely non-agricultural *hukou* holders, many URWs were just like RMWs, who did not have that kind of social network resources. However, the RMWs he met worked extremely hard to achieve a good performance in the bank, through both working overtime and active learning, whilst his urban background colleagues who had no social network resources could not bear the burden of working too hard:

> '*Like what I have just mentioned, in an investment bank, you either work very hard or have very good social networks. Urban kids usually cannot take the hard working bit, but people from rural backgrounds can take it and work really very, very hard […] and would like to spend a lot of time on learning things. If a normal person usually spends 10 hours on working daily, our rural background colleagues will spend 14 hours daily. However, some urban kids have very good family backgrounds which allowed them to maintain a good relationship with the people who are rich so they do not need to work very hard to achieve good work performance.*' (U7, Male, First job non-manual, 29)

U7 himself is not the kind of URWs who has a lot of wealthy friends, however, he also did not want to work as hard as his rural background colleagues did. He changed to work in several other investment banks and found that the situations were similar. Luckily, the salary for a banker is high and he had saved a great amount of money. He ended up using his savings to start his own business in the fashion industry.

Is this recurring account (i.e., the hard-working spirit of RMWs leads to their career success) consistent with the account of the diligence dependence theory? Yes and no! Indeed, both accounts narrated that the extra effort of learning of RMWs led to the gap closing between RMWs and URWs in occupational mobility. However, the diligence dependence theory has explained the structural issue behind this ‘gap-closing’ observation, that it reflects rural background individuals’ resources deprivation. In comparison, participants’ accounts did not particularly articulate the disadvantage of RMWs in the urban labour market, but praised their hard-working spirit as their common merit. The diligence dependence theory also tells us another side of the story: without extra effort on learning like UIL or other forms of working, RMWs experienced great disadvantage in occupational mobility. For example, as shown in the quantitative findings, RMWs who did not engage in UIL actively had a higher chance to experience downward mobility, whereas risk of downward mobility for URWs is not subject to engagement in learning like UIL. Presumably, people constructed and shared an account of ‘RMWs are hard-working creatures’ to make sense of the observation of rural background individuals’ over-working in their daily lives. However, the reality of the mechanism behind that observation might be at odds with common sense. What I speculate is that the ‘RMWs being hard-working’ is actually a survivorship bias: hard-working is never an intrinsic characteristic among RMWs (or any other ‘group’ of humans); but only the most hard-working RMWs could ‘survive’ and could be seen in the urban labour market, which contributes to the ‘RMWs being hard-working’ observation. URWs do not need hard-working measures like UIL to save them from downgrading. Discourses that overpraised the hard-working deed of RMWs as a kind of role model behaviour might distract attention away from the concern of the structural-level disadvantages they are experiencing.

6.5.6. Summary

To refine the interpretation of the underlying mechanisms of the observed heterogeneity of the ‘UIL-mobility’ association between RMWs and URWs, this section brought qualitative evidence of participants’ accounts on their occupational mobility as well as their perceptions on the RMW-URW difference in occupational mobility to compare with the explanation brought by the diligence dependence theory. Firstly, echoing the diligence dependence theory, non-skill-related advantages (mostly social network resources) in occupational achievement exist among the URW participants, but not the RMWs. In a relative sense, it is very likely that URWs are more likely to have non-skill-related advantages, which plays a role in explaining why the association between UIL and occupational mobility is stronger for RMWs. However, noteworthily, it might be wrong to assume that possessing non-skill-related advantages is very common among URWs. At least among our participants, the kind of resources that could offset the role of work skills in occupational mobility was rare and held by the individuals who probably had highly advantaged social backgrounds. The urban background white-collar workers who did not have those non-skill-related advantages were also concerned about skill devaluation and engaged in means like UIL to keep themselves competitive in the workplace, just like RMWs. Secondly, the scrutinizing of participants' consensus over URWs being 'knowledgeable' highlighted that the so-called 'skill and knowledge gap' between RMWs and URWs is not simply a result of the deprivation of educational resources for acquiring knowledge, but also the urban-biased definition of professional knowledge and skills, a critical aspect of which the diligence dependence theory fails to capture. The knowledge of urban culture and lifestyles is recognised as professional knowledge and work skills in some workplaces. So presumably, for RMWs, extra learning activities like UIL are required to fill the so-called 'knowledge and skills gap' in the urban labour market. Lastly, both the diligence dependence theory and participants' own accounts portray the additional learning performed by RMWs, such as UIL, in general offsets the gap between rural and urban background workers. However, participants praised the 'hardworking spirit' as a kind of merit of RMWs but failed to recognise that this actually reflects the disadvantaged position RMWs occupy in the urban labour market.

6.6. Concluding remarks

This chapter aims to answer the second question: *when having similar* *participation in UIL, do RMWs benefit more from UIL on occupational mobility?* Drawing on previous empirical investigations and theoretical accounts, this chapter firstly proposes a preliminary theory called *the diligence dependence theory*. This theory envisages that due to the relative resource deprivation of the disadvantaged background individuals, they are more reliant on performing extra labour of learning, such as UIL and other means for work skill development, in order to secure a good occupational mobility outcome and therefore economic life chances improvement. In contrast, advantaged background individuals are less subject to the additional effort of taking on extra learning and are still able to have a good labour market outcome even without any engagement in UIL.

To what degree does this theory make sense? This chapter firstly used quantitative data to compare the 'UIL-mobility' associations from samples of RMWs and URWs. The analysis sought to search for the evidence of two envisaged empirically observable patterns: a stronger UIL-mobility association among RMWs and a declining RMW-URW gap in occupational mobility along with increasing activeness in UIL. The results did show that, in general, the UIL-mobility association seems to be greater for RMWs. Regarding downward mobility, the results show strong evidence that the RMW-URW gap in downward mobility rate was significantly lower among the individuals who were most active in UIL, compared to those who had no internet use at all. For the workers who did not even have internet use, RMWs had a considerably higher risk of experiencing downward mobility, compared to URWs. Having used the internet but without active learning did not significantly reduce the gap between RMWs and URWs. However, when reaching the most active UIL level, the probabilities of downward mobility between RMWs and URWs became very close. Interestingly, even when there was no internet use, URWs did not show a statistically higher upward mobility rate than RMWs. The results do give evidence to support the claim that whilst disadvantaged groups like RMWs are more reliant on UIL to secure their occupational attainment, the risk of downgrading for URWs is generally low, even when they were not actively engaged in UIL.

In addition, this chapter further refined the interpretation of the underlying mechanism behind the observed patterns of heterogeneity of the ‘UIL-mobility’ associations by comparing participants’ accounts on their life experiences and perceptions and the explanation from the diligence dependence theory. First, although those who had non-skill-related advantages (e.g., social network resources) in occupational achievement were from urban areas, it might be wrong to assume that having non-skill-related advantages is a common feature among URWs. Holding the kind of resources that could offset the role of work skills in occupational mobility are probably related to a highly advantaged social background, which might only account for a minor subset of the non-agricultural *hukou* holders. Nevertheless, the between-group differences in non-skill-related advantages are likely playing a role in explaining the heterogeneity of the ‘UIL-mobility’ associations between RMWs and URWs. Second, the so-called ‘skill and knowledge gap’ between RMWs and URWs is not simply a result of the deprivation of education resources for acquiring knowledge, as articulated by the diligence dependence theory. The ‘skill and knowledge gap’ also exists because of the urban-biased recognition of professional knowledge and skills (familiarity with urban culture and lifestyles being recognised as a kind of professional knowledge) in the first place. Thus, when entering a place where their previously developed capabilities were not appreciated, RMWs were seen as not as ‘knowledgeable’ as those from urban backgrounds. Measures like UIL might be adopted as a means for them to acquire knowledge of urban culture and lifestyles in order to fit in the workplace. Third, while both the diligence dependence theory and participants’ accounts view the extra effort of additional learning and the popular depiction of RMWs as a ‘hardworking’ group of people as instrumental in closing the gap between RMWs and URW in occupational mobility, participants praised the ‘hardworking spirit’ of RMWs as a kind of merit. This attachment to the stereotype of RMWs as ‘hardworking’ might prevent people from noticing the structural-level barriers RMWs faced, and perpetuate the gap between the two groups.

Pooling our quantitative and qualitative results together, the findings suggest that the extra effort of learning via UIL might have partly helped RMWs secure their employment and offset the risk of downward mobility in the urban labour market. Simply being from a non-agricultural population does not guarantee a significantly higher chance upward mobility success. In fact, the URW group's advantage might not be in further career progression, but in their employment security, compared to the newcomers in an urban setting. The urban labour market is an environment where the wisdom and capabilities gained from socialisation and experiences in rural areas are not transferable or appreciated as skills in their own right. In addition, those from urban backgrounds not only have the advantage of growing up in an environment where a knowledge of the culture and lifestyle counts towards potential employability, but they might also have other non-skill-related resources (such as valuable social networks) to help them secure their employment and economic life chances. As a result, the extra effort of learning like UIL might have become a way for RMWs to 'catch up' with their urban peers. In fact, their very survival in the urban labour market may have depended on it.

The investigation in this chapter only tells part of the story of the extent to which UIL mitigates the unequal occupational mobility. Indeed, the results suggest that when being very active in UIL, the gap in downward mobility risk between RMWs and URWs has become smaller. But this is not sufficient to claim that RMWs benefit more from UIL, if RMWs are not even as active as URWs in UIL. Even though the 'diligence rewards' for URWs might not be that much, if those advantaged populations were more active in UIL than RMWs, then actually more URWs could get benefits from UIL than RMWs, which manifests a further aspect of inequality in getting dividends from UIL. Thus, the next step of this study is to investigate this issue, equality in UIL participation between RMWs and URWs, which will be presented in the next chapter.

Chapter Seven: Inequality in learning online?

7.1. Introduction

The preceding chapter has shown that the labour market returns to UIL are stronger among RMWs, although that actually reflects the existing structural inequality and the relative resource deprivation of RMWs. In particular, RMWs had a relatively high risk of experiencing downward mobility in their work lives if less active in UIL, whilst the URW group's downward mobility risk is less subject to variation in UIL. Thus, findings from Chapter Six did show a 'compensatory effect' (i.e., UIL being more helpful for disadvantaged background individuals' mobility) of UIL for the occupational mobility of RMWs, one of the conditions for the mitigation of unequal occupational mobilities. As discussed in Chapter Three, to evaluate the extent to which UIL mitigates the unequal occupational mobilities between RMWs and URWs, the analysis also needs to look at another condition - equality of participation in UIL.

This chapter sets out to answer the third research question: *do RMWs and URW have similar participation in UIL?* Firstly, this chapter reviews previous studies on inequality in participation in adult learning activities, the digital divide, and the interaction between the two – the divide in UIL. It then follows by building a preliminary theoretical account by adopting a Bourdieusian perspective – the practical action theory of UIL – to envisage and make sense of the differences between RMWs and URWs in participation in UIL. Subsequently, the study uses both quantitative and qualitative evidence to examine the validity of the practical action theory of UIL. Quantitative evidence is used to make a robust comparison of the participation levels in UIL between RMWs and URWs. Qualitative evidence is then used to examine the extent to which the mechanisms behind the observed differences between RMWs and URWs in UIL is adequately explained by the initially proposed account of the practical action theory of UIL.

7.2. Literature review

In this section, I give a comprehensive review of the previous studies that are closely related to inequality in UIL. I begin by introducing and evaluating the works in the areas of a) inequality in adult learning and b) the digital divide. I then move on to discuss the studies that research this intersection – the divide in UIL, in particular.

7.2.1. Inequality in adult learning

Adult learning in working life is often thought to be a means of increasing competitiveness in the labour market. For those who did not have a strong educational or advantaged social background, it is a way to upgrade their skill levels and to improve their economic life chances. However, workers' participation in learning activities is also famously characterized by inequality and the reproduction of advantage (i.e., 'the Matthew effect' (Merton, 1968)), rather than as compensating the disadvantaged which common sense often envisages (Boeren, 2009, 2016; Bukodi, 2017). Rubenson notes that the measures proposed to reach disadvantaged groups often end up serving the interests of the advantaged (1999, p. 116).

Many existing studies show a consistent pattern that the workers who are more active in additional learning during their work lives are most likely to be those who already have good educational backgrounds and skilled white-collar jobs (Jenkins et al., 2003; OECD, 1999, 2003a; Desjardins et al., 2006; Boeren, 2009; Blanden et al., 2010; Boeren, 2017). Regarding the role of educational background, two landmark inquiries (OECD, 1999, 2003a) by the Organisation for Economic Co-operation and Development (OECD) in nine selected counties[22] found that whilst the highest educational achievement was not always associated with the highest participation rates in further learning opportunities,[23] the lowest level educational background was consistently

[22] These countries are: Canada, Denmark, Finland, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[23] That was the case in the other eight countries but with the exception of Portugal.

related to the lowest further learning participation rates across all the investigated countries. Likewise, drawing on data from the International Adult Literacy Survey (IALS) and Adult Literacy and Life skills Survey (ALLS), an international comparative research project on 21 counties[24] by Desjardins et al., (2006), also found that adults with low levels of education were much less likely to attend adult education and training programs in all countries. In addition, probably due to the skill requirement, skilled workers with a permanent contract attended more learning and training opportunities (Boeren, 2017; Dämmrich et al., 2014). Interestingly, the participation in work-related training and educational programmes was more pervasive among low-skilled, white-collar occupations than high-skilled, blue-collar occupations (Desjardins et al., 2006, p. 72). According to Desjardins et al. (2006, p. 72), the result suggested that learning participation is associated with the level of literacy practice of the jobs.

A lot more research has been undertaken to explain the relationship between educational background/literacy and workers' participation in learning. On the one hand, it is said that the low participation rate in further learning among adults with low-level educational backgrounds might be related to their low confidence in achieving a good learning outcome due to their low literacy (e.g., OECD, 2003b, p.81; Illeris 2004; Boeren, 2009). Literacy gives individuals the competency to learn, or put another way, basic education provides individuals with a readiness to achieve a better learning outcome (Desjardins *et al.*, 2006, p. 67). Boeren (2009) conceptualises this as a 'dispositional barrier' – low confidence 'blocks' individuals' participation in further learning. Even when participating in learning activities, Dæhlen and Ure's (2009) study of learning motivation in Norway shows that adults with low literacy and low-level educational backgrounds have less interest in learning and a stronger feeling that they are obligated to learn. On the other hand, inequality in learning participation is thought to be strongly related to

[24] Australia, Bermuda, Canada, Chile, Czech Republic, Denmark, Finland, Hungary, Ireland, Italy, Norway, Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, Switzerland, United Kingdom, United States

the unequal provision and acquisition of learning opportunities. Whilst the IALS survey shows that employers are the most common sources of financial support for adult education and training programmes in most OECD countries (Desjardins *et al.*, 2006, p. 82), learning opportunities supported by employers often follow a ‘trainability’ principle. That is, employers consider the already well-educated workers as more trainable, as each unit of training could produce a greater enhancement in overall productivity (Blundell et al., 1996; Desjardins et al., 2006, p. 68; Kilpi-Jakonen et al., 2015; Xu, 2013). Surprisingly, the IALS survey also shows that the government-supported schemes favour those who have good prior educational achievement (Desjardins et al., 2006, p. 92). Without external support, self- or family-support might not be effective for disadvantaged individuals’ learning participation. For example, ‘lack of money’ is often reported to be a barrier for individuals’ participation in learning (Boeren, 2009), and it might be even more likely for those who are already doing low-paid and low-skilled jobs with a low-level of educational achievement.

Moreover, the association between advantaged backgrounds and learning participation could be intergenerational. A positive relationship between parental educational backgrounds and adults’ learning participation has also been found, and this is more the case in countries and regions with a high level of social inequality (e.g., Desjardins et al., 2006; Lee and Desjardins, 2019). However, the observed relationship is rather indirect, as when taking into account workers’ educational achievement and occupational attainment, the extent of association is reduced (Lee and Desjardins, 2019, p. 66). Furthermore, in Britain at least, workers’ attainment of further academic and vocational qualifications through adult education programs seem to be related to those from the managerial and professional family background but with a relatively poor initial academic performance (Bukodi, 2017). This has been considered as a way to prevent downward mobility for those from advantaged social origins (Ibid.).

Furthermore, inequality in learning participation is also predicted by gender. The international comparative research project by Desjardins *et al.*, (2006, p. 65) does not report that men participate more in adult education and training than women[25] in many countries and regions except for Czech Republic, Poland and Slovenia. However, the OECD (2003a, pp. 255-256; 2004, pp. 192-194) studies show that women were less likely to receive employers' financial support for learning opportunities considering their family responsibilities, warning of a danger of a rise in the existing gender pay gap if employers become a primary source of support for workers' learning opportunities.

Studies on the occupational attainment of RMWs in urban China (e.g., Han, 2006; Tian *et al*., 2013) often concluded with a simple suggestion that skill-development and further training are ideal ways of improving employability for high-paying occupations, yet those studies fail to consider the practicality of acquiring learning opportunities and resources for RMWs. Li's (2018) study shows that RMWs had low enrolment rates in training programs supported by employers, government, or training institutes, let alone successfully getting nationally recognizable certificates. Most of the learning of RMWs was from informal or non-formal contexts (self-learning, learning from experts, friends, relatives, or fellow villagers), but there is a lack of comparative study informing the difference between RMWs and URWs in informal and non-formal learning (Ibid.). Examination of the barriers of acquisition of learning opportunities and resources for RMWs shows a lot of similarities to the findings discussed above. Firstly, although employers do want workers to be proactive in learning, employer-provided learning opportunities do not favour those from rural areas since employers often consider RMWs as not being stable in the urban areas and that the investment in them cannot ensure productivity in return due to their low literacy (Zhu, 2004; Xu, 2014). Moreover, acquiring learning opportunities (e.g., training courses) and resources (e.g., self-learning materials) from for-profit private

[25] In Denmark, Finland and Switzerland, women have a higher participation rate.

providers might not be realist for RMWs, because of the financial burden involved (Lei, 2004; Zhu, 2004; Xu and Liu, 2005; Xu, 2014). Whilst governmental schemes and public provision are supposed to play a bigger role to support learning for RMWs, funding for learning (e.g., vocational education) for RMWs is very limited (Xu, 2013). Since some government-supported training schemes cannot be provided for free, RMWs do not show a strong willingness to attend those training opportunities (Zhu, 2004).

7.2.2. Digital divide(s)

New communication technologies, and the internet in particular, are considered to have the potential to provide relatively flexible and affordable access for learning opportunities (e.g., Gulati, 2008). This idea has often been forwarded by technological optimists who picture a potential to reduce inequality or exclusion in learning, whilst they overlook the fact that access to and the use of the internet has become a new gap in learning participation between the socio-economically advantaged and disadvantaged (Selwyn *et al.*, 2001; Eynon and Helsper, 2011). The issue of the disparity in using the internet or new digital communication technologies, in general, has become a new focus among academic researchers and policymakers since the late 1990s and is commonly termed as the *digital divide* (van Dijk, 2005, p. 2).

Initially, the term digital divide simply referred to the gap between those with and without access to the internet or new digital communication technologies (van Dijk, 2006), which we now call the first-level digital divide. Because internet use had become an essential component for many daily economic, social, political, and educational activities, a gap between the internet 'haves' and 'have-nots' had become a crucial aspect of social inequality since the second half of the 1990s (Norris, 2001, p. 68; Castells, 2002, p. 247). In terms of physical access to digital devices and the internet, earlier studies often found that socio-economically better-off individuals had relatively high internet adoption rates. Investigations in the US and European countries (NITA, 1995, 1999; Norris, 2001; van Dijk and Hacker, 2003; Katz and Rice,

2002) showed that income was a crucial factor determining people's possession of ICTs and access to the internet. Norris (2001) explained that economic resources are a key factor influencing people's ability to afford a home computer and an internet connection (e.g., the cost of using dial-up telephone modems was expensive at that time). Also, high-income populations are often occupied in managerial or professional positions in the service sector, so high-performance computers and high-speed networks were usually already equipped in their offices (Norris, 2001). The fact that income differences can adequately account for the variance in internet adoption is even more common in undeveloped and developing countries since, in the early years, digital products were essentially items of luxury for ordinary people (International Telecommunication Union, 2002). In addition, internet adopters were more likely to be from well-educated populations (Norris, 2001; Van Dijk and Hacker, 2003; Katz and Rice, 2002). Schools and colleges have provided rich material access, raised students' awareness of learning up-to-date knowledge, and trained them in analytical and informational skills by using high-tech equipment (Norris, 2001; van Dijk, 2005). Moreover, educational achievement is also related to people's subsequent higher chances in attaining high-income managerial or professional positions, which have more information-processing work tasks involved (Norris, 2001).

In the early 21st century, with digital devices becoming cheaper, high-speed internet access infrastructure being built more widely (Compaine, 2001), and the interfaces of new digital devices becoming increasingly user-friendly (Tambini, 2000), internet use has diffused to a growing proportion of the population (NTIA, 2002; Fallows, 2004). This was certainly the case within rich and developed countries, and subsequent policy and scientific conferences have increasingly drawn less and less attention to the issue of digital divide, with some observers claiming that the issue had practically been solved (van Dijk, 2006). However, van Dijk (2006) contended that perceiving the digital divide as a kind of binary, absolute, and static social inequality is a common misunderstanding, and this misunderstanding is often linked to ideas of technological determinism. Internet-related inequalities were far from being overcome, and several digital divide scholars suggested a ‘beyond access’ shift of the research focus (e.g., DiMaggio and Hargittai, 2001; Hargittai, 2002; van Dijk and Hacker, 2003; van Dijk, 2006).

The shift first led to a focus on how people use the internet, a defining character of how much benefit people could gain by getting online, which is now commonly called the second-level digital divide. On the one hand, some scholars studied people’s digital skills (usually measured by self-reported skill-levels and task-completion experiments). Advantaged individuals were consistently found to have better digital skills and educational achievement was one of the key destemming factors (e.g., Hargittai, 2002; Van Dijk, 2005; Hargittai and Hinnant, 2008; Deursen and Van Dijk, 2010; Hargittai and Dobransky, 2017; Scheerder et al, 2017). Even among the older adults, who are generally less active in internet use, those with higher educational levels had relatively advanced internet skills (Hargittai and Dobransky, 2017). On the other hand, the differentiation in online activities is another big focus, especially the focus on the divide in the so-called ‘capital-enhancing’ use of the internet, where UIL resides. DiMaggio and Hargittai (2002) used the term ‘capital-enhancing’ to refer to online activities (e.g., political participation, job-seeking or other career-related, learning or education, searching for health-related information) that are more directly related to the multiple aspects of life chances improvement. Therefore, a socio-economic divide in participation in those online activities will once again reproduce the advantaged groups’ advantages. In general, research findings (e.g., Hargittai and Hinnant, 2008; Helsper and Galacz, 2009; Van Deursen and Van Dijk, 2014; He and Wang, 2014; Van Deursen, et al., 2015; Stoycheff et al., 2016; Scheerder et al, 2017) confirmed a socio-economic divide in the ‘capital-enhancing’ use of the internet, and show that many aspects of pre-existing social inequality is being reproduced and maintained by the differentiation in online activities.

Some more recent updates on the divide in beneficial outcomes to internet use has been labelled as the third-level digital divide, although this area is far less studied than the second-level digital divide (Scheerder et al, 2017). A landmark investigation by Van Deursen and Helsper (2015) shows a complex picture of the socio-economic divide in the beneficial outcomes gained from internet use. The well-educated internet users perceived themselves as having more e-commerce economic gains and more beneficial educational outcomes. However, unemployed users reported more labour market benefits from internet use and people with an average income gained more economically from e-commerce than low- and high-income individuals (Ibid.).

In China, although the internet economy plays a critical role in recent economic growth, the issue of the digital divide remains severe. An ‘internet boom economy’ is currently taking place in China (Jung, 2016), and the services provided by some internet-related companies (especially those related to e-commerce) are world-leading (Larson, 2016). ‘Internet Plus,’ an application to use the internet to promote innovative development of conventional industries and government services, has been proposed by the Prime Minister Li Keqiang as a core theme of the current stage of economic innovation policies (China Daily, 2015). However, the basic digital divide among the population remains wide. Currently, China is the country with the largest population of internet users – 854 million (CNNIC, 2019). However, the figure also shows that internet adoption rate (i.e., the percentage of people who use the internet out of the whole population) in China stood as 61.2%, meaning that nearly 40% of the population does not go online (CNNIC, 2019). Moreover, the gap between urban (74.6%) and rural areas (38.4%) is still huge (CNNIC, 2019). These figures show that only a third of rural populations go online. While there is a lack of up-to-date data revealing the internet adoption gap between rural migrants and urban citizens in urban areas, the above findings may suggest varied rates of internet adoption among RMWs and URWs.

Certainly, internet-related inequalities are beyond the first-level digital divide in China. Within an environment what Castells (1989; 1998) called an 'informational city' that information technologies are employed to restructure and reproduce urban capitalism, a lack of access to ICTs and global connectivity for resources exchange constitutes a new form of social exclusion (Castells, 1998). However, inequality also exists among those who have the access to the internet. Echoing the trend of moving beyond the focus on the binary disparity between those who have and have not got internet access (e.g. DiMaggio and Hargittai, 2001; van Dijk and Hacker, 2003), Jack Qiu and his colleagues (Cartier, Castells and Qiu, 2005; Qiu, 2009a; Qiu, 2009b) identified the 'information have-less' – those who depend on low-end digital products, have limited access to ICTs and enjoy limited functions of the internet – to be a key issue of internet-related social stratification in urban China. Being excluded does not have to be without any access to the internet, but could be only with low-quality access and enjoying restricted informational functions (Jung, Qiu, and Kim, 2001; Cartier, Castells and Qiu, 2005). For them, RMWs are the major members of the internet have-less in urban China, who often could only afford low-end digital products and go to internet cafes to use the internet (Cartier, Castells and Qiu, 2005; Qiu, 2009b; Qiu and Gu, 2013). Moreover, since the have-less like RMWs often lack key economic, cultural and social resources for various kinds of online activities, they could only enjoy restricted informational functions by using the internet (Cartier, Castells and Qiu, 2005; Qiu, 2009b). Research shows that urban internet users have significantly longer weekly internet usage hours and are more likely to engage in recreational activities, informational activities, and e-commerce than the rural internet users (CNNIC, 2016). The longitudinal trend shows that the usage gap in entertainment-related activities (online music, video, gaming, and chatting) and e-commerce are in decline, while the gap in informational searching and news consumption has barely changed (CNNIC, 2016). This comparison does not directly reflect differences in internet activities between rural and urban origins workers in urban areas, but still hints that inequalities in internet activities might have existed between these two groups.

7.2.3. The divide in UIL

Participation in UIL has similar patterns of inequality in traditional forms of learning activities. Initially being expected to widen participation in learning, UIL is still found to be more pervasive among advantaged populations, who are always more engaged in traditional adult learning and educational activities (Gorard and Selwyn, 2005). Therefore, Gorard and Selwyn (2005, p. 85) observe that ICTs has simply provided traditional learners with an alternative channel for learning. In addition to the positive association between educational background and internet adoption as shown in the last section, studies also show that well-educated internet users are much more likely to participate in both informal and formal learning with the use of the internet (Selwyn *et al.*, 2006; Helsper and Galacz, 2009; Eynon, 2009; van Dijk and van Deursen 2010; Helsper and Eynon, 2010; Eynon and Helsper, 2011; van Deursen and van Dijk, 2014; van Deursen et al., 2015). Occasionally, income and occupational status are also found to be independently related to UIL participation, although the conclusions are inconsistent (Ibid.). Consider the case of participation in MOOCs, one of the most well-known practices of online learning, learners have a noticeably high rate of university graduates with many already having some prior knowledge related to the course content (Karmijn et al., 2016). Moreover, subject-specific work or educational experience is related to a higher chance of completing the course (e.g., Engle et al., 2015; Greene et al., 2015; Masanet et al., 2014).

Some online learning opportunities might reduce a number of traditional barriers like cost and geographical barriers, but at the same time they might require new resources (e.g., digital devices and internet access) and cultural competencies (e.g., digital skills) (Selwyn *et al.*, 2001). Indeed, studies show that internet skills and UIL participation are highly correlated (e.g., Eynon 2009; Eynon and Helsper, 2011). Moreover, van Dijk and van Deursen (2010, 2014) remark that on the one hand, the engagement with information content online requires new skills to operate digital devices and browsers; on the other hand, it levels up the requirement for traditional literacy beyond simply being able to read and write but to be able to quickly navigate, evaluate, and filter useful information content and strategically make use of the selected information to reach particular goals (e.g., develop new understandings in order to deal with particular work tasks). Thus, they (van Dijk and van Deursen, 2010) believe that the digital world not only makes the well-educated and literate people stand out more, but it enables their additional learning, too. Even after selecting learning resources, qualitative inquiries on MOOC learners' experiences found that the deficiency in prior knowledge leads to learners' feelings of panic and incompetency, which results in drop-outs (e.g., Belanger and Thornton, 2013; Park, Jung, and Reeves, 2015). This is consistent with our prior discussion of learning being a 'literacy-dependant' activity, and those with low confidence in achieving a good learning outcome are less likely to engage in learning activities.

7.3. Theorising the divide from a Bourdieusian perspective: towards a practical action theory of UIL

On the one hand, advantaged and disadvantaged groups have clearly different participation rates in learning activities, ICT use, and UIL. On the other hand, the decision-making of participation in learning activities, ICT use, and UIL 'resides in individuals' own heads', affected by individuals' motivation to learn and the perceived benefits through learning. However, individuals' subjective choice-preference and the objective disadvantages/advantages do not contradict each other, as individuals' available choices are embedded within a social context (e.g., Eynon and Helsper, 2011).

In this study, I adopt a Bourdieusian lens to theorize the differentiation in UIL participation, which I call the *practical action theory of UIL*. When explaining individuals' social actions, Bourdieu's *theory of practice* has the merit of attempting to reconcile the false opposition between objectivism and subjectivism, of structure and agency (Ritzer and Stepnisky, 2004, p. 517).

Rather, Bourdieu viewed objective structures and subjective phenomena in a dialectical relationship (Bourdieu, 2010, p. 15). The observed regularity cannot be explained by a ‘rule-obedience’ story that a specific social group are told to behave in a certain way by some social norms (Bourdieu, 1990, p. 63). An action is certainly an outcome of an individual’s mindful decision, based on their careful consideration (Bourdieu, 1990, p. 63). However, pure free will and an ideal-typical rational action only exists in an imaginary world (Bourdieu, 1990, p. 50). In reality, agents’ calculations are situated in a *practical relation* to the world, constrained by social conditions, especially the availability of economic and cultural resources (Ibid.). Partly, this socially constrained rational action means partial rationality. That is, in practical situations agents would not possess the complete information, knowledge and skills to successfully calculate the ideal action which could lead to the outcome of ‘profit-maximization’ (Bourdieu, 1990, p. 63). On the other hand, rational action is socially constrained, in the sense that the calculation takes into account the practical accessibility of the opportunities or resources for agents’ ‘profit-maximization’ (Ibid.).

Speaking of the constraints on agents’ free actions, another key strength of Bourdieu’s theory is its clear articulation of the practical availability of resources regarding the cultural domain (i.e., the idea of *cultural capital*), which is critical within the context of UIL participation. His idea of ‘practical action’ owes a debt to Marx’s (1970, p.3) historical materialism that ‘social life is essentially practical’, although Marx’s articulation of the practical constraints on social life is primarily related to the economic domain (Jenkins,1992, p. 41). Weber’s conception of *lifestyles*, the outcome of the interaction of *life chances* (the availability of choices accessible to individuals, conditioned by one’s class and status) and *life choices* (individuals choose to act in a preferred way among the available choices) (Weber, 1978, p. 537; Abel and Cockerham, 1993) share some similarities to Bourdieu’s partially free action claim. However, again the role of socially conditioned cultural competency in individuals’ decision-making in action is not particularly highlighted in the Weberian framework.

7.3.1. The labour market as a field

Instead of using the term ‘society’ to vaguely refer to the environment within which individuals are situated (and this amorphous term has, on occasion, been handy for some who want to shift its meaning in order to make an argument), Bourdieu likes to use the term *field* to refer a specific ‘arena of battle,’ similar to a social space within which individuals struggle over resource-acquisition is a key feature (Bourdieu and Wacquant, 1992, p. 101). Each field has its logics, rules, and the ways of distribution of important resources, often characterized by inequality and domination. Within each field, individuals are assumed to be self-interested agents oriented towards the maximization of profit through their actions (Bourdieu, 1986). A labour market can be seen as one of those ‘arena-like’ fields, especially given its competitive nature. Within this field, for wage workers, ‘the rule of the game’ is to try to secure employment with good remuneration. As discussed in Chapter Five, whilst the labour market is often characterized by stratification, the development of scarce work skills is one channel through which a relatively advantaged occupation might be obtained. To achieve that goal, the action of participation in learning, regardless of the format, serves as a possible means for workers.

7.3.2. The availability of economic and cultural capital for UIL

Within the labour market field, competition is not a discontinuous series of games, but an ‘accumulated history’ (Bourdieu, 1986). That is to say, some ‘players’ continuously play the game relatively better as they have accumulated more valuable resources, which puts them into an advantageous situation during the game-playing and could potentially help them more easily gain valuable resources (Ibid.). For example, while acquiring scarce skills is one way to secure employment with good remuneration in the labour market, the already well-educated and skillful workers might be more able to update the latest advanced-level skills more easily. In this sense, those important resources could be considered as ‘capital.’

To participate in UIL, previous studies have demonstrated two major forms of critical resources. The first one is economic resources. Participation in some traditional forms of further learning (e.g., off-line training course attainment) requires economic resources in most learning contexts. As discussed above, a lack of economic resources plays a significant role in the disengagement of RMWs in learning participation. It is expected in the context of learner-instructor interaction that, even the instructor’s tutorial service will take place online, economic resources would still be a barrier for the engagement for RMWs. Although the rhetoric of ‘affordable and flexible alternatives for learning’ emerged to describe the potential of ICTs, in many cases the material base of UIL (e.g., electronic devices, internet access) also required the cost of individuals’ economic resources (Selwyn et al., 2001).

Moreover, cultural resources certainly play a profound role in UIL participation. Two forms of cultural capital are particularly important, the *objectified* and the *embodied*. Objectified cultural capital refers to material cultural goods (Bourdieu, 1986) for UIL activities (e.g., devices, digital books, course videos) and embodied cultural capital refers to individuals’ cultural competence (Ibid.) affecting UIL participation.

UIL draws upon the use of relevant objectified cultural capital. As mentioned above, the acquisition of digital devices and internet access, which I call *hardware objectified cultural capital*, usually follows a market-mechanism by costing individuals’ money. Additionally, especially in the context of learner-content interaction, learning activities are premised on the availability of learning resources (*content objectified cultural capital*), but the acquisition of useful learning resources often requires individuals embodied cultural capital. The abundance of online information resources seems to be able to provide a low-cost alternative, but the acquisition of those abundant and useful resources relies on users' effective online searching. Van Dijk and Van Deursen's (2010) work on internet skills provides a good indication of two critical cultural competencies for successful information searching. The first is one's technical competency to operate digital devices and to browse and navigate the internet (Ibid.), which I will call *technical embodied cultural capital*. In addition, the extent of effective information resource searching (e.g., keywords searching, evaluating, filtering) also relates to one's accumulated knowledge in a specific area (Ibid.). Information overload leads to the difficulty of useful content selection (Anderson, 2008; David, 2017), and those who had prior knowledge in an area, which I call *expertise embodied cultural capital*, had some strengths to select high-quality information resources (van Dijk and van Deursen, 2010) for further learning activities. Thus, the acquisition of the objectified cultural capital for learning relates to the accumulation of both economic and embodied cultural capital.

Moreover, the *expertise embodied cultural capital* helps one acquire scarce professional knowledge and work skills more effectively. Knowledge development is not akin to 'transcribing things onto a blank slate' (Locke, 2007). Rather, according to currently prevailing cognitive theory, developing new understandings is a process of forming connections to what is already known (e.g., Schunk, 1991), which presupposes learners' prior knowledge. As discussed, literacy and subject-knowledge prepare one for readiness to learn (Desjardins et al., 2006, p. 67). This might be more relevant in the context of UIL, where leaner-content interaction practice is more prevalent given the abundance of online information content. Those with expertise embodied cultural capital have the strengths to decode the meaning of information content (van Dijk and van Deursen, 2010) and to develop new understandings or skills after inculcation or practice. It seems to suggest an overall trend that the knowledgeable get more knowledgeable while the ill-informed get confused in the age of information overload.

7.3.3. The disposition and the practice of UIL

The accumulation of economic and cultural capital affect individuals' participation in UIL. As mentioned in the beginning, this observed regularity does not demonstrate 'rule-obedience,' such that a specific social group are compelled to behave in a certain way by social norms (Bourdieu, 1990, p. 63). Instead, an action is an outcome of individuals' mindful decision-making and that decision-making is situated in a practical relation to the world, constrained by real social conditions, especially dependent on the availability of economic and cultural resources (Bourdieu, 1990, p. 50).

To explain the relationship between structural force and individuals' mindful action, Bourdieu invented his famous 'thinking tools': *habitus* and *disposition*. Although claiming those thinking tools as a 'temporary construct which takes shape for and by empirical work' (Wacquant,1989, p. 50), those concepts are in fact highly sophisticated and criticised as 'emphatically *not* a temporary construct subordinate to the needs of empirical research,' despite the insightfulness derived from those concepts (Jenkins, 1992, p. 40).

In Bourdieu's conception, *habitus* refers to 'systems of durable and transposable dispositions, structured structures predisposed to function structuring structures.' (Bourdieu, 1977, p. 72). By saying disposition, Bourdieu refers to a 'predisposition, tendency, propensity, or inclination' of future actions affected by the outcome of individuals' past actions (Bourdieu, 1977, p. 214). Habitus, the system of shaping dispositions, are 'structured' by individuals' past or current circumstances in a field. On the other hand, *habitus* is also a 'structuring structure' as it organises future actions as well as the perceptions of actions (Bourdieu, 2010, p. 166).

Individuals' choice of UIL participation is a result of a decision-making process constrained by the practicality, the actual social forces. First, the decision-making takes account of the practicality of the accessibility of the economic and cultural capital (the money, the devices, the internet access, the technical medium skills, the informational content, the basic literacy, the professional knowledge) for UIL. For example, downloading a free digital book to read from a peer-to-peer sharing platform might be a cost-effective choice for the existing internet users, but not for those who could not even afford a digital device to get online. Second, individuals attempt to make a cost-effectiveness analysis of UIL, but drawing upon the available wisdom derived from their dispositions of UIL, which was conditioned by their previous UIL experience and social circumstances. This is in line with most psychological models (among which the best-known is Cross' (1981) chain of response model[26]) on the learning participation decision-making process that individuals' perceptions and attitudes on learning shape their tendencies of learning participation, and in return their actual learning experience also affects their perceptions and attitudes on learning.

7.3.4. The division in UIL participation

Thus, the advantaged (i.e, those who are more likely to obtain rich economic and cultural capital in the field as well as possessing positive UIL experiences in the past) have developed a disposition of 'UIL proximity,' which then shapes more active participation in UIL in future. The structural inequality then turns into an observable scene of division in UIL between advantaged and disadvantaged groups. RMWs, who are more likely to be deprived of economic and cultural capital in the urban labour market field, are expected to be less likely to develop a disposition of UIL proximity. As an effect, it is expected that RMWs and URWs will have an observable 'divide' in the participation in UIL.

[26] The model can be seen as a cycle consisting of self-perceptions and attitudes of learning, expected goal-achievement, opportunities and barriers, actual participation in learning, then amendment/consolidation of self-perceptions and attitudes of learning (Cross, 1981).

7.4. Quantitative evidence

7.4.1. Analytical strategy

This part of the analysis uses quantitative data to make a robust comparison of the participation in UIL between RMWs and URWs. Since there is a variable *ku701* (How frequently did you use the internet for learning in the past year? 1= almost every day; 2= Three or four times a week; 3= One or two times a week; 4= Two or three times a month; 5= One time a month; 6= One time several months; 7= Never) effectively measures the actual frequency of UIL at wave 2014 and 2016 (but not at wave 2010), the analysis in this chapter only uses data from the 2014 and 2016 waves. Thus, drawing on data from CFPS2014adult and CFPS2016adult, a series of mixed-effects modelling and bivariate analysis are conducted.

To begin with, the practical action theory of UIL predicts that RMWs will be less active in actual UIL participation, due to their relative lack of relevant economic and cultural capital. It is also expected that the divide is due to the relatively low rate of internet use among RMWs and low rate of UIL participation among those who used the internet. I, therefore, propose the following hypothesis:

> ***H1.*** *Overall, RMWs are less active in UIL than URWs (H1a). Not only do RMWs exhibit a lower rate of internet use (H1b), RMW internet users are also less active in UIL (H1c).*

The practical action theory of UIL argues that a lower activity in UIL among RMWs is not related to the *hukou* status *per se*, but is to a large extent related to people from rural backgrounds' relative lack of economic resources and cultural competency to participate in UIL activities. Those conceptual factors can never be measured perfectly. However, to a large degree, available economic resources can be represented by individuals' family earnings, and educational achievement is a useful proxy to indicate the relevant cultural competency. Thus, we expect that family income and educational background are related to the overall UIL participation and internet adoption among all the workers, and the UIL participation among all the internet users. On the other hand, if we control for family income, educational background, and some other demographic factors (age, gender, ethnicity), we could make a hypothesis that RMWs and URWs will have similar participation in UIL. Thus, I propose the following hypotheses:

H2. *After controlling for family income, educational background, age, gender, and ethnicity,* hukou *type is no longer related to UIL participation (H2a) and internet adoption (H2b) among all the workers, and the UIL participation (H2c) among internet users.*

H3. *Educational background is related to the overall UIL participation (H3a) and internet adoption (H3b) among all the workers, and the UIL participation (H3c) among internet users. URWs are more likely to have a better educational background (H3d).*

H4. *Family income is related to the overall UIL participation (H4a) and internet adoption (H4b) among all the workers, and the UIL participation (H4c) among internet users. URWs usually have relatively high family income (H4d).*

Valid sample

Table 7.1. summarises the process of valid sample selection. Similar to the sample selection in Chapter Five, the target population should be those non-agricultural wage workers who were living in urban areas. So initially, I selected 5,156 eligible cases from wave 2014 and 6,470 cases from wave 2016. Due to panel data's nature of repeated measures of the same individual, for the missing data of the explanatory variables whose values are less time-

variant, I imputed available values from other available waves. Overall, the issue of missing data is not serious as the missing data does not account for more than 7% in 2014 and 4% in 2016. As such, I carried out complete case analysis after listwise deletion.

Table 7.1. The process of valid sample selection

			2014	2016
Step One: Eligible Cases Selection	1. Total Nationally Representative Sample		N=34,731	N=33,797
	2. Eligible Sample Selection: urban-living, employed as non-agricultural worker, and not self-employed		N=5156	N=6470
Step Two: Dealing with item missing		*hukou* type	215 missing originally; 42 missing after imputation from wave 2012, 2010	7 missing
		Internet use	313 missing	0 missing
		UIL	313 missing	1missing
		Education	33 missing originally; 7 missing after imputation from wave 2012, 2010	341 missing originally; 159 missing after imputation from wave 2014, 2012 and 2010
		Income	347 missing originally; 30 missing after imputation from wave 2012 and 2016	122 missing originally; 33 missing after imputation from wave 2014
		Age	0 missing	0 missing
		Gender	0 missing	0 missing
		Ethnicity	0 missing	0 missing
Valid N of observation after listwise deletion			4825 (93.58%)	6271 (96.92%)
Valid N of individuals			8153	

Key variables

Since the proportional odds assumption does not always hold (see the Brand test results in Appendix E), the analysis did not run mixed-effects ordinal logistic regression models on the ordinal variable *ku701*[27]. Instead, this study

[27] How frequently did you use the internet for learning in the past one year? 1= almost everyday; 2= Three or four times a week; 3= One or two times a week; 4= Two or three times a month; 5= One time

used two binary variables *WeeklyUIL* (Use the internet for learning at least weekly? 1=Yes; 0=No) and *NoUIL* (Never use the internet for learning in the past year? 1=Yes; 0=No) to measure the *most active* and the *least active* scenarios of UIL. Both variables derived from recoding the original ordinal variable *ku701*. Specifically, the binary variable *WeeklyUIL* indicates whether or not individuals participated in UIL as active as at least weekly (i.e., *WeeklyUIL*=1 if *ku701*=1, 2 or 3; otherwise *WeeklyUIL*=0). On the other hand, the binary variable *NoUIL* measures the least active situation of UIL that individuals did not have any UIL activities over a whole year (*NoUIL*=1 if *ku701*=7; otherwise *NoUIL*=0).

In addition, the binary variable *Internet* (1= Use the internet; 0= No internet use) is used to measure individuals' internet adoption.

For the economic resources, a scale variable *income* is used to measure family yearly income *per capita* (by Chinese Yuan). In CFPS, the variable family income *per capita* measures the average income earned per person in a family, calculated by dividing the total family income by its family size. An ordinal variable *education* (1= low, below middle school; 2= intermediate, middle school or high school graduates; 3= high, higher education) is used to measure individuals' formal educational achievement. Both of these variables have limitations. First, the educational background can be used as a proxy for one's cultural competency, but it is not a perfect operationalization of our concept of cultural capital. Second, the relationship between family income and UIL could only represent a two-way association.

In addition, demographic variables (*age*, *gender* and *ethnicity*) are also included in the analysis. In all the models, variables *occupation* and *year* are included as controls.

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a month; 6= One time several months; 7= Never

Statistical Models

After showing the weighted descriptive statistics, a series of mixed-effect binary logistic regression models (see (7.1)) with a subject-specific random intercept (u_i) included were conducted to test our hypotheses.

$$\text{Log}(P_{it}/1- P_{it}) = a + b*X1_{it} + \ldots + \textit{year} + u_i + e_{it} \tag{7.1}$$

Firstly, I built Model 1 (*hukou*) and 2 (*hukou* x *occupation*) to test H1, with *weeklyUIL*, *noUIL*, and *internet* as response variables. Both models include explanatory variables *hukou type*, *year*, and *occupation*, but Model 2 added an interaction term of *hukou type* and *occupation* to explore whether the *hukou*-related differences vary across occupational groups. Next, to test H2 and H3, based on Model 1 and Model 2, Model 3 (hukou + controls) and 4 (hukouXoccupation + controls) further added explanatory variables *income*, *education*, *age*, *gender*, and *ethnicity*. In the end, I supplement a comparison of the educational background and family income between RMWs and URWs, drawing on the results of some bivariate analyses.

7.4.2. Descriptive statistics

Table 7.2. shows us the weighted descriptive statistics of internet adoption, and different kinds of UIL participation. Among all the workers, the internet adoption rates were around 58.88% in 2014 and 62.17% in 2016, respectively. More than half of the workers did not have UIL activities in the past year. There were about a third of the workers having UIL activities weekly in 2014 and around a quarter had weekly UIL in 2016. If we only look at those who were online, at least 40% of them used the internet for learning weekly. However, even among the internet users, there were still around one-third of them who did not have UIL activities for a whole year at each wave.

Table 7.2. Weighted descriptive statistics on internet use and UIL

		Weekly UIL	From once a year to two-to-three times a month	No UIL	Internet use
All workers	2014 (N=4825)	31.56%	10.72%	57.72%	58.88%
	2016 (N=6271)	26.95%	12.05%	61.00%	62.17%
All internet users		Weekly UIL	From once a year to two-to-three times a month	No UIL	
	2014 (N=2709)	53.61%	18.21%	28.17%	
	2016 (N=4527)	43.36%	19.38%	37.27%	

Next, Table 7.3. summarises the weighted descriptive statistics of other variables. From 2014 to 2016, there were slightly more managerial and professional staff whilst less routine non-manual workers among all the workers and internet users. Manual supervisors only accounted for a small proportion of all the samples. In both samples, more than half of the cases had finished secondary education but did not have higher education. Among the internet users, only around (in the 2016 sample) or less than (in 2014 sample) a tenth did not have secondary education experience. In all samples, the mean income is much higher than the median, indicating positive skew. The internet user sample had higher average income (mean and median) than all the worker samples. Interestingly, the mean difference in age is larger than 2, which indicates a possible heterogeneity of the participants filling the observations in 2014 and 2016. Overall, the URW-RMW ratios are close to 1. Similarly, around 40% of the cases are female and more than 50% are male. *Han* ethnicity majority were consistently around 93% within all samples.

Table 7.3. Weighted descriptive statistics on explanatory variables

		All workers		All internet users	
		2014	2016	2014	2016
Occupation	Higher managerial and professional	10.59%	13.31%	14.83%	18.12%
	Lower managerial and professional	15.34%	20.54%	20.55%	22.85%
	Routine non-manual	21.03%	17.31%	26.45%	20.56%
	Manual supervisor	2.50%	7.40%	3.11%	9.70%
	Skilled manual	18.81%	16.90%	15.44%	15.39%
	Semi-unskilled manual	31.72%	31.19%	19.62%	22.11%
Educational background	Low	18.62%	25.03%	7.32%	12.49%
	Medium	53.80%	54.02%	52.03%	56.04%
	High	27.58%	20.96%	40.65%	31.47%
Income	Mean (S.D.)	24146.41 (41985.32)	31614.72 (74601.89)	26467.81 (50408)	36431.37 (83671.77)
	Median (IQR) (unweighted)	16668.33 (16666.67)	22182.29 (22541)	20000 (19666.67)	24250 (25000)
Age	Mean (S.D.)	38.31 (11.61)	44.078 (11.88)	33.56 (9.93)	38.99 (10.17)
Hukou type	Agricultural	44.84%	50.01%	37.75%	56.46%
	Non-agricultural	55.16%	49.99%	62.25%	43.54%
Gender	Male	57.83%	59.17%	55.89%	56.49%
	Female	42.17%	40.83%	44.11%	43.51%
Han ethnic group	Yes	93.57%	93.56%	93.58%	93.42%
N		4825	6271	2709	4527

7.4.3. The overall divide in UIL

Firstly, I investigated the overall RMW-URW difference in UIL participation. In particular, I look at the proportions in the two most extreme situations of UIL participation: having *UIL weekly* and *not having UIL in a whole year*. Table 7.4. shows the result of mixed-effects binary logistic models on *weekly UIL* among all workers. Model 1 includes explanatory variable *hukou* and has no other controls except for occupational group and year. The reference observation is the odds of RMWs from the higher managerial and professional background in 2014. The odds ratio of *hukou* is 1.884 and is statistically significant, meaning that their urban background counterparts were almost two times more likely to use the internet for learning weekly than those from rural backgrounds.

In the case of *hukou*-related UIL participation, differences vary across different occupational groups, Model 2 added an interaction term of *hukou* and occupation. Compared to the reference group, being an urban background worker ($OR_{\text{Non-agricultural}} = 1.560$, $p < 0.01$) means a significantly higher likelihood to have UIL every week. Among those interaction terms, only the interaction between the lower managerial and professional occupational group and non-agricultural *hukou* type is statistically significant. The odds ratio of 'Lower managerial and professional x Non-agricultural' is 1.873, meaning the RMW-URW gap in having UIL weekly is even larger (1.560 x 1.870 =2.922) among the lower managerial and professional workers. To further clarify the interaction effects, predicted probabilities with 95% confidence intervals grouped by occupation group and *hukou* type were plotted and shown in Figure 7.1. Overall, the probabilities of weekly UIL decreased gradually from the higher managerial and professional groups to the semi-unskilled manual group. The graph 'Total' at the end further confirmed that on average URWs were more active in weekly UIL than RMWs, supported by the significantly higher predicted probability among URWs. No *hukou*-related statistically significant difference in weekly UIL participation is found amongst higher managerial and professional staff, manual supervisors, and routine non-manual workers. However, among lower managerial and professional workers and manual workers, URWs had significantly higher probability of weekly UIL participation.

Next, Model 3 controlled for individuals' educational background, family income, age, gender, and ethnicity. Even after adding the controls, URWs were still associated with a significantly higher chance of weekly UIL ($OR_{Non\text{-}agricultural}$=1.584, p<0.001). In accordance with our assumption, educational background was strongly associated with learning activities with the use of the internet on a weekly basis. Compared to those who had not finished secondary education, middle school or high school graduates were 3.4 times more likely to have weekly UIL ($OR_{Intermediate} = 3.472$, $p < 0.001$), and college graduates were 12.43 times more likely to use the internet for learning every week ($OR_{High} = 3.472$, $p < 0.001$). In addition, family income is positively associated with the probability of weekly UIL. Compared to the bottom quartile earners, the top two quartile earners' chances of participating in UIL weekly were significantly higher ($OR_{Third\ quartile} = 1.389$, $p < 0.001$; $OR_{Fourth\ quartile} = 1.895$, $p < 0.001$).

Model 4 further added an interaction term of *hukou* and occupation. Still, the odds ratio of *Non-agricultural* is higher than 1, although only being significant at the 90% confidence level. Educational background and family income were also consistently associated with a higher chance of using the internet for weekly learning purposes. The significant interaction term 'Lower managerial and professional x Non-agricultural' indicates that the difference in weekly UIL participation is more salient among the lower managerial and professional occupational group. Within that group, URWs were around two times (1.369 x 1.475 = 2.2) more likely to have UIL weekly. Figure 7.2. plotted the predicted probabilities of weekly UIL with the 95% confidence intervals based on Model 4 estimation, grouped by occupation and *hukou* type. At first glance, the graphs looked quite similar to those in Figure 7.1. The average URWs probability in weekly UIL was still significantly higher than the figure for RMWs. Furthermore, among lower managerial and professional and semi-unskilled workers, the URW group's participation in UIL weekly was predicted to be significantly higher. Additionally, results from Model 3 and 4 also show that weekly UIL is positively associated with young and male workers (see Table F6 in Appendix F).

Table 7.4. Mixed-effects binary logistic models on **WEEKLY UIL** among all workers (odds ratios and standard errors)

	(1)	(2)	(3)	(3)
	Model 1 (Hukou)	Model 2 (Hukou x Occupation)	Model 3 (Hukou + Controls)	Model 4 (Hukou x Occupation + Controls)
Hukou type (Ref: Agricultural)				
Non-agricultural	1.884***	1.560**	1.584***	1.369+
	(0.129)	(0.260)	(0.117)	(0.229)
Occupation (Ref: Higher managerial and professional)				
Lower managerial and professional	0.536***	0.363***	0.736**	0.574**
	(0.056)	(0.063)	(0.076)	(0.100)
Routine non-manual	0.325***	0.361***	0.460***	0.488***
	(0.034)	(0.064)	(0.048)	(0.086)
Manual supervisor	0.296***	0.394**	0.526**	0.625
	(0.073)	(0.132)	(0.129)	(0.206)
Skilled manual	0.099***	0.092***	0.242***	0.221***
	(0.013)	(0.017)	(0.030)	(0.040)
Semi-unskilled manual	0.060***	0.050***	0.205***	0.172***
	(0.007)	(0.009)	(0.023)	(0.030)
Interaction				
Lower managerial and professional x Non-agricultural		1.873**		1.475+
		(0.401)		(0.315)
Routine non-manual x Non-agricultural		0.862		0.922
		(0.184)		(0.196)
Manual supervisor x Non-agricultural		0.477		0.615
		(0.236)		(0.301)
Skilled manual x Non-agricultural		1.112		1.138
		(0.258)		(0.262)
Semi-unskilled manual x Non-agricultural		1.391		1.333
		(0.297)		(0.285)
Education (Ref: Low)				
Intermediate			3.472***	3.441***
			(0.402)	(0.398)
High			12.243***	12.115***
			(1.758)	(1.738)
Family income *per capita* (Ref: First quartile)				
Second quartile			1.163	1.158
			(0.107)	(0.107)
Third quartile			1.389***	1.384***
			(0.129)	(0.128)
Fourth quartile			1.895***	1.891***
			(0.179)	(0.179)
Other controls	a	b	a	b
Constant	0.989	1.118	1.267	1.384
	(0.099)	(0.158)	(0.293)	(0.350)
Observations	11,096	11,096	11,096	11,096
Individuals	8,153	8,153	8,153	8,153
Wald Chi-square	730.6	739.6	901.4	904.3
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1; a: year; b: year, age, gender, ethnicity; Coefficients of controlled variables presented in Table F6; Source: CFPS 2014 and 2016

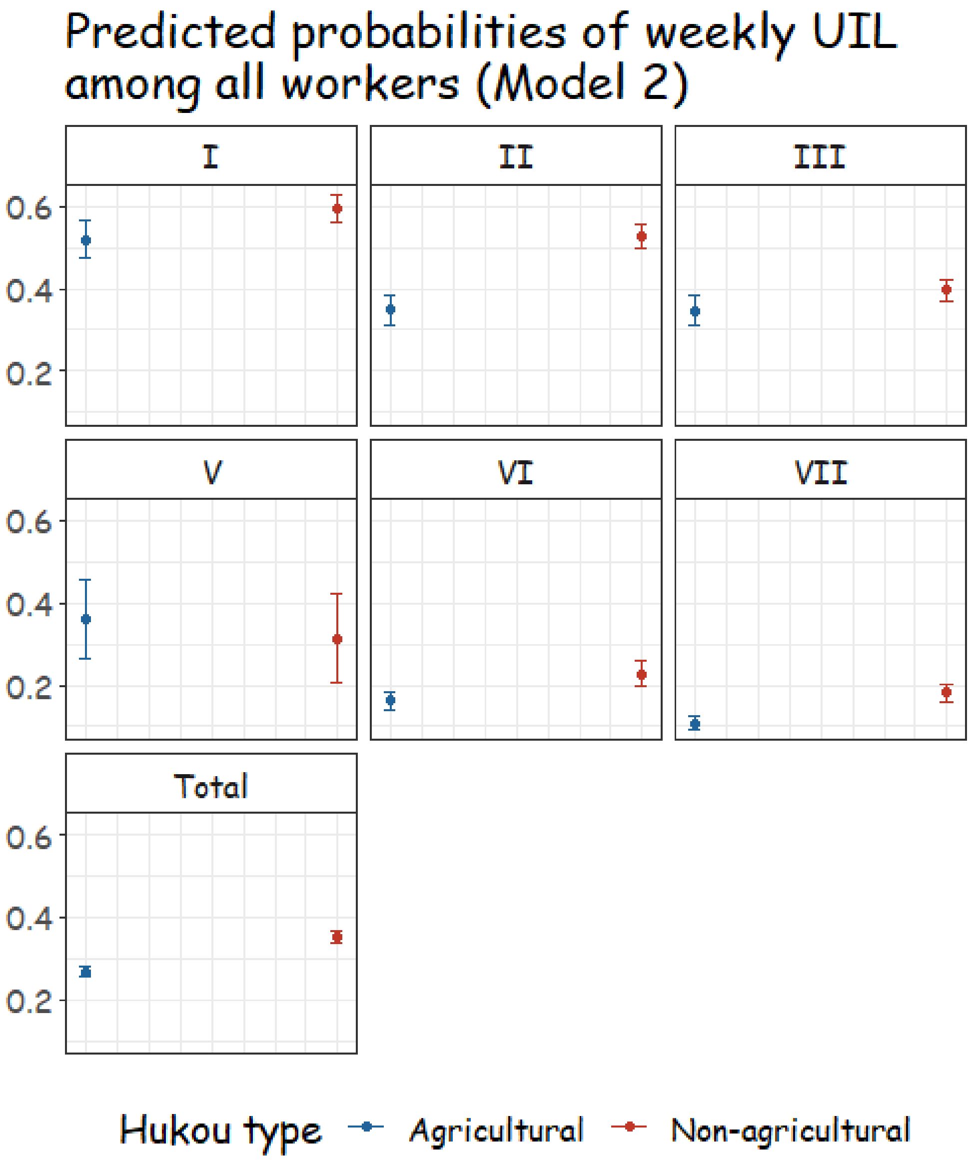

Figure 7.1. Predicted probabilities of weekly UIL with 95% confidence intervals among all workers (Model 2). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

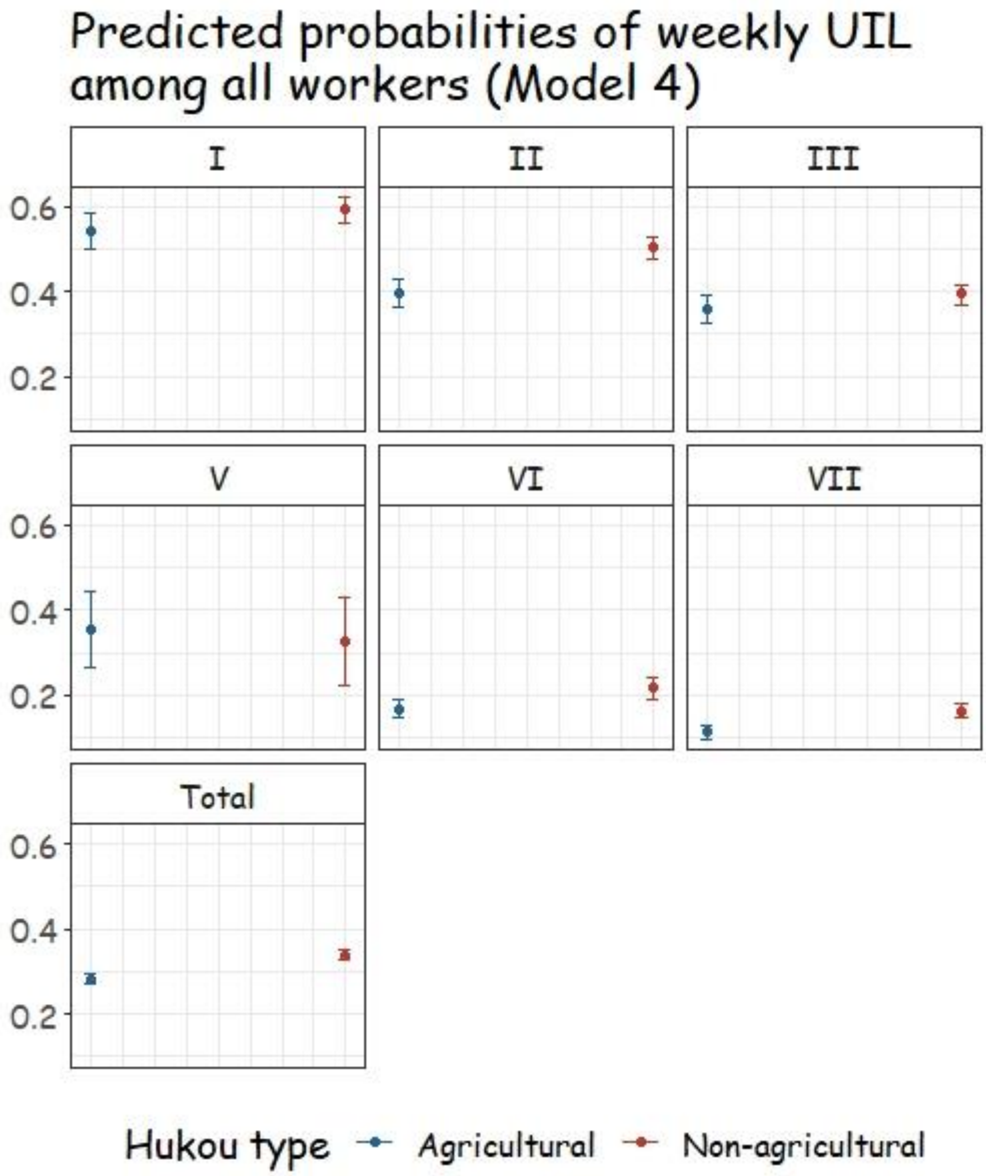

Figure 7.2. Predicted probabilities of weekly UIL with 95% confidence intervals among all workers with controls (Model 4). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

Next, we looked at the comparison on another extreme — *no UIL at all in a whole year*. Table 7.5. presents the results of mixed-effects binary logistic models on no UIL in the past year**,** reporting odds ratios. Model 1 only included explanatory variables *hukou*, *occupation*, and *year*, which can estimate an overall RMW-URW difference in no UIL. The odds ratio of *Non-agricultural* is 0.480 and significant at the 99.9% confidence level. That implies that the urban background higher managerial and professional workers were half as likely to have no UIL in a whole year, compared to their rural background peers.

In case the *hukou*-related differences varied across different occupational groups, Model 2 added an interaction term of *hukou* and *occupation* to compare the conditional differences. The odds ratio of *Non-agricultural* is 0.579 and still statistically significant (p <0.01), meaning rural background higher managerial and professional workers' had a higher chance of not using the internet for learning in a whole year, compared to their urban background counterparts. In addition, the interaction term *Lower managerial and professional x Non-agricultural* is 0.514 and significant at 95% confidence level, which indicates that the gap in not having UIL between RMWs and URWs is even greater in the lower managerial and professional occupational group, compared to the higher managerial and professional occupational group. Based on Model 2, Figure 7.3 plotted the predicted probabilities of no UIL among RMWs and URWs in the past year with the 95% confidence intervals, conditioned by occupation. At first glance, all the predicted probabilities of no UIL were higher among RMWs than the URW groups. The 'Total' graph shows that on average the chance of no UIL among RMWs was significantly higher than 60%, whilst the probability of URWs was significantly below 60%. Except for higher managerial and professional and manual supervisor groups, the predicted probabilities of no UIL for RMWs were higher than the URW group in all other occupation groups. Combining the results of Model 1 and 2 together, we can see that an overall difference in no UIL is clear between RMWs and URWs.

Model 3 added controls of *education*, *family income*, *age*, *gender*, and *ethnicity* but with no interaction effect. Even after further controlling for economic, cultural, and other demographic factors, URWs were still almost 50% less likely ($OR_{\text{Non-agricultural}} = 0.534$, $p < 0.001$) to have no UIL in a whole year compared to RMWs. No UIL is highly related to one's educational background. Those who were below secondary educational level were almost 4 times more likely to have no UIL than the middle or high school graduates ($OR_{\text{Intermediate}} = 0.256$, $p < 0.001$), and 20 times more likely ($OR_{\text{High}} = 0.05$, $p < 0.001$) than the college graduates. Furthermore, No UIL is also associated with family income negatively. The top quartile earners were less than half as likely to have no UIL in a whole year than the bottom quartile earners ($OR_{\text{Fourth quartile}} = 0.486$, $p < 0.001$).

In the end, based on Model 3, Model 4 further added an interaction term of *hukou* and *occupation* to compare the conditional differences. As shown, the odds ratio of *Non-agricultural* is 0.652 and significant at the 95% confidence level, indicating rural background higher managerial and professional workers' higher chance of not using the internet for learning compared to their urban background counterparts, when controlling for educational background, economic resources, age, gender, and ethnicity. However, none of the interaction terms is statistically significant, meaning there is no strong evidence to support that the RMW-URW differences in UIL vary by occupation. Nonetheless, we still employed Model 4's estimation to compare the conditional predicted probabilities of no UIL between RMWs and URWs. The predicted probabilities with 95% confidence intervals were plotted in Figure 7.4. The patterns were almost identical to Figure 7.3. Among lower managerial and professional, routine non-manual and manual workers, the likelihoods of no UIL were significantly higher among RMWs than URWs. Thus, the results from Model 3 and 4 indicate that even after controlling for cultural, economic, and demographic factors, RMWs still had relatively high chances to not to use the internet for learning over a whole year.

Additionally, results from Model 3 and 4 also indicate that older and female workers were more likely to have no UIL over a whole year (see Table F6 in Appendix F).

To sum up, this part of the analysis has firstly revealed the overall divide in UIL participation between RMWs and URWs. In many cases, rural background workers were less likely to have UIL weekly, but more likely to not use the internet for learning purposes over a whole year. Thus, *H1a has gained some support*. However, even after controlling for cultural, economic, and demographic features, the divide in UIL participation still existed. Therefore, *H2a is not supported by the evidence*. Educational background and family income were positively related to UIL participation. Thus, *H3a* and *H4a have gained some support*.

Table 7.5. Mixed-effects binary logistic models on **NO UIL** among all workers (reporting odds ratios and standard errors)

	(1)	(2)	(3)	(3)
	Model 1 (Hukou)	Model 2 (Hukou x Occupation)	Model 3 (Hukou + Controls)	Model 4 (Hukou x Occupation + Controls)
Hukou type (Ref: Agricultural)				
Non-agricultural	0.480***	0.579**	0.534***	0.652*
	(0.037)	(0.120)	(0.043)	(0.133)
Occupation (Ref: Higher managerial and professional)				
Lower managerial and professional	2.614***	3.876***	1.741***	2.225***
	(0.336)	(0.801)	(0.215)	(0.448)
Routine non-manual	4.341***	4.030***	2.909***	3.096***
	(0.562)	(0.848)	(0.360)	(0.635)
Manual supervisor	3.977***	3.888***	1.912*	2.303*
	(1.117)	(1.483)	(0.508)	(0.835)
Skilled manual	17.017***	17.874***	5.526***	6.225***
	(2.577)	(3.847)	(0.760)	(1.255)
Semi-unskilled manual	34.143***	39.105***	7.072***	8.192***
	(5.168)	(8.407)	(0.929)	(1.615)
Interaction				
Lower managerial and professional x Non-agricultural		0.514*		0.672
		(0.133)		(0.169)
Routine non-manual x Non-agricultural		1.105		0.907
		(0.283)		(0.225)
Manual supervisor x Non-agricultural		1.143		0.718
		(0.636)		(0.380)
Skilled manual x Non-agricultural		0.960		0.840
		(0.257)		(0.216)
Semi-unskilled manual x Non-agricultural		0.785		0.792
		(0.195)		(0.190)
Education (Ref: Low)				
Intermediate			0.256***	0.257***
			(0.029)	(0.029)
High			0.050***	0.050***
			(0.008)	(0.008)
Family income *per capita* (Ref: First quartile)				
Second quartile			0.830*	0.830*
			(0.078)	(0.078)
Third quartile			0.677***	0.677***
			(0.065)	(0.065)
Fourth quartile			0.486***	0.484***
			(0.049)	(0.049)
Other controls	a	b	a	b
Constant	0.383***	0.342***	0.112***	0.098***
	(0.046)	(0.060)	(0.029)	(0.028)
Observations	11,096	11,096	11,096	11,096
Individuals	8,153	8,153	8,153	8,153
Wald Chi-square	742.7	748.8	902	901.6
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.1; a: year; b: year, age, gender, ethnicity; Coefficients of controlled variables presented in Table F6; Source: CFPS 2014 and 2016

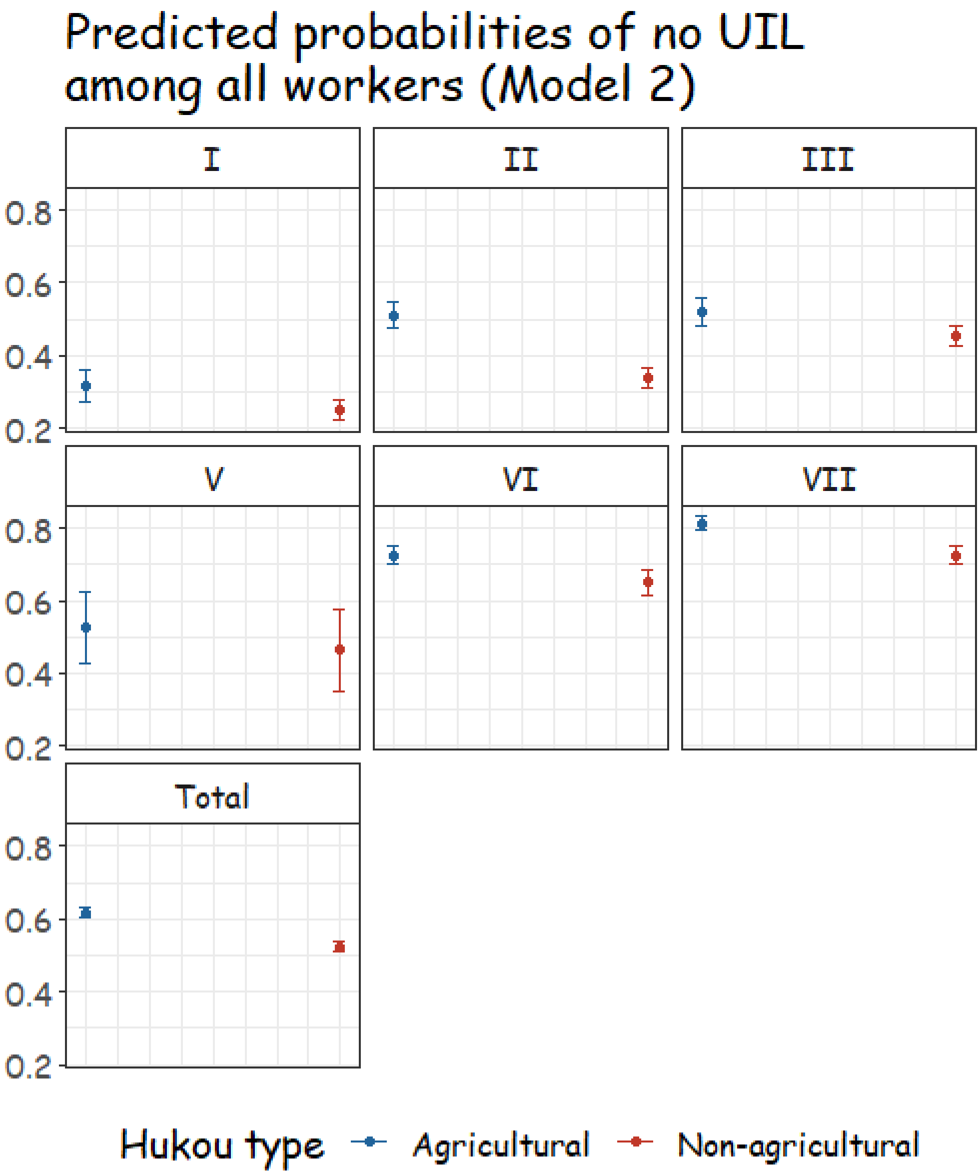

Figure 7.3. Predicted probabilities of no UIL with 95% confidence intervals among all workers (Model 2). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

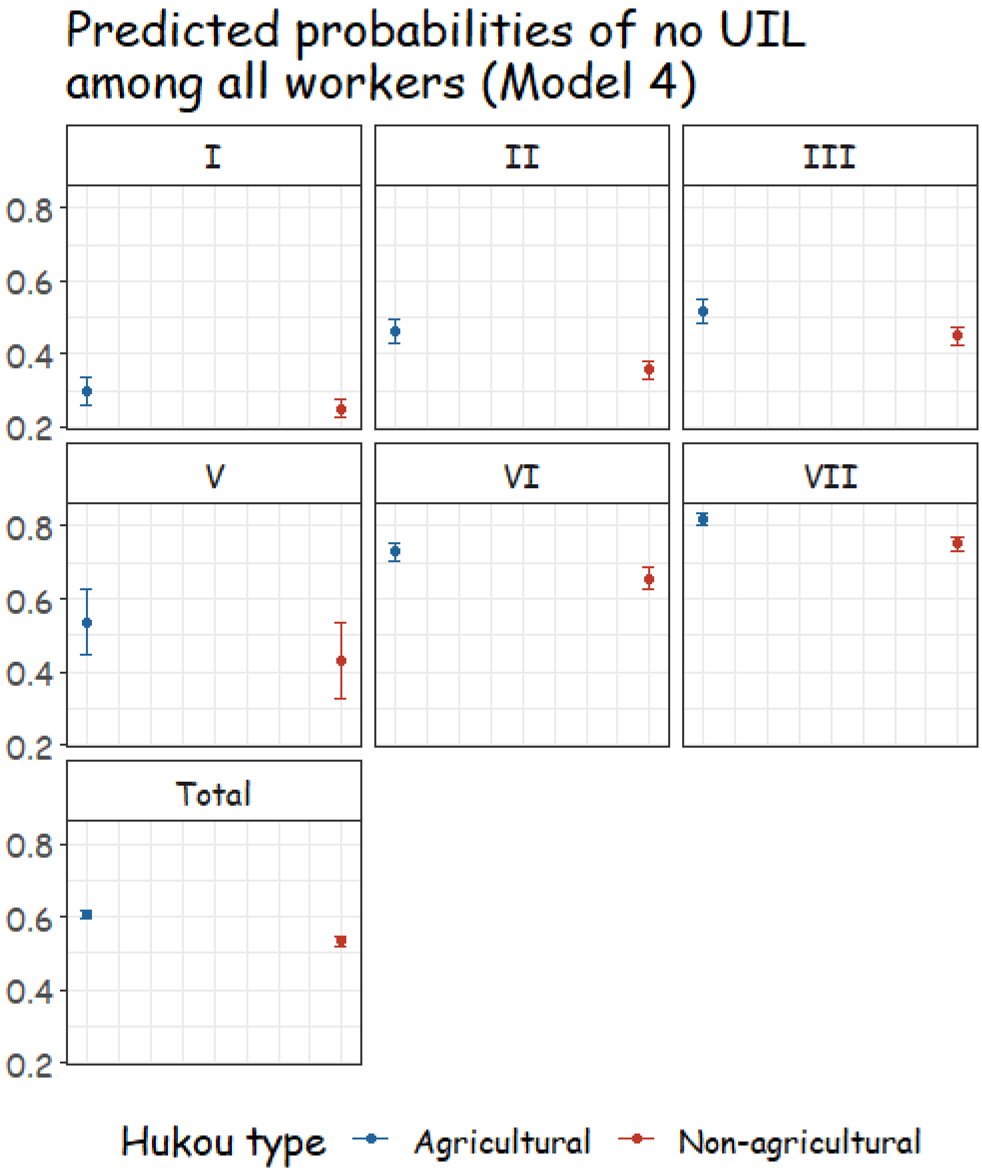

Figure 7.4. Predicted probabilities of no UIL with 95% confidence intervals among all workers with controls (Model 4). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

7.4.4. The divide in internet use

To disentangle the divide in UIL, firstly, we can look at the divide in internet adoption between RMWs and URWs, as shown in Table 7.5. Model 1 estimates the average *hukou* effect on internet adoption, controlling for year and occupation group. The reference observation is the internet adoption rate of rural background higher managerial and professional staff in 2014. The odds ratio of *Non-agricultural* is 2.130 (p <0.001), meaning that the urban background counterparts were more than two times more likely to have internet adoption than the reference group.

Model 2 added an interaction term of *hukou* and *occupation*, in case the *hukou*-related differences in internet adoption varied across occupational groups. The odds ratio of *Non-agricultural* is 2.328 and remains statistically significant at the 99% confidence level. However, the result does not show any statistically significant interaction effect, indicating no strong evidence supporting the variation in RMW-URW differences across occupational groups. Based on Model 2's estimation, Figure 7.5 plotted the predicted internet adoption rates among RMWs and URWs with the 95% confidence intervals grouped by occupational group. On average, the URW group's internet adoption rate was predicted to be significantly higher. Except for manual supervisors, predicted probabilities of internet adoption were higher among URWs than RMWs in other occupational groups. In particular, among lower managerial and professional and semi-unskilled manual workers, the differences were statistically significant at the 95% confidence level. Pooling the results of Model 1 and 2 together, we could see some evidence of an overall RMW-URW difference in internet adoption.

Next, in addition to variables *hukou, occupation,* and *year*, Model 3 further controlled for individuals' *educational background*, *income*, *age*, *gender*, and *ethnicity*. Even after adding controls, the odds ratios of *Non-agricultural* is still more than 2 and significant at the 99.9% confidence level, indicating rural background workers' relatively low use of the internet. Compared to those who did not finish higher than primary school level education, college graduates were more than 15 times more likely to use the internet (OR_{High} = 15.659, $p < 0.001$) and middle or high school graduates were 4 times more likely to use the internet ($OR_{Intermediate}$ = 4.008, $p < 0.001$). Moreover, family income is positively associated with internet use.

Lastly, based on Model 3, Model 4 added an interaction term of *hukou* and *occupation*. Controlling for educational background, family income, age, gender, and ethnicity, urban background managerial and professional workers were more 2.6 times more likely to use the internet over no internet use compared to their rural background counterparts. As in Model 3, educational background and family income were positively related to internet use. Based on Model 4's estimation, Figure 7.6. plotted the internet adoption rates of RMWs and URWs with 95% confidence intervals, grouped by occupational group. At first glance, the patterns look similar to those in Figure 7.5. The graph 'Total' shows that overall URWs had nearly a 10% higher internet adoption rate than RMWs, the difference being statistically significant at the 95% level. In all the occupational groups, the URW group's internet adoption rates were higher than the figures of RMWs. The differences were statistically significant at the 95% level in the lower managerial and professional and semi-unskilled occupational groups. The results of Model 3 and 4 show that even after controlling for cultural, economic, and demographic factors, the RMW-URW gap in internet adoption still persists.

In addition, the results of Model 3 and 4 also show that older, female and ethnic minority people were less likely to use the internet (see Table F7 in Appendix F).

In this part, we have compared the internet adoption rates between RMWs and URWs internet adoptions. Overall, the results show that RMWs had a lower internet adoption rate than URWs, *which supports H1b*. However, even after controlling for cultural, economic, and demographic factors, the divide in internet adoption persisted, rendering *H2b failing to gain some support*. As the findings show that education and family income were positively associated with internet adoption, *H3b and H4b have gained some support*.

Table 7.6. Mixed-effects binary logistic models on **INTERNET ADOPTION** (reporting odds ratios and standard errors)

	(1) Model 1 (Hukou)	(2) Model 2 (Hukou x Occupation)	(3) Model 3 (Hukou + Controls)	(3) Model 4 (Hukou x Occupation + Controls)
Hukou type (Ref: Agricultural)				
Non-agricultural	2.130***	2.328**	2.352***	2.662***
	(0.220)	(0.727)	(0.228)	(0.760)
Occupation (Ref: Higher managerial and professional)				
Lower managerial and professional	0.304***	0.238***	0.524***	0.521*
	(0.058)	(0.071)	(0.088)	(0.140)
Routine non-manual	0.316***	0.415**	0.514***	0.571*
	(0.059)	(0.125)	(0.086)	(0.158)
Manual supervisor	0.194***	0.329*	0.464*	0.547
	(0.074)	(0.172)	(0.154)	(0.254)
Skilled manual	0.049***	0.063***	0.212***	0.249***
	(0.010)	(0.019)	(0.037)	(0.064)
Semi-unskilled manual	0.020***	0.019***	0.174***	0.184***
	(0.004)	(0.006)	(0.029)	(0.046)
Interaction				
Lower managerial and professional x Non-agricultural		1.555		1.025
		(0.591)		(0.350)
Routine non-manual x Non-agricultural		0.658		0.849
		(0.250)		(0.291)
Manual supervisor x Non-agricultural		0.309		0.726
		(0.232)		(0.476)
Skilled manual x Non-agricultural		0.569		0.722
		(0.214)		(0.239)
Semi-unskilled manual x Non-agricultural		1.101		0.924
		(0.387)		(0.288)
Education (Ref: Low)				
Intermediate			4.008***	4.021***
			(0.465)	(0.467)
High			15.659***	15.537***
			(2.957)	(2.941)
Family income *per capita* (Ref: First quartile)				
Second quartile			1.398**	1.399**
			(0.145)	(0.145)
Third quartile			2.363***	2.362***
			(0.264)	(0.264)
Fourth quartile			4.096***	4.080***
			(0.518)	(0.516)
Other controls	a	b	a	b
Constant	11.714***	10.975***	645.817***	584.619***
	(2.171)	(2.874)	(246.209)	(245.780)
Observations	11,096	11,096	11,096	11,096
Individuals	8,153	8,153	8,153	8,153
Wald Chi-square	605.5	605.6	651.7	652.5
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1; a: year; b: year, age, gender, ethnicity; Coefficients of controlled variables presented in Table F7; Source: CFPS 2014 and 2016

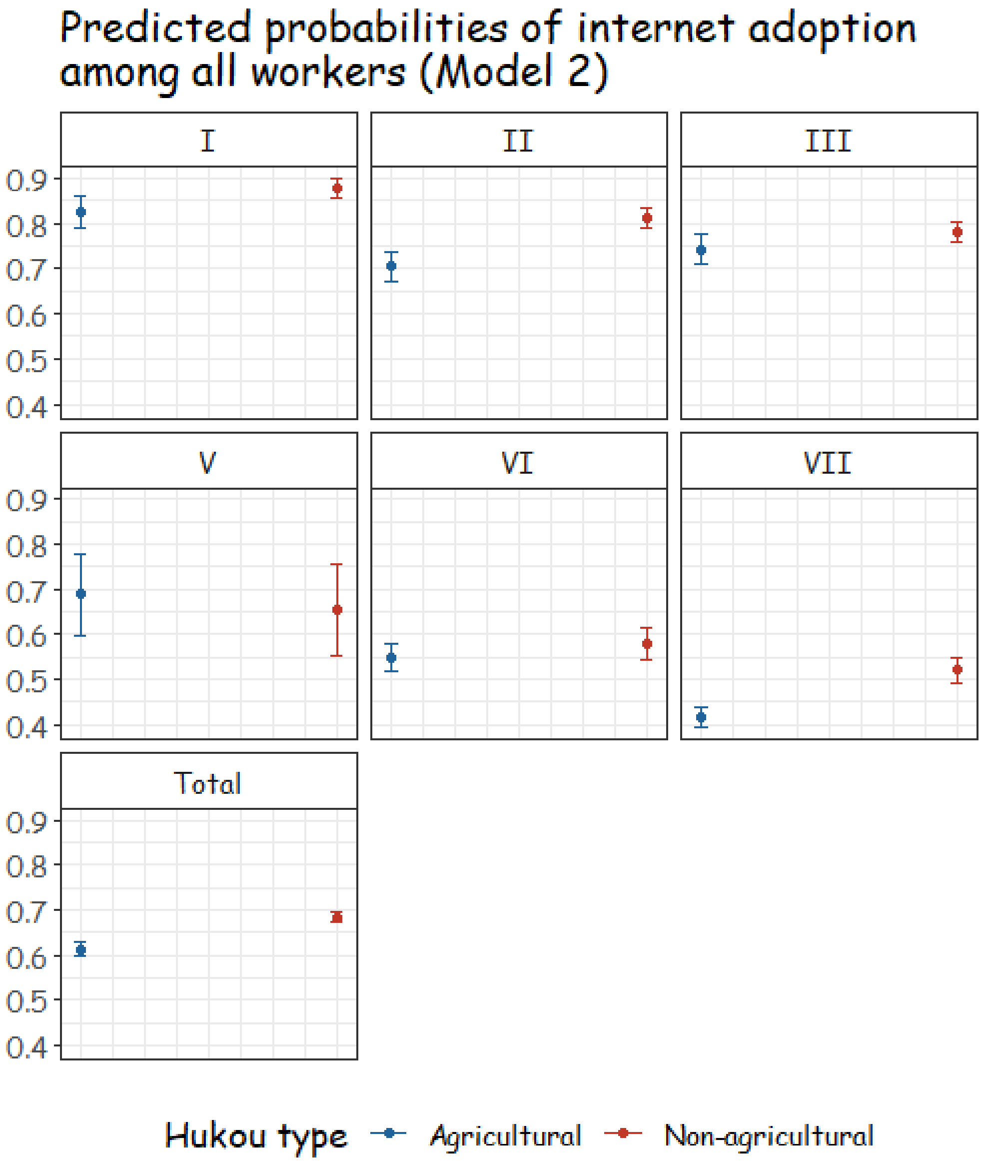

Figure 7.5. Predicted probabilities of internet adoption with 95% confidence intervals among all workers (Model 2). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

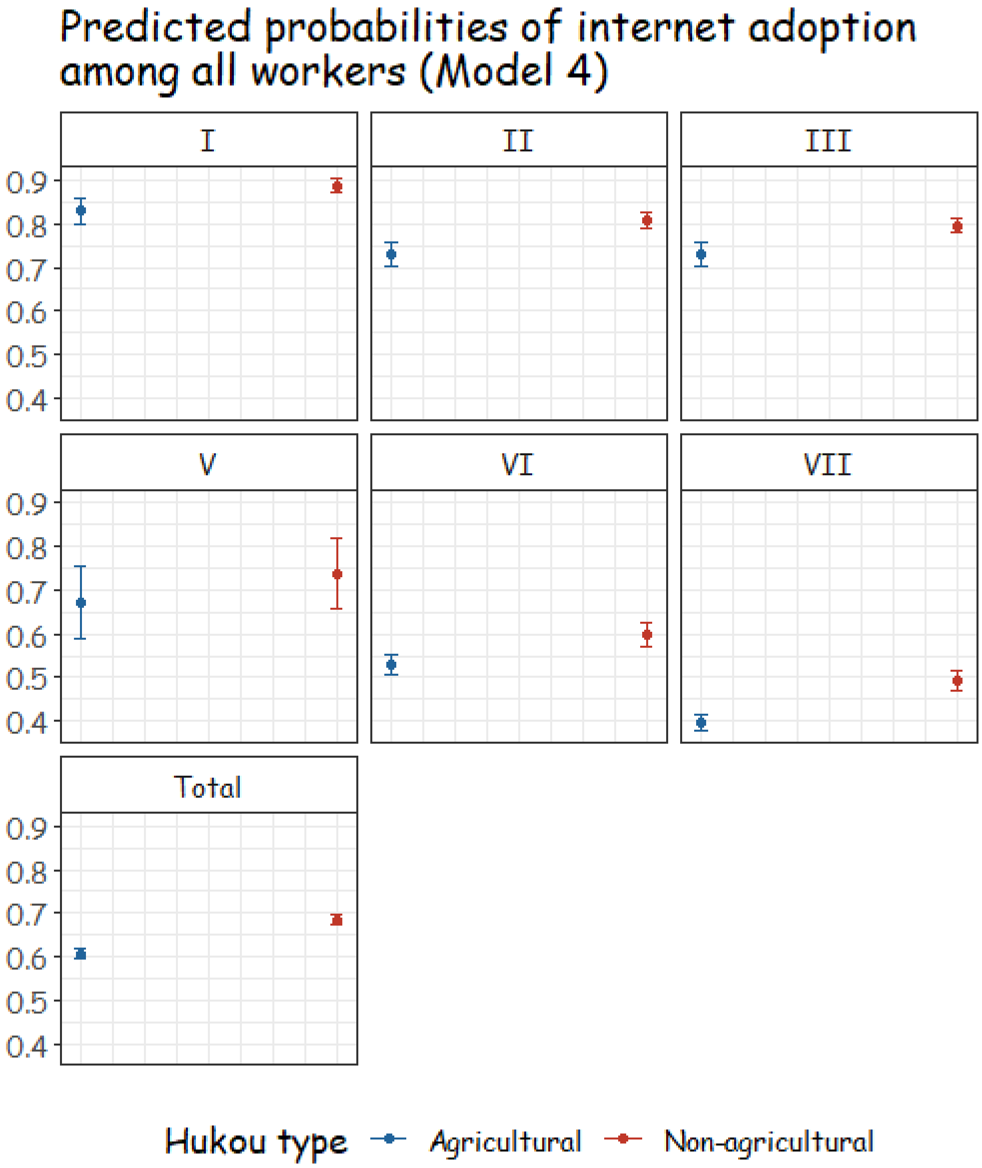

Figure 7.6. Predicted probabilities of internet adoption with 95% confidence intervals among all workers (Model 4). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill

7.4.5. The divide in learning among internet users

The previous part has shown that regarding the divide in UIL between RMWs and URWs, the first level digital divide (i.e., internet adoption), in part, still plays a role. To further break down the RMW-URW divide in UIL we move on to study internet users. This part sets out to compare rural and urban internet users' participation in UIL.

Firstly, we can compare rural and urban background internet users' likelihoods of weekly UIL, as a sign of active participation in UIL. The results are shown in Table 7.7. Model 1 only contains variables *hukou*, *occupation*, and *year*. Compared to the reference group (i.e., rural background higher managerial and professional internet users), the urban background counterparts were 1.5 times more likely to use the internet for learning weekly, suggested by the odds ratio ($OR_{\text{Non-agricultural}} = 1.579$, $p < 0.001$). This indicates that even among those who used the internet, an overall divide in weekly learning activities still exists.

In case the *hukou* effects varied across occupational groups, Model 2 added an interaction between *hukou* and *occupation*. The odds ratio of *Non-agricultural* has become nonsignificant, indicating no significant *hukou*-related difference in weekly UIL among higher managerial and professional internet users was predicted. The interaction term *Lower managerial and professional x Non-agricultural* is 1.8 and statistically significant at the 99% confidence level. This suggests that the *hukou*-related differences in weekly UIL among lower managerial and professional internet users were significantly greater than in the group of higher managerial and professional internet users, with the URW group's weekly UIL being more likely. Figure 7.7 plotted the predicted probabilities and 95% confidence intervals of weekly UIL among the internet-using rural and urban background workers, grouped by occupation. In Figure 7.7, the last graph 'Total' shows that even among those who use the internet, URWs had a significantly higher rate of using the internet for learning every week. Except for manual supervisors, all other occupational groups showed a higher weekly UIL rate among URWs. In particular, the differences were statistically significant among lower managerial and professional and manual workers.

Next, Model 3 included variables *year*, *hukou*, *occupation*, *education*, *income*, *age*, *gender*, and *ethnicity*. After adding control variables, the odds ratio of *Non-agricultural* was slightly higher than 1 ($OR_{Non\text{-}agricultural} = 1.23$, $p < 0.05$) and still significant at 95% confidence level, predicting a small difference in weekly UIL participation. Educational background was positively associated with weekly UIL among internet users. However, regarding the association with family income, only being in the top-earning quartile of internet users was related to a higher chance of weekly UIL. The likelihoods of weekly UIL among other quartile income levels seemed to be quite similar.

Based on Model 3, Model 4 further included an interaction term of occupation and *hukou*. Controlling for other factors, the odds ratio of *Non-agricultural* was very close to 1 and insignificant, meaning that rural and urban background higher managerial and professional internet using workers did not have any significant difference in weekly UIL. The interaction term *Lower managerial and professional x Non-agricultural* was 1.5 and statistically significant at the 95% level, meaning the RMW-URW gap in weekly UIL among lower managerial and professional internet using workers was significantly greater than the gap within a higher managerial and professional group. To further clarify the interaction, grouped predicted probabilities of weekly UIL with 95% confidence intervals were plotted in Figure 7.8. It is clear that except for the graph of manual supervisors, all other graphs show a smaller gap in weekly UIL between RMWs and URWs compared to the graphs in Figure 7.7. Especially, for higher managerial and professional and routine non-manual workers, the predicted probabilities of weekly UIL looked very close between RMWs and URWs. The 'Total' graph in the end shows that the overall RMW-URW difference in weekly UIL was very small and not statistically significant. However, among lower managerial and professional internet using workers, those from urban backgrounds were still predicted to have a significantly higher weekly UIL rate than those from rural areas.

Additionally, Model 3 and 4 show that male and young internet-using workers were more likely to use the internet weekly for learning purpose (see Table F8.).

Table 7.7. Mixed-effects binary logistic models on **WEEKLY UIL** among all internet users (reporting odds ratios and standard errors)

	(1) Model 1 (Hukou)	(2) Model 2 (Hukou x Occupation)	(3) Model 3 (Hukou + Controls)	(3) Model 4 (Hukou x Occupation + Controls)
Hukou type (Ref: Agricultural)				
Non-agricultural	1.579***	1.273	1.230**	1.019
	(0.109)	(0.208)	(0.095)	(0.172)
Occupation (Ref: Higher managerial and professional)				
Lower managerial and professional	0.695***	0.473***	0.822+	0.611**
	(0.072)	(0.082)	(0.086)	(0.107)
Routine non-manual	0.394***	0.404***	0.518***	0.528***
	(0.041)	(0.070)	(0.055)	(0.094)
Manual supervisor	0.384***	0.451*	0.566*	0.663
	(0.097)	(0.151)	(0.145)	(0.225)
Skilled manual	0.192***	0.163***	0.312***	0.273***
	(0.024)	(0.030)	(0.039)	(0.050)
Semi-unskilled manual	0.164***	0.141***	0.297***	0.244***
	(0.020)	(0.025)	(0.035)	(0.044)
Interaction				
Lower managerial and professional x Non-agricultural		1.850**		1.596*
		(0.396)		(0.347)
Routine non-manual x Non-agricultural		0.972		0.974
		(0.205)		(0.208)
Manual supervisor x Non-agricultural		0.599		0.599
		(0.303)		(0.307)
Skilled manual x Non-agricultural		1.309		1.232
		(0.307)		(0.293)
Semi-unskilled manual x Non-agricultural		1.282		1.387
		(0.280)		(0.307)
Education (Ref: Low)				
Intermediate			2.241***	2.216***
			(0.279)	(0.276)
High			6.706***	6.592***
			(1.002)	(0.983)
Family income *per capita* (Ref: First quartile)				
Second quartile			1.001	0.996
			(0.099)	(0.098)
Third quartile			1.042	1.036
			(0.102)	(0.101)
Fourth quartile			1.295**	1.294**
			(0.128)	(0.128)
Other controls	a	b	a	b
Constant	2.362***	2.715***	0.918	1.044
	(0.246)	(0.392)	(0.218)	(0.271)
Observations	7,236	7,236	7,236	7,236
Individuals	5,606	5,606	5,606	5,606
Wald Chi-square	390.7	398.4	484.7	488.8
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1; a: year; b: year, age, gender, ethnicity; Coefficients of controlled variables presented in Table F8; Source: CFPS 2014 and 2016

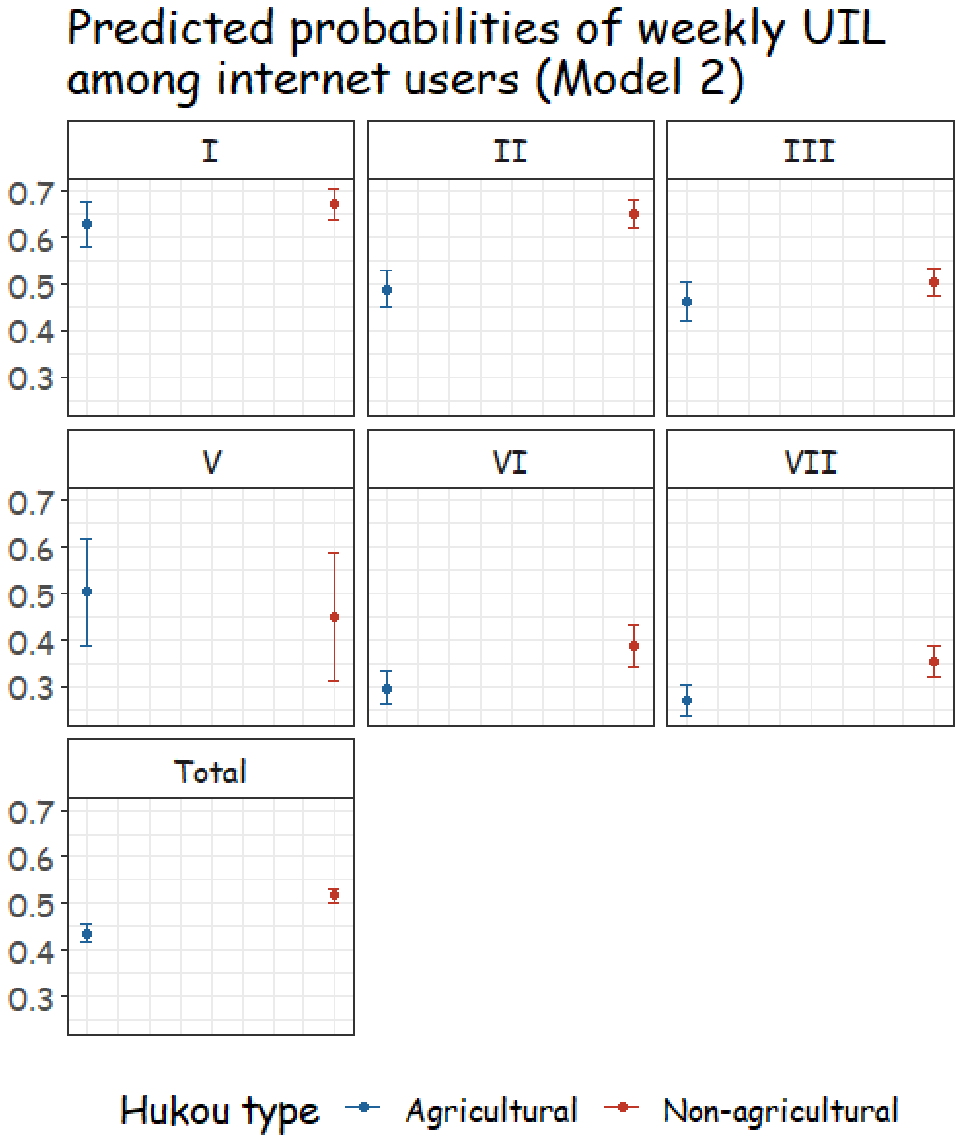

Figure 7.7. Predicted probabilities of weekly UIL with 95% confidence intervals among internet users (Model 2). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

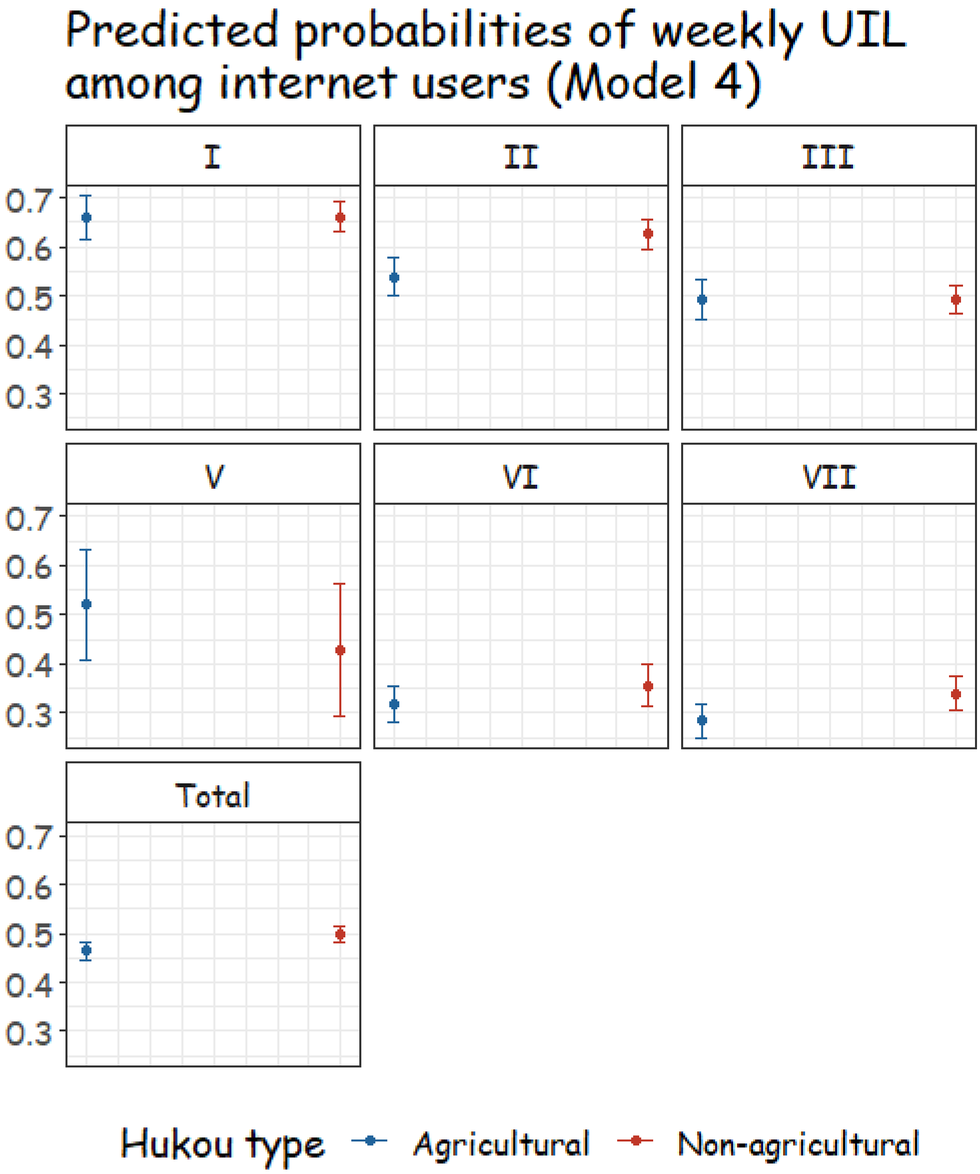

Figure 7.8. Predicted probabilities of weekly UIL with 95% confidence intervals among internet users (Model 4). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

Finally, we come to assess the differences in no UIL participation over a whole year between rural migrant and urban resident internet-using workers. Table 7.8 shows the results of mixed-effects binary logistic regression models on no UIL among internet users with odds ratios reported. Firstly, Model 1 shows the result of estimation with explanatory variables *occupation, hukou,* and *year* included. In this model, the odds ratio of *Non-agricultural* is 0.593 and significant at the 99.9% confidence level, meaning the rural background higher managerial and professional internet-using workers' chances of no UIL was significantly higher than their urban background counterparts.

Considering the possible interactional effect, Model 2 added an interaction term of *hukou* and *occupation*. The odds ratio of *Non-agricultural* is statistically insignificant, indicating that among the internet-using higher managerial and professional workers, the *hukou*-related difference in no UIL was not substantial. However, the significant interaction term 'Lower managerial and professional x Non-agricultural' (OR = 0.488, p < 0.001) suggests that for the lower managerial and professional group, RMWs had a higher rate of no UIL than URWs. To further clarify the interaction effect, based on Model 2's prediction, Figure 7.9 plotted the predicted probabilities of no UIL of RMWs and URWs, grouped by occupational group. On average, even having internet access, not using the internet for any learning activities was relatively more likely among RMWs. This is evident as the 'Total' graph indicates that the urban background internet-using workers were predicted to have a significantly lower likelihood of no UIL in a whole year at the total average level. Within all the occupational groups, RMWs had higher predicted probabilities of no UIL, although the gap in the higher managerial and professional group was very small. In lower managerial and professional and skilled manual groups, the differences were predicted to be statistically significant.

In Model 3, we included variables *hukou*, *occupation*, *education*, *income*, *age*, *gender*, and *ethnicity*, but no interaction effect. When controlling for educational background, income, and other demographic factors, rural background workers still had a higher chance of having no UIL over a whole year, as indicated by the odds ratio (OD $_{\text{Non-agricultural}}$ = 0.725, $p < 0.001$). Compared to those who had not finished secondary education, those who had better educational achievement were far less likely to have no UIL over a whole year. However, the no UIL patterns did not seem to vary much from the lowest to highest quartile earning groups.

In the end, based on Model 3, Model 4 included the intersectional effect of *occupation* and *hukou*. The odds ratio of *Non-agricultural* is very close to 1, indicating that the difference in no UIL between rural and urban background internet-using higher managerial and professional workers is negligible. Compared to the higher managerial and professional group, the *hukou* background difference in no UIL might be larger among the lower managerial and professional workers, although the interaction term is only significant at the 90% confidence level. Figure 7.10 plotted the predicted probabilities of no UIL in a whole year among RMWs and URWs with the 95% confidence intervals, grouped by occupation group. Compared to the totals in Figure 7.9, the RMW-URW differences in no UIL became slightly smaller in each group. The graph 'Total' shows that on average URWs were still significantly less likely to have no UIL at the 95% level. Except for the group of lower managerial and professional, no statistically significant difference in no UIL was found in other occupational groups.

Model 3 and 4 show that even amongst the internet users, female and older workers were more likely to have no UIL activities over a whole year (see Table F8 in Appendix F).

To sum up, this part of the analysis has firstly shown an overall divide in UIL between the internet using workers from rural and urban backgrounds. The differences were marked in both weekly UIL and no UIL over a whole year, the two most extreme scenarios of UIL practices. Thus, *H1c has gained some support*. When controlling for the cultural, economic, and demographic factors, the *hukou*-related differences in weekly UIL were very small, except for the lower managerial and professional group. The predicted probabilities in no UIL also reduced slightly, but the total average difference between RMWs and URWs still existed and remained statistically significant. This indicates that *H2c has gained some weak support*. While education is still positively related to participation in UIL, the relationship between UIL and family income among internet users was quite interesting. Only the top quartile internet using earners had significantly higher weekly UIL rates and slightly lower odds of no UIL than the other earning groups. As such, it is fair to say that *whilst the evidence for H3c is still strong, H4c has only gained weak evidence*.

Table 7.8. Mixed-effects binary logistic models on **NO UIL** among all internet users
(reporting odds ratios and standard errors)

	(1) Model 1 (Hukou)	(2) Model 2 (Hukou x Occupation)	(3) Model 3 (Hukou + Controls)	(3) Model 4 (Hukou x Occupation + Controls)
Hukou type (Ref: Agricultural)				
Non-agricultural	0.593***	0.775	0.725***	0.971
	(0.047)	(0.168)	(0.064)	(0.217)
Occupation (Ref: Higher managerial and professional)				
Lower managerial and professional	1.854***	2.833***	1.525**	2.113***
	(0.251)	(0.617)	(0.209)	(0.468)
Routine non-manual	3.635***	3.911***	2.737***	3.121***
	(0.491)	(0.858)	(0.374)	(0.698)
Manual supervisor	2.640**	3.312**	1.650	2.186+
	(0.808)	(1.320)	(0.507)	(0.875)
Skilled manual	7.712***	9.180***	4.291***	5.215***
	(1.200)	(2.057)	(0.656)	(1.163)
Semi-unskilled manual	10.404***	11.503***	5.034***	6.110***
	(1.594)	(2.565)	(0.739)	(1.345)
Interaction				
Lower managerial and professional x Non-agricultural		0.488**		0.584+
		(0.134)		(0.163)
Routine non-manual x Non-agricultural		0.885		0.816
		(0.234)		(0.219)
Manual supervisor x Non-agricultural		0.648		0.581
		(0.407)		(0.365)
Skilled manual x Non-agricultural		0.743		0.732
		(0.210)		(0.209)
Semi-unskilled manual x Non-agricultural		0.867		0.737
		(0.229)		(0.198)
Education (Ref: Low)				
Intermediate			0.404***	0.406***
			(0.051)	(0.051)
High			0.089***	0.091***
			(0.015)	(0.016)
Family income *per capita* (Ref: First quartile)				
Second quartile			0.997	0.997
			(0.108)	(0.108)
Third quartile			0.986	0.988
			(0.108)	(0.108)
Fourth quartile			0.827+	0.821+
			(0.093)	(0.093)
Other controls	a	b	a	b
Constant	0.103***	0.088***	0.189***	0.157***
	(0.016)	(0.018)	(0.053)	(0.049)
Observations	7,236	7,236	7,236	7,236
Individuals	5,606	5,606	5,606	5,606
Wald Chi-square	348.1	353.2	435.4	437.1
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1; a: year; b: year, age, gender, ethnicity; Coefficients of controlled variables presented in Table F7; Source: CFPS 2014 and 2016

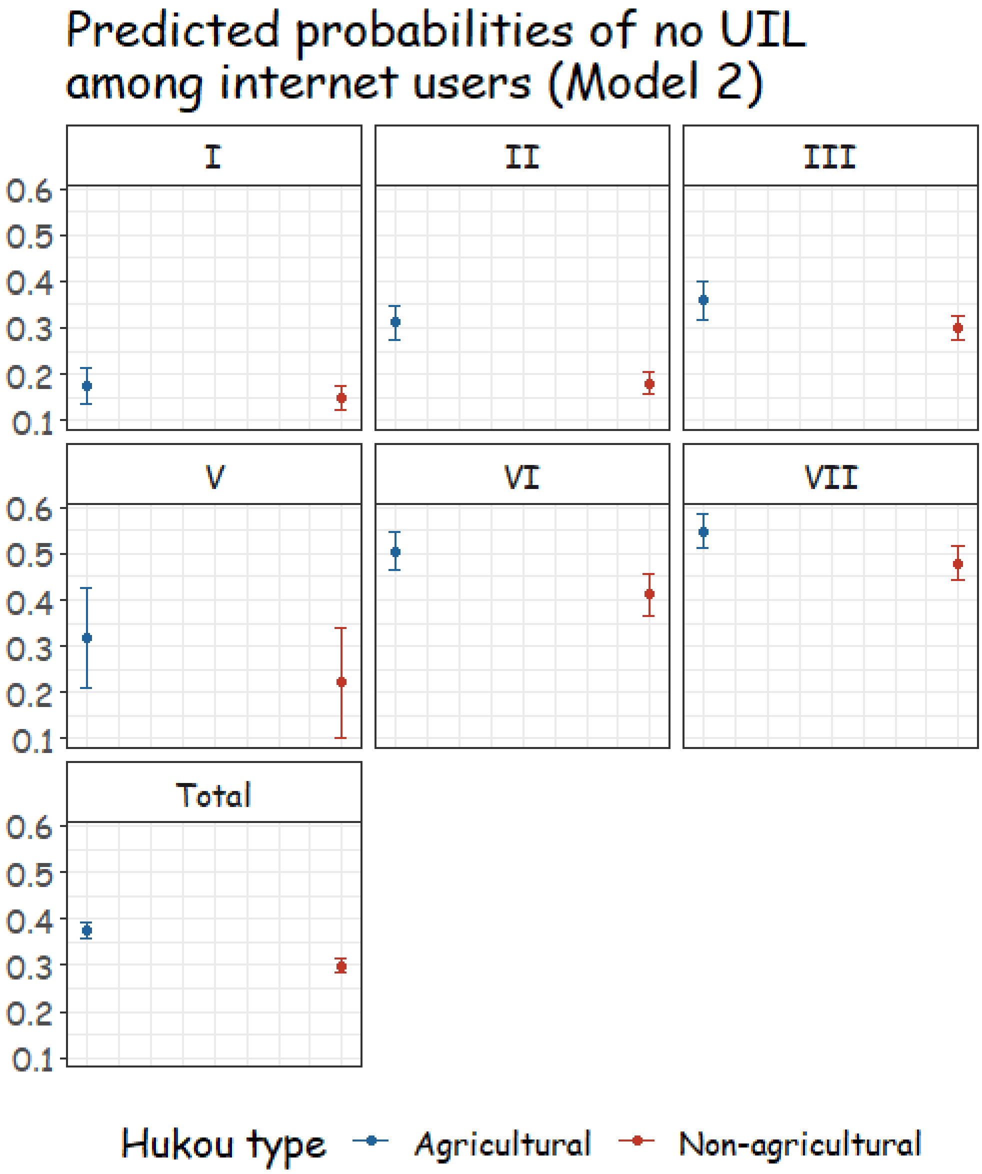

Figure 7.9. Predicted probabilities of no UIL with 95% confidence intervals among internet users (Model 2). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

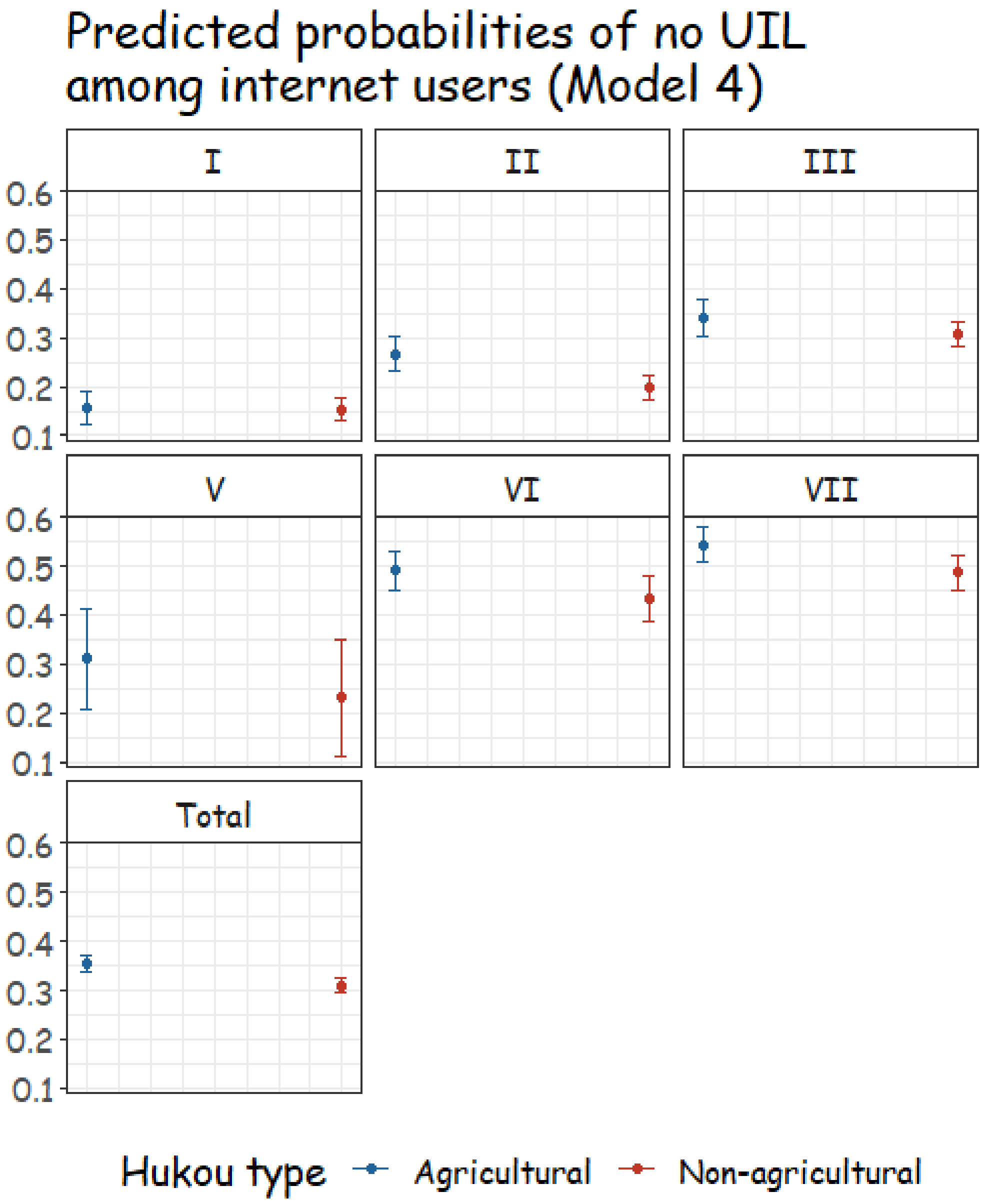

Figure 7.10. Predicted probabilities of no UIL with 95% confidence intervals among internet users (Model 4). I= Higher managerial and professional; II= Lower managerial and professional; III= Routine non-manual; V= Manual supervisors; VI= Skill manual; VII= Unskilled or semiskilled manual. Source: CFPS 2014 and 2016

7.4.6. An uneven accumulation of economic and cultural capital

In this part, I supplement a comparison of educational background and family income between RMWs and URWs, drawing on the results of some bivariate analyses, which could provide some insight on their differences in accumulated cultural and economic capital for UIL participation.

First, Figure 7.11 presents the result of the comparison of educational background, grouped by occupational group. Among all the workers, regardless of their internet adoption in 2014 and 2016 (i.e., 2014-W and 2016-W), RMWs had a higher proportion of lower-level education, and a relatively low percentage of college graduates in each occupational group (although the difference was small among semi-unskilled manual workers in 2016). In those white-collar occupational groups (i.e., I, II and III), where high literacy is generally expected, RMWs also had higher proportions of middle or high school graduates in 2014 and 2016 than URWs within each white-collar occupational group. Within those manual occupations (VI and VII), in addition to having more college graduates, URWs also had a slightly higher proportion of people having finished secondary education. Except for the manual supervisors in 2016, the Chi-square results suggest that in each occupational group, rural and urban background sub-groups had quite different distributions of educational achievement in both 2014 and 2016.

Even among those who had internet access (2014-I and 2016-I), the result is also quite similar to the 'all worker' sample's result. Among all the internet-using workers in all the occupational groups, those from rural backgrounds had fewer college graduates, and more who did not finish secondary education, in both 2014 and 2016. Similar to the 'all worker' sample, except for manual supervisors in 2016, the Chi-square results suggest that rural and urban background internet-using workers had different distributions of educational background in all occupational groups in both years.

Overall, the result confirms that for each occupational group, and regardless of using the internet or not, the rural background workers had relatively poor educational backgrounds compared to their urban resident peers.

Second, Figure 7.12 presents a comparison of family income *per capita* between RMWs and URWs in each occupation-by-year group. Due to the high skewness towards extremely high earnings values of the income distributions, I employed box-plots without the outliers to measure the distributions of income and supplemented with the Wilcoxon-Mann-Whitney test for each group. In general, the typical income values descended from the top occupational group to the manual occupations. Among all the workers (the graph at the top), almost in all the occupation-by-year groups (with an exception of manual supervisors), the comparison of median family income and the middle 50% range shows that in general those from rural areas had less family income than those from urban areas. The Wilcoxon-Mann-Whitney test results suggest that it is very unlikely that RMWs and URWs had similar family income distributions, except for the manual supervisor group. Even among the internet users, the patterns were the same, as shown by the graph at the bottom. As such, it is fair to conclude that having relatively rich economic resources is rather common for URWs. Thus, both *H3d and H4d have gained some support from the evidence*.

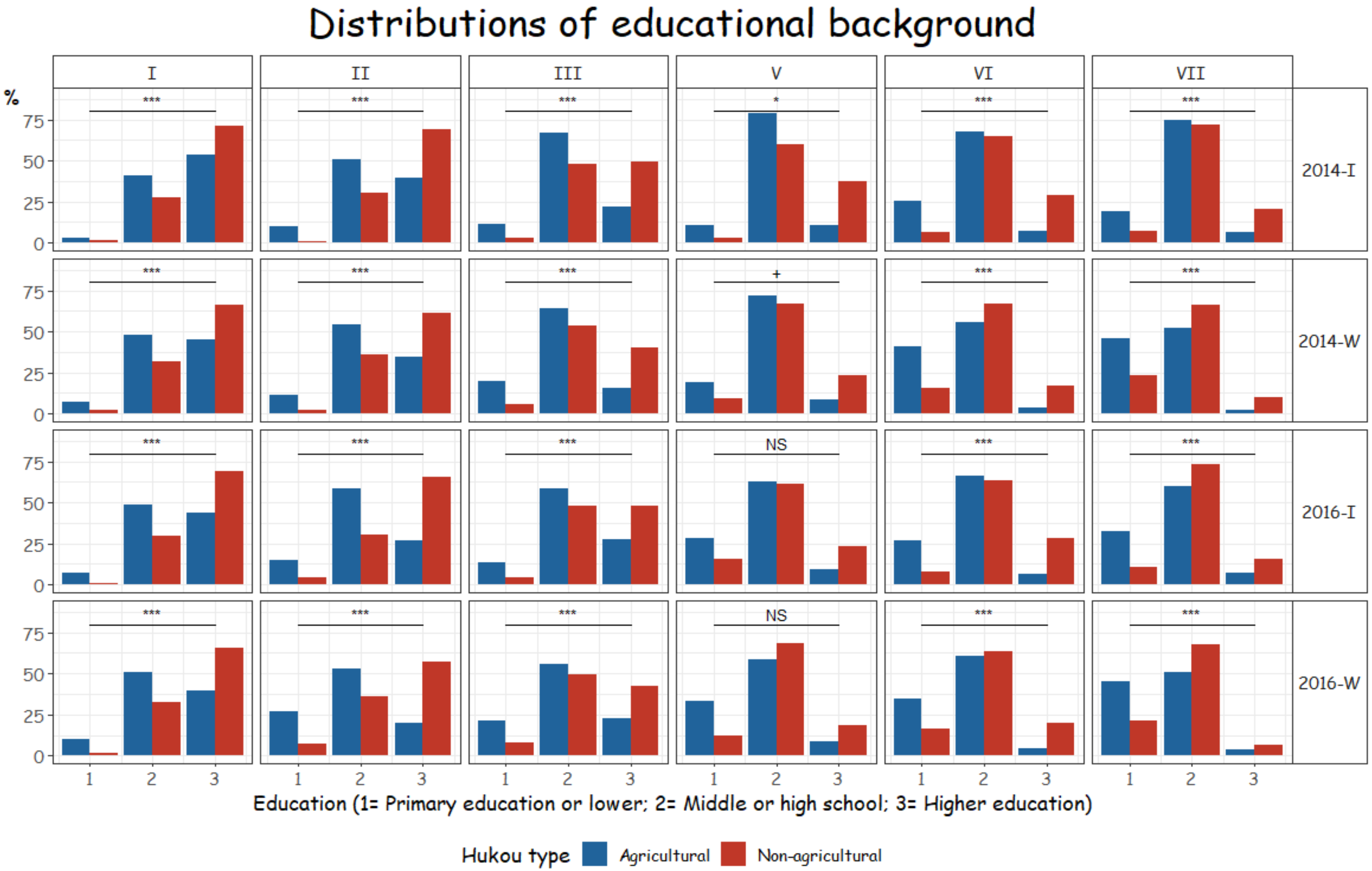

Figure 7.11. Comparison on educational background between RMWs and URWs with Chi-squared test results (*** p<0.001, ** p<0.01, * p<0.05, + p<0.1 , NS= nonsignificant), grouped by occupation and year. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual; 2014-W=All workers in 2014; 2014-I=Internet using workers in 2014; 2016-W=All workers in 2016; 2016-I=Internet using workers in 2016; Source: CFPS adult2014 and 2016

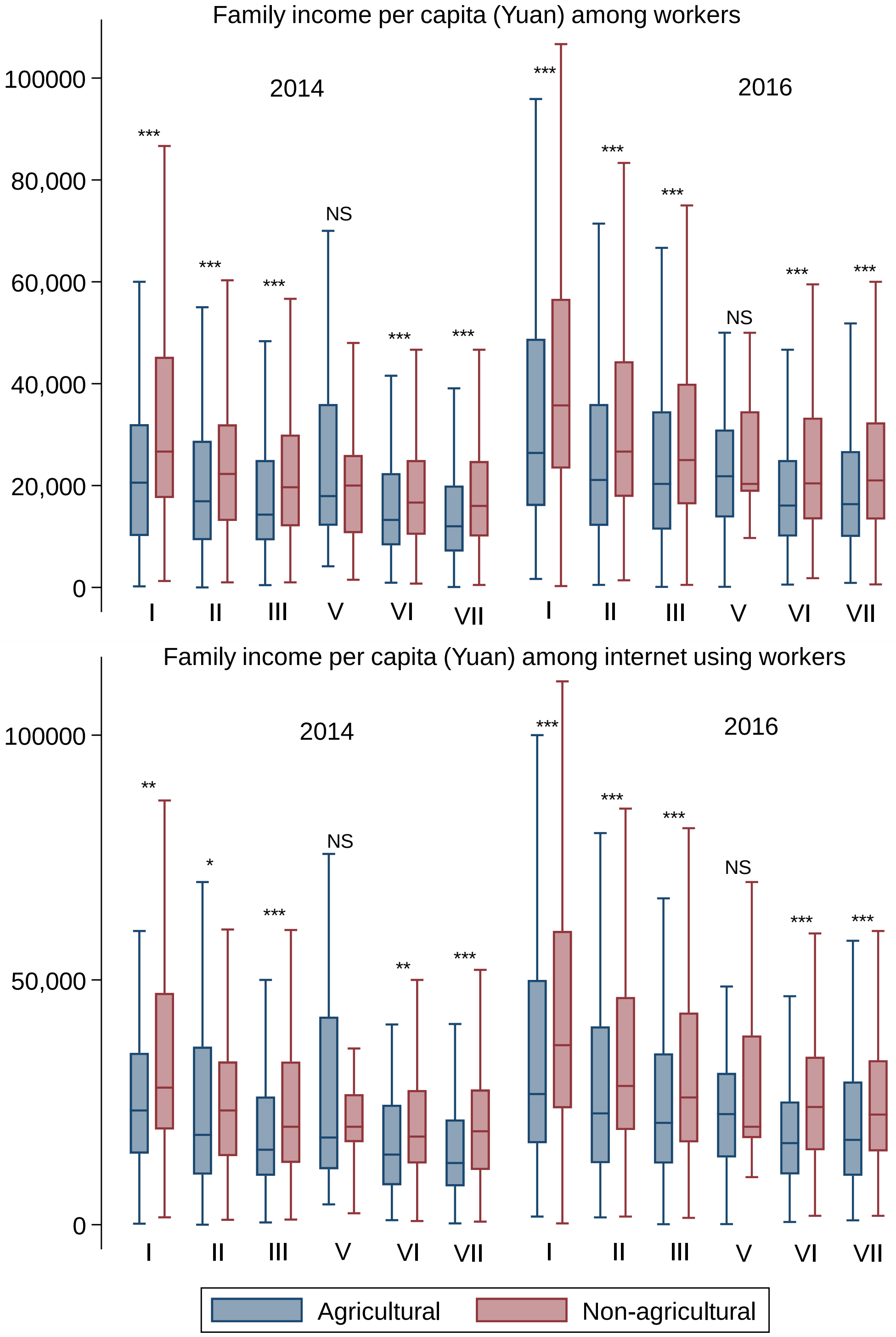

Figure 7.12. Boxplots of family income *per capita* of RMWs and URWs with the results of Wilcoxon Mann Whitney test (*** p<0.001, ** p<0.01, * p<0.05, NS= nonsignificant), grouped by year and original occupation. I =Higher managerial and professional, II=Lower managerial and professional, III= Routine non-manual, V=Manual supervisor, VI=Skilled manual, VII=Semi-unskilled manual; Source: CFPS adult 2014 and 2016

7.4.7. Summary

In short, the results are largely consistent with our initial hypotheses, except for *H4*, as even after controlling for economic, cultural, and demographic factors, the differences in UIL between RMWs and URWs were still found.

Overall, RMWs and URWs did not have similar participation in UIL, as suggested by the results. Not only could we see a divide in participation in learning activities, RMWs and URWs also differed in their internet adoption rates, namely the first level digital divide. In general, the differences were more noticeable among manual workers and lower managerial and professional staff, but relatively minor among higher managerial and professional and routine non-manual workers. The patterns for manual supervisors were full of irregularity, presumably affected by the small sample size.

Even after controlling for economic, cultural, and demographic factors, the overall RMW-URW differences in UIL and internet adoption still existed. However, among the internet-using workers, after taking economic, cultural, and demographic factors into account, the RMW-URW differences in predicted probabilities in weekly UIL and no UIL became very small. The persistence of the RMW-URW divide in UIL might be due to many reasons. First, possibly it is related to the imperfection of the operationalization of the conceptual framework, especially embodied cultural capital. Indeed, educational background does not perfectly reflect professional knowledge, let alone the skills to operate digital devices and to browse the Web. Second, it could be that other factors explaining the RMW-URW differences in UIL have not been considered, which led to the persistence of the RMW-URW divide in UIL. Nevertheless, at least the results have given a clear indication that for those who are from similar occupational and educational backgrounds and with similar earnings, rural background workers were still less likely to have active UIL regardless of age, gender, and ethnicity.

Family income and educational background were positively associated with UIL participation and internet adoption, whilst RMWs were less likely to have a good educational background and more family earnings in the first place. Educational background has been consistently associated with a higher turn-up rate for UIL and a higher internet adoption rate. Whilst family income was positively related to all workers' UIL participation and internet adoption rate, among the internet users, only the top earnings quartile seemed to be related to a higher chance of UIL.

7.5. Making sense of different UIL participation: the qualitative result

7.5.1. Analytical strategy

The preceding quantitative analysis comparing the participation in UIL between RMWs and URWs has shown that RMWs were less active in UIL, meeting the expectation envisaged by the practical action theory of UIL. Even after controlling for economic and cultural factors, some small RMW-URW differences in internet use and UIL still exist.

This section further examined the explanatory power of the practical action theory of UIL, when making sense of the mechanisms causing the observed RMW-URW differences in UIL, drawing on our qualitative data from the 24 semi-structured interviews. Our interview data documented participants' storytelling of their own internet use and UIL experience. The analysis focused on participants' narratives on the perceived factors affecting their own internet use and UIL participation, followed by a comparison with the factors and the mechanisms highlighted by the practical action theory of UIL. The analysis then looks at and discusses the reasons behind the discrepancies between our proposed theory and participants' sense-making of their own experiences, a process seeking to identify the limitations of our initially proposed theory and exploring other neglected mechanisms. Finally, drawing on the analysis of the factors affecting participants' internet use and UIL, a discussion was conducted on the implications for the RMW-URW differences in UIL.

The analysis firstly looked at the factors affecting internet use in general, with two important themes (initial means of access and digital skills) identified and discussed. Again, Moore's (1989) interaction-based learning activities typology (i.e., learner-content interaction, learner-learner interaction, and learner-instructor interaction) is used to classify UIL activities. As no significant findings emerged to indicate the distinctive factors affecting *learner-learner interaction* and no implications could be made to explain the RMW-URW differences, the following discussion only includes *learner-content interaction* and *learner-instructor interaction*.

7.5.2. Internet use

Initial means of access

At the time the interviews took place, among the 24 participants, 22 of them used the internet. All the internet using participants (N=22) had access to the internet by using their *mobile devices*. Two other internet non-users did not have smart mobile devices to get online, but one had a home computer with internet access for his son's usage.

All 22 internet-using participants had at least seven years of internet using experience. Except for one participant, starting his internet use in 1999, and one participant starting in 2011, all other internet using participants started their regular internet use within the first decade of the 21st century. However, when telling the stories of their initial internet adoption, RMWs and URWs were different in their means of access in the beginning.

For the rural background internet-using participants (N=13), having a home computer was not a very common thing when they first started using the internet. For those originally from rural areas, except for two participants who have always been non-users, two participants said they started their regular internet use on their home devices, whilst other 11 participants said their initial regular internet use was in internet cafes (N=9) or in educational institutions (N=2). Those two RMW participants whose first internet use was on their home devices had already migrated to cities and had stable jobs at that time. Whilst others did not explicitly say anything about why they did not have a home device in the beginning, only R10 explained that 'affordability' was her family's major concern:

> '*Our family could not afford a personal computer when I was still at school […] when I had some spare money I would go to the internet cafe.*' (R10, Female, First job non-manual, 29)

Among those nine participants whose initial regular internet use was in internet cafes, six had said the internet cafes they went to were in cities or nearby towns, whilst the other three did not mention the locations. In other words, for those whose initial regular internet use was in an internet café, no one said the internet cafes they went to were located in rural areas. They traveled from their initial local communities to use the internet.

However, among the participants who are URWs (N=9), only one participant said initially he used the devices in college for regular internet use, whilst the other eight participants said they used their own computers for initial internet usage at home.

When talking about the perception of RMW-URW differences, U3 believed that there is a 'technology-gap' between the rural and urban background workers in his workplace. And he believed those that grew up in urban areas had early access to the latest technologies and have since had more experience using them:

> '*Compared to them [his rural background colleagues], we grew up in an environment full of new technologies and we played with those new*

technologies earlier than them.' (U3, Male, First job manual, 22)

In a similar vein, when speaking of his urban background cohorts at college, R12 perceived that their better-off backgrounds allowed them to have home devices and internet access in the earlier days:

> '*[His urban background cohorts] they generally had a privileged family background which allowed them to have a family computer and internet access. The majority of them had a computer and internet access at home. But having a computer and internet access was a rare thing in rural areas [in 2004].*' (R12, Male, First job non-manual, 35)

Although neither participants' perceptions nor a small sample investigation could confirm a general between-group difference, they identified some potential areas of the RMW-URW differences in technology adoption for future robust confirmatory analysis. The differences in initial means of access to the internet might play a role in explaining the differences in active internet use between RMWs and URWs. Although RMWs and URWs seem to have started their internet use within the same decade, they might have had unequal accumulated experiences of internet use due to URW's better quality of access. A lack of personal access in the beginning constrains how much and how freely one can use the internet (Eynon and Geniets, 2016), and can therefore affect the accumulation of prior internet use experience and skills (this will be further discussed in the next section) and one's active internet use (e.g., van Dijk, 2005; Hargittai 2010). Furthermore, if the differences in means of access in the earlier days of internet adoption hold, that could further imply that URWs usually have better access to the latest technologies. It might not solely be related to the difference in affordability due to families' or individuals' disposable economic resources, but it might also be related to the regional differences in prevalence and accessibility of the latest technologies. It is possible that quality of access to the latest technologies might be related to more active internet use. As rapid obsolescence is a common characteristic of technology, better access to the latest devices and applications might allow urban people to have better adaptability to the online world, rendering their continual active internet use. Experience and familiarity are all linked to one's capability to make good use of the internet, which, as will be discussed in the following section, affects people's motivation for active internet use.

Digital skills

Poor digital skills, or a lack of *technical embodied cultural capital* according to our theoretical framework, is seen as a crucial factor preventing people from active internet use. Among our participants, two of them did not use the internet in their daily lives. Both of them were male, older, from a rural background, and working as manual workers at the time of being interviewed. Both of them mentioned that their internet non-use was related to a lack of basic skills to operate digital devices like computers and smart mobile devices.

R15, who was already 60 when being interviewed, mentioned that some electronic devices are too difficult for him to use:

> '*I have never tried [to use the internet]. Not even by mobile phone. I do not know how to use those electronic things. Even my mobile phone you know it is this [not a smart phone]. I only know how to use it to call and receive a call.*' (R15, Male, First job non-manual, 60)

However, for R15, in addition to not having the skills to operate electronic products, lacking interests and needs to try and learn is also related to his personal internet non-use:

> '*My fellows in our village did not use it as well. We have no interest. Except for those who had some education and worked as civil servants in the village. You know even though they are old they still try to learn new things.*' (R15, Male, First job non-manual, 60)

Unlike R15, R14 had a strong interest to learn computer and internet skills, but he failed to learn the essential skills to operate computers and to use the internet:

> ‘*Yes, I did [try to learn to use the internet]. I did try to learn to use a computer and the internet. I failed to learn things although I really wanted to learn how to use a computer. Many years ago, I tried to learn how to use computers in my company […] It was very difficult to learn […] There were no teachers available to teach me. I was completely lost and did not know what to do with computers. Things were very ‘abstract’ to me.*’ (R14, Male, First job manual, 46)

R14 claimed that his self-trying failed to let him acquire the essential skills to use computers and the internet. He wished there had been a teacher to teach him, which he expected would have helped him to acquire the basic computer skills more effectively. A lack of essential digital skills stopped him from participating in online surfing.

Among the internet using participants, R1 was the only one who expressed low-confidence in her capabilities to use computers and the internet, mainly when she was making a comparison with her colleagues. When describing her internet usage, she perceived herself as not using the internet very often, and even disliking using the internet a bit, which was linked to her poor computer skills:

> *‘[Since I started to work as an accountant in a real-estate company], I kept learning computer skills as my computer skills did not meet the role requirement […] In my workplace people laugh at me because of my poor computer skills […] I do not think I am very good at finding useful*

learning resources online [...] Actually I don't like using the internet very much as I am not that good at the computer things. [When mentioning other people do online shopping a lot] I don't even have a Taobao account [a popular e-commerce platform in China]. I am actually the kind of person who does not often go online and does not like the internet much.' (R1, Female, First job non-manual, 32)

This link between no active internet use and poor digital skills echoes the CNNIC's (2019) latest investigation on internet non-users in China. According to the report, poor computer or internet skills (54.5%) is rated as the primary reason of non-internet use, followed by self-perceived low-literacy (33.4%) (Ibid., p.20). The internet is not always seen as a 'convenient tool' for everyone. The three examples above show that when one does not possess the essential skills to operate digital devices and applications, using the internet is not perceived as 'handy' and might even be stressful for them, which could demotivate their internet use.

When telling the stories of initial digital skills acquisition, four sources were mentioned by the participants: computer courses in school or colleges (N=10), computer courses in workplaces (N=1), learning from friends (N=11) and self-trying (N=6). In particular, computer courses are mentioned to build their basic computer operational skills, as exemplified by U8's words:

'*[In school] I was taught how to operate computers and use the IE explorer to browse and search for information.*' (U8, Female, First job non-manual, 30)

However, given the unequal rural-urban educational resource distribution, the rural background population is less likely to have received the good quality computer education that individuals with urban backgrounds more often enjoy.

Furthermore, whilst self-trying is also mentioned as a source of acquiring digital skills, that is premised upon individuals' possession of or at least having access to digital devices. As discussed in the last section, it is possible that URWs have better means of access to the latest technologies and better experience of internet use. Individuals from an urban background have had better access to the latest technologies and this has allowed them to have greater autonomy over using technologies, to accumulate more experience, and to develop up-to-date digital skills (Hargittai, 2010) to adapt to the latest developments in the online world. Due to their economic and/or regional advantage, those from urban areas might have been better-equipped (with advanced digital skills) to adapt to the latest developments in the online world. Both these things imply that URWs might have had relatively good opportunities to develop their digital skills for device operation and internet use, which ultimately matter in order to maintain active on the internet.

7.5.3. Participation in learner-content interaction

Among all types of UIL activities, learner-content interaction occurred most frequently. Among our participants, the mentioned learner-content interaction practices were: browsing webpages in general (e.g., using search engines, official websites of an institution, online forums, social media), reading other text-based materials (e.g., books, articles, blog posts, workplace documents), listening audio-based materials (e.g., broadcast, audiobooks, audio-recordings of lectures) and watching video-based materials (e.g., video-recordings of presentations or lectures, educational animation videos).

Accessing learning content

Learner-content interaction is premised upon the availability of informational content for learning, the *content objectified cultural capital*. In terms of the acquisition of online learning resources, indeed, digital content online was perceived as low-cost by all the participants who used the internet. However, the perception of the ease of acquiring useful learning resources online is contextual and conditional.

The practical action theory of UIL postulates that the accumulation of *expertise embodied cultural capital* (one's accumulated knowledge in a specific field) and *technical embodied cultural capital* (one's technical competency to operate digital devices and to browse and navigate the internet) affects an individual's searching and selecting ability regarding useful learning resources from the internet. Regarding the role of expertise embodied cultural capital, six participants had explicitly mentioned the importance of prior knowledge in a specific field for searching and selecting useful learning resources when reflecting on their UIL experience. No participant mentioned anything disputing this point.

Firstly, four participants said prior knowledge in a specific field helped them proceed to start searching. U1's example (see below) shows a typical situation of online information searching – keyword searching on search engines. For instance, the decision of what keywords are used actually reflects how much one already knew in a given subject area. As a result, those with a good understanding of a specific subject area are very likely to have a more effective keyword search. Another three participants also mentioned that prior subject knowledge helped them go beyond simply having an awareness of learning to having a sense of what kinds of information they should look for. For example, U2 perceived that prior understanding from his work experience helped him clarify what kinds of professional knowledge they should look for online.

> '*Before you start your 'keyword searching,' I will say the most important thing is you have to have known something in this area [IT and Web development], otherwise, you will not be able to proceed with your search […] For example, when our boss gives us a task of web development […] we need to use the knowledge we have learnt,*

otherwise you don't even know what keywords you should use […] When my boss claimed his task demands, you firstly need to translate the demands into a technical language in IT.' (U1, Male, First job non-manual, 26)

'*Firstly, learn things from your actual working experience. Then you might know what kinds of questions you want to ask, and then search for some professional knowledge online which might help you.*' (U2, Male, First job manual, 31)

Moreover, three participants expressed the view that prior knowledge affects effective information selection. Whilst acknowledging the abundance of information resources available, they regarded that selecting useful learning resources was not an easy task and effective selection was premised on the prior accumulation of professional knowledge. For instance, R1 mentioned that when trying to learn new knowledge about preschool education, she was not confident in selecting learning resources by herself and the selection was more reliant on her professional peers' advice:

'*I think basically a large amount of information we can very easily get access to. But the problem is that the information online is too 'scattered' […] I do not think I am very good at finding useful learning resources online. I do not have the expertise to select the right information resources by myself […] When I want to learn new things and need information sources, I often just ask our peers, who have some expertise [in preschool education].*' (R1, Female, First job non-manual, 32)

As for the role of technical embodied cultural capital for searching learning resources, seven participants highlighted the importance of one's digital skills to operate computers and mobile devices, to browse webpages and even to have some advanced searching skills. No participants expressed anything disputing this point. For example, U1, illustrated that advanced searching skills like bypassing the 'the Great Fire Wall,' the internet censorship that blocks foreign websites in China, helps him improve the effectiveness in information resource searches:

'*Of course, we should know how to use the search engine, which is crucial [...] But using the search engine more effectively enables you to get access to better quality information. [...] to be able to bypass 'the Great Fire Wall' is an example. We need to bypass the Great Fire Wall to use Google to conduct better information searches.*' (U1, Male, First job non-manual, 26)

Whilst no participants dispute the role of expertise and technical embodied cultural capital in online resources searches and selection, participants' experiences also suggest that searching by oneself is not the only way to acquire online learning resources, a scenario that the practical action theory of UIL did not envisage. Two participants told their stories of acquiring online learning resources from their social networks with less dependence on their own embodied cultural capital (R1 and R5).

R1, who worked as a departmental manager in a pre-school education centre, said she acquired most of her learning resources from her company's internal system and her professional colleagues' recommendations, whilst admitting that she did not have the expertise in selecting learning resources online:

'Since I started to work at a pre-school education centre, I have learnt a lot of professional knowledge of pre-school education from the learning materials on our internal online system [in the company], as well as the links recommended by my professional colleagues. However, I did not

do a lot of searching by myself, as I was not very good at selecting the right information resources by myself [...] When I want to learn new things and need information sources, I often just ask our peers, who have some expertise [in pre-school education].' (R1, Female, First job non-manual, 32)

R4 had always worked as a manual worker in manufacturing factories. Whilst not having any prior knowledge in computer programming for online searching, that did not stop him from getting digital resources for learning programming, because his IT professional cousin sent him the learning resources:

'*I had a cousin working in computer programming. He said programming is the future and he wanted to help me get a better career. He sent me a lot of texts teaching programming. I spent some time trying to learn [...].*' (R5, Male, First job manual, 27)

The experiences of R1 and R4 show that in terms of learning resource acquisition, sometimes knowing professional people is as effective as personally possessing professional knowledge for searching and selecting information online. Individuals could bypass the process of information resources searching and selection by themselves when someone with the expertise is doing the searching and are happy to share the resources with them. This is a scenario that has not been highlighted by our practical action theory of UIL, although it does echo the overall principle that information resources acquisition is still 'capital-dependent.' At least R1's and R4's examples show that their learning resources acquisitions are premised on social network resources. Although both examples appeared in our rural background participants, the implication for the RMW-URW difference in network-dependent learning resources acquisition is quite the opposite to RMWs having any advantage. In reality, it is very likely that URW's social networks enable them to bypass the process of searching and selecting learning resources by themselves online, thus given them the upper hand over their RMWs counterparts when it comes to acquiring learning resources online. It is more likely that individuals from urban backgrounds have better connections with professional people with specialised expertise than those from rural areas.

Interaction with content

The practical action theory of UIL envisages that the process of interacting with information resources is also premised on the accumulation of *expertise embodied cultural capital*, one's accumulated professional knowledge in a specific area. Echoing points have often been made by the participants when reflecting their experience of learner-content experience.

13 participants explicitly highlighted the essential role of basic knowledge in the area they wanted to develop for effective interactions with the learning content. No participants mentioned anything disputing this point. For example, R5, who received additional IT programming learning resources from his cousin, demonstrates that even once having received the learning resources, a lack of basic knowledge hindered him from effective self-learning:

> '*He [his cousin who worked in IT] sent me a lot of texts teaching programming. I spent some time trying to learn. But self-learning is very difficult. I barely understood those materials my cousin sent me. It was in English and full of jargon. Each simple sentence required a whole page of words to explain the meaning. It was just too difficult.*' (R5, Male, First job manual, 27)

Simply possessing a text containing information is not enough to help one get anywhere. Even though he had access to new learning material, R5 failed to fully take advantage because he did not understand the texts and he did not have the basic knowledge or ability to decode IT-related jargons and terms in a foreign language. As a result, he described his self-learning journey as ‘very difficult.’ This poor learning experience demotivated him from continuing to engage in the interaction with the texts. In the end, he just gave up trying to learn programming:

> ‘*I spent some time trying to learn but I did not understand anything and failed to learn anything in the end. Later, I just gave up […] Without a strong motivation, I just gave up […] I don’t think I had more learning activities afterwards*’ (R5, Male, First job manual, 27)

As for the acquisition of basic knowledge for making sense of and making good use of the acquired learning resources, formal education (N=5), self-learning (N=1) and work experience (N= 5) were mentioned as the sources by our participants. All these three sources implicate an RMW-URW difference in the accumulation of *expertise embodied cultural capital* for learner-content interaction, due to a) the rural-urban inequality in educational resources and opportunities distribution and b) the URW group’s advantages in occupational attainment.

7.5.4. Participation in learner-instructor interaction

As discussed above, self-learning with the use of online information resources is perceived as being reliant on one’s accumulated cultural capital, which leads to a result that the already knowledgeable can learn more. When perceiving the difficulties of learner-content interaction based on their experience, seven participants expressed that if only considering the effectiveness of learning, learner-instructor interaction (e.g., professionals’ private tutoring) is the most effective practice. This echoes Moore’s (1989, p.2) remark that learner-instructor interaction is ‘regarded […] as highly desirable by many learners’. As introduced in Chapter Five, no participants had the experience of online learner-instructor interaction, but participants' offline learner-instructor interaction experience (official on-the-job training, professionals' private tutoring, external training courses, and formal education) made them perceive that the availability of instructors' feedback helped learners progress more effectively:

> '*Learning things from online sources completely depends on your own. A tutor will keep trying to explain things to you if you fail to follow. No one will be there to help you when you are searching information online.*' (U3, Male, First job manual, 22)

Certainly, learner-instructor interaction could take place online. However, the use of the internet does not seem to make an instructor's service less scarce. For example, when talking about the online personal tutorial services, economic resources are still the primary factor R3 spoke of:

> *'Of course, if you have money, you can buy some advanced online courses with the top teachers. They will give you personal tutoring services and make sure you can learn things effectively […] If you buy a service of someone teaching you, it will be the most effective.'* (R3, Male, First job non-manual, 34)

R3's perception is in line with our practical action theory of UIL. Personal tutorial services appear to be an ideal learning practice to ensure desired learning outcomes, but it is conditional on one's economic resources. However, individuals do not make a decision simply on 'theoretical effectiveness'. Learner-instructor interaction will be the most effective if one has enough economic resources to afford the service and will only be 'theoretically effective' for those who could not afford the tutorial service. In other words, the decision-making of participation in learner-instructor interaction takes into account individuals' practical availability of financial resources to afford instructors' tutorial services.

When economic resources are still a significant prerequisite for participation in learner-instructor interaction, this may play a role in explaining the RMW-URW divide in UIL. RMWs might be less likely to engage in online learner-instructor interaction, at least partly because the rural background workers are more likely to be short of economic resources to support this type of learning activity.

7.5.5. Summary

The qualitative evidence has enriched our understanding of the conditions affecting people's internet use and UIL participation beyond what was initially envisaged by the practical action theory of UIL, which helps us further make sense of the difference in UIL between RMWs and URWs.

At the time when the interviews took place, no participants had told a story of internet non-use or less active use related to a lack of material access, but related to a lack of good digital skills to use the devices and the internet, the technical embodied cultural capital. For some, information technology education at educational institutions helped them develop essential digital skills for internet use. However, *hukou* background-related educational inequality (e.g., differences in educational resources distribution, individuals' educational achievement) may have contributed to differences in accessing information technology related educational opportunities. Secondly, the differences in initial access to up-to-date technologies and applications might have a long-term impact on digital skill development for internet use. Once they have access, having the opportunity to explore and tinker with technology and the internet allows them to accumulate digital experience and familiarity with the latest technologies and applications. This not only builds up a set of necessary digital skills that allows them to adapt to the online world more effectively, but it also gives individuals a confidence to further explore additional learning opportunities. It seems like those from urban backgrounds might have earlier access to the latest technologies and applications, however this point would need further examination in future studies.

Regarding participation in learner-content interaction, in addition to the role of embodied cultural capital (digital skills and professional knowledge), one's social network resources, which is overlooked by the initial practical action theory of UIL, also plays a role. Echoing the practical action theory of UIL, participants mentioned that one's digital skills and professional knowledge are essential for searching, selecting, and making good use of the online learning resources for developing work skills and more professional knowledge. But the initial practical action theory of UIL overlooked the fact that searching for resources online by oneself is not the sole path of acquiring information resources for learning. For example, individuals could bypass searching and rely on their social networks' sharing to acquire useful learning resources from the internet. However, it is more likely that individuals from urban backgrounds have better connections with those professionals who have expertise in searching and selecting useful resources from the overload information resources. This may also play a part in explaining the RMW-URW differences in UIL participation.

Unlike learner-content interaction, whose effectiveness is premised upon individuals' prior knowledge accumulation, leaner-instructor interaction is seen as more effective in ensuring a better learning outcome. However, like traditional offline training programs, a tutorial service is still premised on the availability of relatively rich economic resources, even if the service takes place online. Thus, it is foreseeable that RMWs and URWs differ in the participation in learner-instructor interaction online due to their unequal access to economic resources.

7.6. Concluding remarks

This chapter investigated the possibility of inequality in UIL between RMWs and URWs, the third research question of our inquiry. Drawing on previous empirical findings on adult learning inequality and the digital divide, and adopting a Bourdieusian theoretical perspective, this study firstly proposed a *practical action theory of UIL*. This theory envisages that whilst participation in UIL is an individual's subjective choice-preference, this choice-preference is affected by the objective social circumstances in which they are embedded. In particular, the availability of economic and cultural resources affects individuals' actual and perceived UIL experience and outcomes, which is then taken into account during the individual's decision-making process of whether or not, and how, to participate in UIL. Due to the relative resource deprivation among RMWs, it is envisaged that RMWs are less likely to participate in UIL.

This chapter then used quantitative data to provide a robust comparison of UIL participation between RMWs and URWs. The quantitative evidence shows that, compared to URWs, RMWs are generally less likely to participate in UIL or even to use the internet. Even among the internet users, *hukou*-background differences in UIL still exist, albeit less so. Even after controlling for economic, cultural, and demographic factors, the RMW-URW differences in UIL and internet use still exist. In addition to the fairly impoverished operationalization, the persistence of the RMW-URW differences in UIL could be due to some other factors affecting the RMW-URW differences in UIL which are neglected by our practical action theory of UIL. Individuals' educational backgrounds and family income levels are all associated with UIL and internet use. However, RMWs and URWs also differ in their educational achievements and family income levels.

Qualitative data analysis is then followed to refine the interpretation of the practical action theory of UIL when making sense of the observed RMW-URW differences in UIL. Overall, participants' narratives are consistent with the overall mechanism that resource deprivation hinders people from participating in UIL. However, some micro-level mechanisms are overlooked by the initially-proposed theory. First, material access to new technology affects individuals' digital skills accumulation for using the internet effectively. Rural and urban background workers might have access to the same digital devices and applications at different times. Second, in the context of learner-content interaction, searching learning resources online by oneself, which premises on one's accumulated embodied cultural capital (digital skills and professional knowledge), is not the sole means of acquiring learning resources. For example, individuals can bypass searching by themselves and rely on their social networks for resources to help them acquire useful learning. In this case, the role of social capital was overlooked in the initial theory. Yet, in relation to having a good network with those who have the skills and expertise to select reliable information, presumably URWs would still have the advantage of knowing someone who is better equipped with good digital skills and professional knowledge.

Overall, the main finding identified in this chapter is that participation in UIL mirrors the pre-existing socio-economic inequality within a society. A successful UIL experience is premised upon individuals' different kinds of tangible and intangible resources, such as financial resources, various kinds of cultural capacities, social network resources or possibly others which have not been examined. Thus, similar to participation in traditional adult learning activities, advantaged and disadvantaged groups – URWs and RMWs in our case – have unequal participation in UIL activities.

The findings of this chapter have an important implication for our evaluation of the role of UIL in mitigating unequal occupational mobilities. Findings from the last two chapters have already shown that UIL might be relevant to workers' occupational mobility in the contemporary labour market, and the effect might be stronger for RMWs. However, despite the seemingly higher labour market returns to UIL for RMWs, they are actually less likely to participate in UIL in the first place. As such, this finding indicates that UIL has failed to mitigate the inequality in occupational mobilities between those in advantaged and disadvantaged positions. The next chapter will lead an extended discussion on the role of UIL in the dynamics of unequal occupational mobilities, drawing on all the findings from chapters five to seven.

Chapter Eight: Mitigation? Reproduction!

8.1. Introduction

The last three chapters have presented results to answer the three key research questions of this study. The findings in Chapter Five show that, in general, UIL is related to individuals' occupational mobility by updating scarce work skills to meet the demands of the labour market, although the independent associations seem weak after taking into account of other factors like educational backgrounds. Further investigations in Chapter Six found the heterogeneity of the UIL-mobility relation, with RMWs being more reliant on UIL to reduce the risk of downward mobility whilst the URW group's mobility was seldom related to UIL. However, results in Chapter Seven show that RMWs are actually less active in participating in UIL when compared to URWs.

Drawing on the results from the preceding chapters, this chapter offers an extended discussion of the central issue this project focuses on: UIL as a new learning opportunity and the possible mitigation of unequal occupational mobilities between RMWs and URWs. The first section will explain the evaluation of the mitigation of unequal mobilities in relation to UIL, based on an evaluation framework first brought up in Chapter One. As will be explained, the results present a configuration showing no signs of mitigation of unequal occupational mobilities between RMWs and URWs. Next, the second section aims to make sense of the observed result. In the second section, I argue that the co-appearance of the compensatory effect of UIL (i.e., UIL seems to be more helpful in occupational mobility for RMWs) and the unequal participation in UIL (i.e., URWs are more active in UIL participation) is inevitable when situated within an unequal social structure that is constantly being reproduced.

8.2. The evaluation framework of mitigation

To what extent can we say UIL mitigates the inequality in occupational mobility between RMWs and URWs? I proposed an evaluation framework considering two key conditions for the equalization of occupational mobilities at the same time. These two conditions are: a) the compensatory effect of new learning opportunities for disadvantaged populations and b) equality of access to new learning opportunities. In short, the compensatory effect, which has been addressed in Chapter Six, assumes an ideal situation that, within a context of URWs having strengths in occupational mobility, the effect of UIL on occupational mobility is stronger for the disadvantaged, i.e., the RMWs, as a way to compensate for their disadvantages in other respects. As when new learning opportunities like UIL compensate disadvantaged individuals' resource-depreciation for career achievement, it is fair to say that new learning opportunities, like UIL, play a role in reducing the gap in occupational mobility. On the other hand, the equality of access condition, having been addressed in Chapter Seven, assumes that disadvantaged people are not excluded from accessing new learning opportunities. Otherwise, the exclusion of accessing new learning opportunities would play a role in deepening the pre-existing unequal occupational mobilities, which is counterproductive to mitigating the inequality in mobility.

Thus, different combinations of those two conditions (i.e., *the compensatory effect of UIL* and *the equality of participation in UIL*) indicate different types of changes of the original unequal occupational mobilities. Table 8.1 shows all the possible configurations and their interpretations. Among them, only those highlighted in green show a potential for mitigating the unequal occupational mobilities. When UIL is found to be more helpful in occupational mobility for RMWs, and RMWs are more active than or at least as active as URWs (the 8th and the 9th configuration) in UIL, we could say that UIL has played a role in mitigating the original unequal mobilities. In this case, UIL has offered RMWs a new opportunity to develop scarce work skills and to help them succeed in their career progression, whilst the new learning opportunities do not exclude RWM from participating. Even when the effectiveness of UIL is equal for RMWs and URWs, if RMWs were to be more active in UIL (the 6th configuration), UIL would provide RMWs with an alternative means to fight for career success. Those three configurations would suggest that the availability of the internet as a tool in assisting learning and skill development helps mitigate the original inequality of career mobility. UIL provides RMWs with a new way of reducing the gap between them and their urban counterparts in labour market achievement, whilst this new means is not excluding RMWs from accessing.

Table 8.1 Possible outcomes and interpretations

Participation in UIL	Effectiveness on occupational mobility	Interpretation
URW>RMW	URW>RMW	Unequal mobility chances deepened
URW>RMW	URW=RMW	Unequal mobility chances deepened
URW>RMW	URW<RMW	Unequal mobility chances remained
URW=RMW	URW>RMW	Unequal mobility chances deepened
URW=RMW	URW=RMW	Unequal mobility chances remained
URW=RMW	URW<RMW	Unequal mobility chances mitigated
URW<RMW	URW>RMW	Unequal mobility chances remained
URW<RMW	URW=RMW	Unequal mobility chances mitigated
URW<RMW	URW<RMW	Unequal mobility chances mitigated

The changes of occupational mobilities: Mitigation No changes or unclear Deepening

In contrast, three configurations (highlighted in red) imply that UIL is widening the gap of occupational change between RMWs and URWs. The second configuration shows a scenario where even when the labour market returns to UIL show no differences between RMWs and URWs, if RMWs are more excluded from participation in UIL, UIL is actually more helpful for the advantaged group's career advancement and enlarging the gap in mobility between them. In a similar vein, the fourth configuration shows that even when RMWs and URWs have similar participation rates in UIL, the result that UIL is more beneficial to the URW group's career mobilities suggests that the original inequality of mobility has been deepened. Without a doubt, if UIL is not only more helpful for the URW group's career mobility, but URWs are also more active in participating in UIL (i.e., the first configuration), UIL clearly plays a key role in widening the gap between RMWs and URWs when it comes to occupational mobility.

However, there are three configurations (highlighted in yellow) showing no clear direction of the shift of the original inequality in mobility. The fifth configuration shows a situation where the labour market returns to UIL are equal to both RMWs and URWs, whilst they also have similar participation in UIL. This scenario suggests that the original inequality in mobility might remain unchanged, since neither RMWs nor URWs show any strengths in participation in and getting labour market benefits from UIL. There are two more configurations (the third and seventh) that are slightly more complicated as the results of the two conditions (i.e., the compensatory effect of UIL and the equality of participation in UIL) seem to give contradictory implications for the change of equality of mobility. For example, the seventh configuration shows a situation where RMWs are more able to access UIL, however URWs could yield more labour market benefits from UIL.

The findings of this study are fundamentally more akin to the third configuration. This configuration is that whilst RMWs might have got more benefits from UIL, they are actually less active in UIL. In this case, neither can we say that UIL is more helpful in occupational mobility for RMWs simply because of more mobility returns to UIL for RMWs, nor is it fair to conclude that UIL only favours URWs simply because they are more involved. Two seemingly contradictory effects – the compensatory effect (i.e., new learning opportunities bring more labour market benefits to the disadvantaged) and the exclusion effect (i.e. the disadvantaged are more excluded from accessing new learning opportunities) – take place at the same time. Thus, this configuration shows no clear sign of whether or not UIL has mitigated or deepened the original inequality in occupational mobility.

It appears like that if we wanted to change the current situation into a new situation where UIL will help alleviate unequal occupational mobilities between RMWs and URWs, the intervention can target on reducing inequality in participating in UIL so that the situation will move from the third configuration, which shows no clear sign of mitigation of the unequal social mobilities, to a configuration like the sixth one, which shows a clear sign of UIL helping alleviate inequality in occupational mobility, since the new learning opportunity is clearly more beneficial for the disadvantaged populations' occupational mobility, while this new learning opportunity is not creating a new form of social exclusion. In that sense, it seems any degree of reduction in inequality in UIL could improve the current situation (i.e. RMWs are less excluded from participating in UIL), although it would not be sufficient to claim that UIL will help mitigate unequal social mobilities. Only when we see the absolute disappearance of any observable RMW-URW gap in UIL, whilst RMWs can still enjoy more labour market returns to learning, we can finally claim that UIL is helping ameliorating inequality in occupational mobility between RMWs and URWs.

However, it is also slightly problematic to have a thinking that the policy response should only target inequality in UIL in order to let UIL fulfil the promise of ameliorating inequality in occupational mobility. According to the proposed theory (i.e. the practical action theory of UIL) and the findings from the preceding chapter, the structural inequality in a society has translated into inequality in participation in UIL. The formation of the daily practice of UIL relies upon individuals' accumulation of various kinds of tangible and intangible resources (e.g. economic resources, cultural competencies and social networks), the differentiation of which are caused by the underlying structural inequality. That is to say, in order to resolve the issue of unequal participation in UIL, all other aspects of structural inequality need to be resolved as well. However, if all other aspects of structural inequality between RMWs and URWs have been annihilated, inequalities in occupational mobilities and economic well-being should also disappear, and therefore it is needless to employ UIL to reduce inequality in occupational mobility. Moreover, it is almost impossible to simply reduce inequality in UIL while to assume that RMWs still enjoy more labour market dividends from UIL, since the phenomena of inequality in UIL and the compensatory effect of UIL for RMWs are not completely independent to each other, although they are also not directly related. Both two observations are caused by the same mechanism – the constant reproduction of the pre-existing structural inequality between RMWs and URWs.

8.3. Making sense of the 'negative selection' phenomenon

Are those two observations (i.e. inequality in UIL and the compensatory effect of UIL for RMWs) really showing two contradictory underlying mechanisms? Is the co-existence of these two observations a coincidence? In this section, I will try to argue that this is not the case. The phenomenon that those who could benefit most from UIL are the least likely to undertake UIL in the first place can be called a 'negative selection' phenomenon in UIL, as opposed to a 'positive selection' that individuals are more likely to access the resources or opportunities thus bringing more benefits to them after a rational calculation (e.g., Carneiro, Heckman, and Vytlacil 2001; Carneiro, Hansen, and Heckman 2003). If we could make sense of this 'negative selection' phenomenon properly, we would find out that a) the co-existence of those two observations is inevitable and b) both of them manifest the same underlying mechanism, the mechanism of the constant reproduction of a pre-existing unequal social structure through advantaged populations' capital accumulation.

8.3.1. The role of UIL in the contemporary urban labour market

It is essential to firstly re-clarify the role of UIL in the contemporary urban labour market, which reveals a situation where 'skill-meritocracy' still plays a role in stratifying wage workers in the urban setting. In Chapter Five, the quantitative results show an overall association between UIL and occupational mobility, although the associations have become weak after taking into account factors like educational backgrounds, industry, sector, and demographic characteristics.

Why are UIL and occupational mobilities related? Initially, a *temporarily scarce skill theory* was proposed to explain the association. The theory argues that among the wage workers who sell their labour power for economic remuneration, those who possess scarce work skills could sell their labour power in exchange for better economic remuneration. However, if powerful tools like the internet are challenging the inaccessibility to learning resources for work-skill-development, the scarce status of work skills can no longer be viewed as stable. The scarcity of certain kinds of work skills is constantly being challenged. For workers, the constant labour of learning with the use of the internet can help them further develop work skills and reproduce the scarcity of their skill-levels, which is a way to secure an improved employment situation (i.e., increase upward mobility chances and reduce downward mobility risks).

Whilst the temporarily scarce skill theory is not a theory that could perfectly explain everything regarding the role of UIL and the patterns of mobility, the theory does capture some critical features. To a large extent, the qualitative evidence of participants' storytelling echoes the theory of temporarily scarce skills. According to participants' narratives, UIL is associated with the development of up-to-date work skills that could secure workers' career prospects, but only when the recruitment of a work position is open and 'skill-meritocratic.' As was made evident by both the quantitative and qualitative findings, although work skills are not the only factor explaining stratification among workers, it is definitely not a negligible one in the contemporary urban labour market.

8.3.2. What has the 'compensation' revealed?

However, why is there a heterogeneity of UIL-mobility associations between RMWs and URWs? In fact, as demonstrated in Chapter Six, it is not really correct to say that new learning opportunities like UIL have had any 'special effects' on a particular group. Rather, the seemingly 'compensatory effect' of

UIL for RMWs simply shows the disadvantages faced by RMWs in the labour market. When not accessing new learning opportunities like UIL and working on developing work skills, the gap between RMWs and URWs is huge, due to the lack of other kinds of resources (e.g., social networks, certificates) for career achievement among RMWs. In a relative sense, URWs do not need to constantly retrain themselves to ensure employability and improved career prospects, as shown by our quantitative evidence. In contrast, UIL is of great benefit for RMWs in terms of occupational mobility, especially in preventing them from experiencing downward mobility. UIL barely matters for the URW group's downward mobility. However, the downward mobility rates of RMWs are significantly higher than those for URWs, unless having active participation in UIL, when their downward mobility rates look very similar.

Both the initially proposed theory, the diligence dependence theory, and the qualitative evidence of participants' narratives have made some contributions in helping us make sense of the observed interaction effect. The proposed diligence dependence theory highlights that heterogeneity of the UIL-mobility relationship is due to the differences in the reliance on learning activities and constant skill-development for securing labour market benefits. Populations from advantaged backgrounds, such as URWs, have access to a network of rich resources which helps them secure employment or even career progression. In terms of labour power, advantaged groups may have easily acquired appreciated and competitive work skills earlier than those from disadvantaged backgrounds. In contrast, to acquire competitive work capabilities, disadvantaged background individuals are more reliant on the extra effort of additional learning by means of UIL. The diligence dependence theory points out that the regional inequality in educational and training resources distribution, as well as the differences in family economic resources for supporting education and training, leads to a result where URWs are equipped with more competitive work skills for occupations with better economic remuneration. Thus, additional learning opportunities like UIL seem to provide the skill-deficient individuals with a chance to 'catch-up' with their peers from advantaged backgrounds. However, this initial view also neglects an important mechanism: that the recognition of certain kinds of human capability as productive work skills is highly contextual and even biased. Our qualitative evidence offers an additional account. In addition to unequal educational and training resources distribution and acquisition, the URW group's 'knowledge and skill advantage' is also related to their experience of simply growing up in an urban setting. In the urban labour market, the familiarity with urban-based culture and lifestyles (e.g., knowledge of popular brands, consumer products, or new technologies) can sometimes be appreciated as a kind of 'work skills' in some workplaces. Whilst URWs acquire familiarity with urban-based culture and lifestyles by simply growing up in an urban setting, RMWs do need to make the extra effort (and time) to learn this 'urban knowledge' in to order to acquire the work skills required in some workplaces.

In addition, as a socio-economically advantaged group, the URW group's strengths in occupational achievement can also be non-skill-related, like utilising social network resources for job acquisition. That plays a role in explaining why the URW group's occupational acquisition is relatively less skill-reliant. For example, a few URWs' job acquisitions in the state sector could even bypass a strictly merit-based selection simply because their parents maintain a good relationship with those in charge of recruitment. So even when not using the internet for learning or participating in other learning activities to enhance and update their work skills, in a relative sense, URWs can still secure good employment or career progression by drawing on other non-skill-related advantages (e.g., monetary resources, social networks, family inheritance). However, RMWs are less likely to enjoy these non-skill-related resources, thus making them more at risk of employment instability and downward mobility, especially if they do not continually 'up-skill' in the workplace. Li (2004, p. 156) remarks that the 'free-market competition' principle is actually more applicable for buying and selling the labour power of RMWs in the urban labour market. What he means is that, unlike URWs who might have other means and advantages of securing employment and economic gain, the employment of RMWs is completely subject to their own labour power and, consequently, they are more vulnerable to redundancies when their labour power is no longer 'appreciated' (Ibid.). To some extent, UIL or other kinds of learning activity can ensure continued employability for RMWs within the labour market when they are equipped with the necessary labour power.

Therefore, the implication of the seemingly 'compensatory effect' of UIL for disadvantaged group's occupational mobility should not be mis-interpreted. Ultimately, disadvantaged groups' reliance on further learning activities like UIL to secure occupational mobility (especially as a preventative measure against downward mobility) actually reveals that the structural inequality in occupational achievement has barely been challenged. Even when URWs do not engage in UIL, they still do not face a high risk of downward mobility compared to RMWs. For policy makers in particular, the take away message should not be the celebration of new learning opportunities brought about by technological development, but rather the revelation of the subtle issue of social inequality, which makes the new learning opportunities *appear* to favour those from disadvantaged backgrounds.

8.3.3. Why unequal participation?

Due to structural inequality, RMWs and URWs also have different participation rates in UIL in the first place. Whilst participating in UIL appears to be an individual's free choice for their daily activities, the between-group differences in UIL actually manifests the issue of structural inequality, since successful UIL engagement is premised upon individuals' economic, cultural, social, and other valuable resources. The quantitative results in Chapter Seven have presented the differences in UIL between RMWs and URWs. RMWs are less likely to have frequent UIL activities (i.e., weekly UIL) than URWs, and are more likely to have absolutely no UIL in a whole year. The first-level digital divide, the divide of whether one uses the internet or not, still persists between RMWs and URWs. However, even among those who have regular internet use, the divide in UIL persists as well. Individuals' economic resources and cultural resources are highly relevant to participation in UIL, and URWs usually have better family earnings and higher educational attainment. Even after controlling for one's family earnings and educational background, the RMW-URW differences in UIL do not completely disappear.

To explain the observed differences, the initially proposed theory - the practical action theory of UIL - points out that a) the propensity of participation in UIL is premised on an individual's accumulation of economic and cultural resources and b) URWs are more likely to have the needed economic and cultural resources for UIL. Economic resources affect individual's affordability of digital devices and internet access, which seems more relevant to the first-level digital divide. In addition, the role of cultural resources is more critical for UIL participation. Not only does one need digital literacy and skills to use the digital devices themselves and to browse the internet, but in order to successfully engage in learning activities (especially those with information content but without a human instructor's guidance), individuals also need some basic foundational knowledge in a specific profession in order to make good use of those useful elements within an overload of information resources online. Those with more economic resources and who are more knowledgeable, like URWs, can more easily utilize the abundant information resources online for further knowledge enrichment and skill-development to maintain their competitive labour power. As a result, pre-existing inequalities are reproduced in the online world.

The subsequent qualitative data analysis revealed some limitations in the preliminary explanation provided by the practical action theory of UIL. For example, whilst rapid obsolescence is a common feature of technological development, a lack of family economic resources as well as the regional differences in importing the latest digital gadgets into the local markets might restrict individuals' access to and experience of the latest ICT products and applications, which, as demonstrated, is essential if they are to maintain their digital skills in a constantly adapting online world. Furthermore, in addition to economic and cultural resources, the role of social network resources or social capital (e.g., some individuals could bypass self-searching and rely solely on their professional peers to share useful information for self-learning) are neglected by the initial theoretical account. Nevertheless, despite overlooking some micro-mechanisms, the overall principle of the practical action theory of UIL (i.e., UIL relies on a variety of important social resources and those from disadvantaged backgrounds are more deprived of the resources necessary to support UIL participation) is still plausible to help make sense of the observed quantitative difference in UIL participation between RMWs and URWs.

Digital inequality is a multifaceted and evolving issue reflecting pre-existing inequalities (DiMaggio *et al*. 2004; van Dijk, 2005). Some practitioners' 'light-touch' approaches, like low-cost internet access and IT course provision, will not be sufficient to deal with the dynamic, and deeply entrenched, issue of inequality as related to internet use. In fact, the issues of inequality of internet use reflect the deep-rooted nature of structural social inequalities (Norris 2001). If we take UIL as an example, it reflects the deeper issues of regional economic disparity and unequal educational resources distribution, at the very least. The policy responses should not simply target how to mobilise more socio-economically disadvantaged individuals to engage in UIL or other forms of lifelong learning activities, but should also consider putting forward effective reforms to eliminate the deep-rooted socio-economic inequality caused by discriminative institutional programs, like the *hukou* system, in China.

8.3.4. The phenomenon of negative selection

Thus, both the observations of the 'compensatory effect' of UIL for RMWs in terms of occupational mobility and the unequal participation in UIL actually reflect the same mechanism of unequal resource accumulation between RMWs and URWs in China's urban settings. The availability of new learning opportunities like UIL has not mitigated the original inequality, but simply manifests and reproduces those pre-existing structural inequalities.

As introduced in Chapter Two, the urban-biased *hukou* system has created a landscape of a dual society in China making those originally from rural areas more likely to be excluded from important resources for economic life chances improvement. Indeed, the right to freedom of migration and residence has given rural residents a new opportunity to improve their life quality. However, while all roads lead to Rome, some people were born in Rome. Rural migrants' migration to cities and participation in non-agricultural works will not immediately change the fact they are still less advantaged than those who had long been urban residents. As Bourdieu's (1986) famous quote goes 'the social world is accumulated history.' In terms of occupational attainment, the better economic, cultural, social networks, and other resource accumulation experienced by URWs, enables them to acquire jobs and succeed in career progression more easily and to be less reliant on further learning activities. Moreover, the relatively rich economic, cultural, social network, and other resource accumulation of URWs' also prepares them for a readiness to adapt to new learning opportunities by using the versatile tool of the internet.

This configuration is akin to Brand and Xie's (2010) *negative selection hypothesis*, which they suggest when describing the associations between accessing higher education opportunities and socio-economic backgrounds. According to that hypothesis, while socio-economic backgrounds affect individuals' likelihoods of attending higher education, those who are least likely to go to colleges or universities (i.e., the most socio-economically deprived) benefit most economically from higher education (Ibid.). Going to universities or not, socio-economically advantaged individuals will have decent earnings regardless (Ibid.). By contrast, the less-educated workers from disadvantaged backgrounds will have bleak earnings (Ibid.). However, those from advantaged backgrounds have more family resources to prepare them for access to higher education opportunities (Ibid.). This is not only the case for participation in higher education, the negative selection phenomenon also appears when considering access to other educational or learning opportunities, such as access to selective high schools (e.g., Bryk et al., 1993). In our study, the association between UIL and the ascriptive *hukou* background also demonstrates a pattern of negative selection. Those who get more benefits from UIL, due to a lack of other sources of help for job attainment, are less likely to participate in UIL in the first place due to their relative resource-deprivation.

8.3.5. Reproducing structural inequality

The negative selection phenomenon in UIL should not be interpreted as a configuration of two outcomes caused by two separate mechanisms. Rather, the configuration simply manifests one process, a process whereby the privileges of the advantaged groups are reproduced, thus maintaining the system of structural inequality. This process is driven by a dynamic of capital accumulation that draws upon the control of some important resources, with some individuals taking advantage to further maximise resource accumulation in order to fulfil their own immediate needs as well as consolidating their influence and control which then further secures more resources. Here, capital is defined in a broad sense to describe a) important social resources that could fulfil individuals' needs directly or indirectly; b) those resources are often scarce, which gives those who exclusively own the resources the power to secure more resources. For example, capital can be the means of production, which allows the owners to have the power to exploit the surplus value produced by others' labour, as accounted in the Marxian political economy (Marx, 2013). Moving beyond the realm of economic production, scholars like Bourdieu (1986) also identify other kinds of critical capital in societies. These include cultural capital (i.e., recognised embodied cultural competencies like language skills or physical cultural objects like books that enable the owners to acquire other forms of benefits more easily), social capital (i.e., resources that linked to a durable network with individuals or groups like the benefits one could get from having a good relationship with government officials) and symbolic capital (i.e., the power to legitimise certain kinds of cultural competencies like to standardise one type of accent as the ‘standard’ accent and to misrecognise other kinds).

Different forms of capital are interacting with each other. Capital differs from ordinary resources in the way that, apart from fulfilling individuals’ immediate needs by itself, capital can serve as a source of power that facilitates the owners’ acquisition of resources more easily (Boudieu, 1986). The kinds of capital for occupational attainment and UIL participation can overlap. For example, professional knowledge helps one obtain a skilled job as well as the readiness to engage in UIL. In return, active engagement in UIL can create opportunities for a bright career by achieving scarce skills development on the one hand, and the knowledge and abilities for more effective future learning practices on the other. As a result, those already knowledgeable will secure their advantaged occupational status, and become more knowledgeable and more capable to learn afterwards. Certainly, the kinds of resources that help one acquire a work position (e.g., social networks with higher officials in workplaces, family enterprise) are not always the same as the resources that directly help one develop the disposition of UIL (e.g., digital devices, internet access, digital skills). However, capital is convertible, as those who have rich capital of one kind can easily acquire the capital of other kinds (Ibid.). For example, although money cannot buy one a job and the skills for UIL directly, urban individuals’ rich family economic resources (e.g., from parents’ non-agricultural jobs and the entitlement to welfare benefits and social services) do support individuals’ successful completion of education, which then leads to the development of professional knowledge for acquiring a skilled job, and a readiness to strategically make good use of the overload of information resources online for learning. All in all, participation in UIL can be seen as one of the many rounds in the processes of capital accumulation. When new learning opportunities like UIL are available, populations from advantaged backgrounds ensure they possess the relevant resources to effectively engage in new learning opportunities, thus accumulating more resources and solidifying their advantaged positions.

In addition, the institutionalization of categorical inequalities sustains the unequal accumulation of capital. Certainly, the urban-biased *hukou* system was not specifically designed to programme RMWs to be less advantaged in the contemporary labour market, nor to intentionally exclude RMWs from active UIL engagement or ICT use. However, the *hukou* system and its legacy does play an important role in maintaining the history of the unequal capital accumulation between these two groups. In Tilly's (1998) *Durable Inequality*, he points out that a critical mechanism that maintains the persistence of inequalities – the normalisation of categorical differences. In a social world where important resources are often scarce, the competition over those resources is fierce (Tilly, 1998, p. 8). To deal with the insecurity of control over the important resources, means like exploitation (original idea from Marx) and opportunity-hoarding (originated from Weber's *closure*) are two critical measures for the advantaged group to build advantage over resource accumulation (Tilly, 1998, p. 94). Those two measures can generate the process of capital accumulation, as discussed above. Through those measures, the possession of important resources becomes the possession of power, and those important resources become capital with its value going beyond the original use value. Exploitation and opportunity-hoarding are certainly reproducing inequalities, however, according to Tilly (1998, p. 8, 85), there is a problem of justification to sustain reliable exploitation and opportunity-hoarding. As such, the institutionalization of categorical forms of inequality is provided as a solution to sustain stable exploitation and opportunity-hoarding (Tilly, 1998, p. 8; 2003). Instead of exposing the naked relations of exploitation and opportunity-hoarding, the installation of category and the normalisation of categorical differences naturalises the appearances of inequalities (Tilly, 2003).

Since 1958, the urban-biased *hukou* system has divided populations into agricultural and non-agricultural categories, with the purpose of exploiting the entire agricultural surplus to support rapid industrial development in cities.

The is a good example of how an institutional apparatus can incorporate categories into relations of exploitation and opportunity hoarding. When industrialisation is regarded as a primary goal of the state's development, urban industrial production is seen as advanced and modern, and agriculture is seen as primitive. Thus, the economic inequality between individuals originating from the distinction between agricultural and non-agricultural categories was normalised and widely accepted. The shift from the planned economy system to a more market-oriented model has not changed the prioritization of urban economic development and the devaluation of rural agricultural production. This only served to stabilise and further strengthen the economic inequality between people originally from rural and urban settings. Moreover, inequalities between agricultural and non-agricultural populations embodied other types of categorical inequalities that were institutionally legitimised. A good example is that, in addition to the *hukou*-based discrimination in some job recruitments, it is widely perceived that RMWs are poorly-educated, low-skilled, late technology-adopters, and slow-learners. These stereotypes are normalised and then used as an excuse for poor economic renumeration when a free market competition logic has been adopted. This construct deprives RMWs of both learning opportunities and the opportunity for career progression. A lack of resource acquisition puts up barriers for RMWs, such as access to further learning via the internet or other ways in which digital technologies can provide 'upskilling.' In the end, this simply reinforces the intersection between RMWs and those additional categories that minimise their standing in the workforce, contributing to their perceived status as undeserving of additional resources.

All in all, the coexistence of the 'compensatory effect' of UIL for occupational mobility for RMWs and the unequal participation in UIL shows a negative selection phenomenon that those who are more likely to benefit from UIL are the least able to access them. This configuration indicates no sign of mitigation of the pre-existing inequality of mobility. The presence of this configuration is not simply a coincidence, but an inevitable outcome of the deep-rooted, resilient structural inequality between RMWs and URWs.

Structural inequality is constantly being reproduced with the appearance of new forms of inequality, like the negative selection in UIL. The process of capital accumulation ensures that individuals from advantaged backgrounds have made good use of new forms of important opportunities which maintain their advantage. When the internet has become a powerful tool for facilitating individuals' learning for work-skill-development, advantaged groups like URWs are better situated to ensure that they are more capable of making better use of those powerful tools, even though advantaged groups are actually less reliant on UIL to secure their occupational mobilities. In addition, the institutionalization of categorical differences further sustains and stabilises the process of capital accumulation, by normalising the inequalities between RMWs and URWs.

8.4. Concluding remarks

This research focuses on a central issue – the extent to which a new learning opportunity, UIL, could mitigate the unequal occupational mobilities between RMWs and URWs. This chapter integrates and interprets the findings from Chapters Five to Seven by discussing the possibility of the mitigation of the unequal mobilities. With the use of the proposed evaluation framework (i.e., the consideration of the compensatory effect of UIL for occupational mobility for RMWs and the equality of participation in UIL), the interpretation of the findings is a state showing no signs of unequal mobilities having been mitigated. It is a negative selection phenomenon in UIL, that while RMWs seem to be able to benefit more from UIL, they are actually less able to access UIL opportunities in the first place. Actually, both of these two observable effects are caused by one common structural issue - the disadvantage of RMWs in urban settings. The appearance of the negative selection in UIL actually manifests an ongoing process of the reproduction of the pre-existing inequalities through advantaged groups' capital-accumulation. The possession of valuable resources (e.g., the economic, cultural, social) enables individuals from advantaged backgrounds to seize new learning opportunities like UIL to further develop competitive work skills for securing decent jobs with good economic remuneration, and to obtain professional knowledge and abilities for future effective learning, which in return consolidates their advantages in an ever-changing world.

One more important implication drawn from the findings is the ineffectiveness of the focus on the opportunity for social mobility, if the ultimate goal is to improve the economic well-being of RMWs. In modern industrial societies, mainstream political discourses promote opportunities for social and occupational mobility as a corrective to issues of economic inequality while completely ignoring the substantial issue of unequal distribution of resources and rewards to individuals. As shown in Chapter Two, there is no exception in China nowadays, since the regime prioritises the efficiency of economic production and even encourages the existence of a small degree of developmental disparity as an incentive to promote competition and development. Then, research agendas are created to look for potential solutions to reduce the inequality of opportunity for individuals' development, such as the evaluation of the effect of the expansion of secondary education, tertiary education, adult education, and now the role of the internet for learning facilitation. However, those imaginary tools are likely to fail in attaining the goal of reducing unequal opportunities, since inequality of occupational mobility is always entangled with inequality of resource acquisition. The relationship between the equal opportunity discourse and the equality of condition is dialectical. Equality of opportunity in mobility is basically impossible in the absence of equality of condition, since the 'free competition' logic derived from the equal opportunity discourses will only favour those already in possession of a rich accumulation of resources (Boliver and Byrne, 2013). Those with rich resources in one form can easily translate this accumulation into other forms of resources which can result in a good outcome of mobility in a hierarchical system. This is evident by Hertel and Groh-Samberg's (2019) latest investigations in 39 countries, which shows that regimes' level of between-class inequality is strongly associated with the level of inequality of class mobility, mediated by the availability of a social-democratic redistributive welfare system. Furthermore, in a society where the allocation of resources is close to equal, and is therefore lacking in stratification and hierarchy, equal opportunity discourses become redundant since there is no need to rely on mobility to improve economic well-being. As Boliver and Byrne (2013) argue, for too long, the idea of social mobility has dominated the measure of a good society, but it really is a wrong focus. Because inequality of mobility and inequality of condition always appear simultaneously, one either needs to accept that a society includes both stratification, and unequal chances for mobility, or one must imagine an alternative model where none of these exists.

Chapter Nine: Conclusion

> ‘[…] *the World Wide Web, thanks to the biographical accounts on its birth and its inventor, represents a synthesis of an imaginary of the future in which collective and egalitarian values such as cooperation, horizontality and openness can be realized owing to the new revolutionary system.*’ (Bory, 2020, p. 117)

In Paolo Bory’s (2020) latest work *The Internet Myth: From the Internet Imaginary to Network Ideologies*, the author argues that the internet is not simply a technical object, but also a project of ideologies. One of the dominant narratives is the imagination of a new decentralised, egalitarian, and interdependent network-like social organisation of humanity’s future lives along with the boom of the *World Wide Web* since the mid-1990s (Ibid.). However, ironically, the so-called ‘golden age’ of decentralised networks has turned into an age for ‘gold-mining,’ serving the interests of a few advantaged actors, and the so-called ‘liberating technology’ has become a powerful tool for a new form of social, economic, and political control used by the establishment (Bory, 2020, p. 1). The imaginary equalising effect of the internet has not come true. In fact, this powerful tool is often used to reproduce the advantages of the privileged few in the information age. The findings of this study further support these claims.

9.1. The tasks of this project

This project is situated in a context in which a) RMWs are an economically disadvantaged group in urban China, b) occupational mobility is promoted as a practical pathway to improve individuals’ economic well-being, and c) the internet is being considered as a tool to provide new learning opportunities that challenges inaccessibility to knowledge, especially given the abundance of shared information resources online. As introduced in Chapter Two, contemporary urban China is famously characterised by economic inequality between RMWs and URWs. In the era of economic reform, China overtly proclaims the prioritization of efficiency for economic growth by adopting a market-driven development process, while economic inequality is tolerated mainly to stimulate competition and growth. Thus, instead of introducing egalitarian redistributive policies, individuals are encouraged to improve their economic well-being through the pursuing of personal career progression by their own efforts. However, in terms of occupational mobility in the urban labour market, RMWs are found to be at a disadvantage. Given the abundance of information resources online and the global-level connectivity powered by the internet, the internet is often presented as a powerful, convenient, and accessible tool for individual learning and skill-development, often thought to be helpful for career mobility. As such, this project aims to evaluate the potential of UIL in mitigating the inequality of occupational mobility between RMWs and URWs in urban China.

To fulfil the research aim, this study has set out to answer three main research questions: *To what extent is UIL related to occupational mobility in general? Is there a stronger UIL-mobility association for RMWs? Do RMWs and URWs have similar participation in UIL?* Among those three questions, the first one is a foundational question aiming to make sense of the role of UIL in the contemporary urban labour market, whilst the following two questions are more directly related to the evaluation of the mitigation of unequal mobilities. As introduced in Chapter Three, the evaluation of mitigation needs to consider two key aspects of the effect of UIL simultaneously: the compensatory effect of UIL (i.e., greater labour market returns to UIL for RMWs) and the inclusivity of participation in UIL (i.e., equal participation in UIL between RMWs and URWs). On the one hand, in order to have an effective strategy of mitigation (of unequal mobilities), ideally, the new learning opportunity should have a greater effect for the disadvantaged group. On the other hand, the disadvantaged group should not be excluded from accessing the new learning opportunity in the first place. This project has developed theoretical knowledge and combined quantitative and qualitative evidence to address each research question. The initial step of theory-building has predicted the hypothetical phenomena and provided preliminary explanations of potential underlying mechanisms. The quantitative and qualitative evidence has been used in a complementary manner, with quantitative data being used to provide robust results of comparisons to test against the hypothetical phenomena and qualitative data being used to explore and refine the explanations to make sense of the observed outcomes.

9.2. A summary of the main findings

The inquiry started by addressing a foundational question: to what extent is UIL related to occupational mobility in general? The findings in Chapter Five show that overall, UIL and occupational mobility are related positively, although not strongly, at least partly because UIL helps workers develop scarce work skills that are relevant for occupational attainment. Based on Wright's (1997, pp. 18-19) scarce skills account (i.e., the scarcity of work skills affects workers' economic remuneration in an employment relationship), the *temporarily scarce skills theory* was proposed and argues that the abundance of online information resources for learning and the changing skill demand in the labour market might constantly challenge the scarcity of workers' acquired work skills. Thus, the constant effort of learning, such as UIL, helps workers develop and reproduce scarce work skills for securing employment stability and career progression. Chapter Five initially offered new quantitative evidence on the overall UIL-mobility association among the overall working population in urban China. The results show that overall, UIL and occupational mobility are positively associated, albeit the associations become somewhat weak after taking into account individuals' educational achievement, work industry and sector, and demographic characteristics. The follow-up qualitative inquiry pointed out a contextual limitation of the proposed temporarily scarce skills theory: the over-generalisation of a 'skill-meritocratic' recruitment in China's urban labour market. Factors like family wealth, inheritance, social networks, and a few state sector workplaces' seniority-based promotion systems still function. In addition, even when workplaces attempted to stick to a 'skill-meritocratic' selection process, the difficulties of screening and signalling workers' newly developed skills are neglected by the temporarily scarce skills theory. Those factors may partly explain why the quantitative results show a positive but somewhat weak UIL-mobility association. Nonetheless, overall, the results are still telling that workers' constant learning and the development of scarce work skills play a role in the stratification of wage workers in China's urban labour market.

Next, when exploring the heterogeneity of the 'UIL-mobility' association, findings in Chapter Six show that the UIL-mobility association is stronger among RMWs than URWs. However, the heterogeneity of labour market returns to learning actually does not suggest that new learning opportunities like UIL favour disadvantaged individuals, but rather indicates the persistence of RMWs disadvantages in the urban labour market. Even without accessing learning opportunities, advantaged populations are still more capable of getting good occupational achievement by using other kinds of resources. The initially proposed theory, *the diligence dependence theory*, suggests that due to the deprivation of various kinds of resources (e.g., educational achievement, social networks), disadvantaged groups like RMWs are more reliant on extra learning like UIL to develop work skills and therefore to secure occupational achievement. The quantitative findings have given some support to the diligence dependence theory. In particular, the findings show that whilst UIL is closely linked to a reduced risk of downward mobility for RMWs, the URW's group downward mobility risk is always lower and barely subject to the change offered by UIL. To explain the observed URW group's strength in resisting downward mobility, even without any UIL shown by the quantitative evidence, the diligence dependence theory explains that it is due, at least partly, to the group's non-skill-related resources (e.g., social networks) and skill-advantages as a result of their good educational achievement. The qualitative findings have contributed an additional source of URW group's skill-advantage: an urban-biased definition of knowledge and skills in the urban labour market. The familiarity with the urban lifestyle and culture (e.g., knowledge of brands, consumer products, new technologies, urban transportation), which has nothing to do with one's educational achievement, can be regarded as 'professional knowledge' in some workplaces in the urban labour market. Unlike URWs who might have acquired familiarity with the urban lifestyle and culture by growing up in cities, RMWs might need to make extra effort to learn what URWs take for grant by means online learning.

However, although UIL could offer potentially more benefits, RMWs are actually less engaged with additional online learning, reflecting the underlying structural inequality between RMWs and URWs. The popular narratives of ICT and the internet transcending formal learning and education by providing a low-cost and convenient alternative have obscured the reality that UIL is still a resource-reliant activity. The relevant resources, tangible (e.g., devices) and intangible (e.g., cognitive skills), are more likely to be owned by populations from advantaged backgrounds. By adopting a Boudieusian perspective, the proposed *practical action theory of UIL* in Chapter Seven argues that individuals' choice to participate in UIL is a result of a partially rational decision-making process constrained by practicality. Not only does the decision-making take into account the practicality of the accessibility of the relevant financial (e.g., money) and cultural resources (e.g., digital skills, professional subject knowledge), the cost-effectiveness analysis of UIL draws upon the available wisdom derived from individuals' previous experiences. Due to the relative lack of rich economic and cultural resources, disadvantaged populations are less likely to have a disposition of feeling comfortable and confident to participate in UIL. The quantitative findings in Chapter Seven confirmed the inequality in UIL and internet use between RMWs and URWs. The additional qualitative analysis showed that in addition to economic and cultural resources, social network resources (e.g., acquiring useful learning resources from professional peers' sharing) might also play a role in explaining the RMW-URW differences in UIL participation. In addition, the findings also show that the learner-instructor interaction, which is seen as the most effective learning practice with less dependence on learners' previous accumulation of foundational knowledge, is not perceived as more economically affordable with the use of the internet, since the scarcity of an instructor's services has not been reduced.

As discussed in Chapter Eight, the findings of this study do not show UIL mitigating the inequality of occupational mobility. This is because the findings show a 'negative selection' phenomenon in UIL: those who could get more benefits from UIL are actually less likely to participate in UIL in the first place. In Chapter Eight, I argued that the co-existence of a) the 'compensatory effect' of UIL for RMWs in terms of occupational mobility and b) the exclusion of RMWs from participation in UIL in the first place is not a coincidence, but rather an inevitable result. We should understand it as a way that advantaged populations constantly reproduce their advantages to secure resources and opportunities. Advantaged groups' cultural, economic, and social resources empower them to be more able to participate in UIL. However, because individuals from advantaged backgrounds have a richer accumulation of resources, they are actually less dependent on further learning like UIL in order to secure occupational mobility. This mechanism of capital accumulation has made certain that the advantaged are able to reproduce their advantage in an ever-changing world. Individuals from advantaged backgrounds also ensure a better use of new forms of important opportunities and resources, like new learning opportunities powered by the internet and ICTs, which helps to maintain their privileged position in an ever-changing world. Additionally, to exercise secure and stable opportunity hoarding or exploitation of produced resources, the institutionalization of multiple forms of categorical differences (e.g., regional differences in educational resources distribution, unequal economic resources distributions to labourers) helps sustain the unequal capital accumulation and the advantaged groups' capital-maximization by normalising the inequalities between different categories.

This study is not without limitations. Firstly, in this study, UIL is defined in a broad way that includes any kind of work-relevant learning activities assisted by the use of the internet. As a study which attempts to gain an overview of the potentials of the internet for facilitating learning and the impact on occupational mobility, this broad definition serves its purpose. However, a consequence of this type of broad definition is that each specific kind of work-relevant learning activity with the use of the internet has not been fully explored. In addition, while the successful quantitative data analysis owes a debt of gratitude to the availability of useful data provided by the CFPS, this study shares a common problem with other research projects using secondary data sets: the imperfection of the operationalisation of concepts. When answering the first and second questions, the measurement of the activeness of UIL contains the use of an attitudinal measure (i.e., to what extent do you think learning is an important part of your internet usage in the last month) rather than the measurement of actual internet use frequencies. The used UIL variables in the quantitative analysis only measures individuals' general UIL activities, not UIL activities specifically for work skills development. And, when answering the third question, the operationalization of the theoretical concepts of cultural and economic capital was not ideal. For example, one's digital skill level and professional knowledge accumulation cannot be perfectly measured by educational background, which is the closest proxy indicator the data sets contain. Lastly, there were some issues of sampling in the qualitative inquiry. In particular, whilst both the latest statistical report on internet development in China by CNNIC (2019) and the quantitative findings of this study show that the internet non-users still account for a considerable proportion of the population in China, this study only managed to recruit two participants who had no internet use in their daily lives (and they shared some demographic similarities: both were mature, male, RMWs, manual workers). This suggests that the understanding of internet non-adoption or, the first-level digital divide, in urban China is still limited. As such, further studies are necessary to investigate internet non-adoption in China.

9.3. A fairer competition environment

Since the earnings of RMWs are mainly from work and employment, making competition fairer in the urban labour market will help to improve the economic well-being of RMWs. People might have different opinions on what a 'fair competition' means, however, there is a consensus that *hukou*-based discriminations and nepotism are definitely damaging fair competition in the labour market.

Hukou-based discrimination, more often reported in the state sector in the past due to local authorities' protectionism, prioritizes the recruitment of local urban residents (recruitment discrimination) and offers remuneration differently according to one's *hukou* status (rewards discrimination) (Chan, 2010b; Yang and Xiong, 2014). Studies (e.g., State Council of the People's Republic of China, 2006b) show that direct *hukou*-based discriminations have reduced significantly since 2000, and in this qualitative inquiry there was no mention of *hukou*-based discrimination. In 2007, *Employment Promotion Law of the People's Republic of China* was enacted with Article 31 protecting job-seeking from discrimination for RMWs in cities: '*It is prohibited to set discriminatory restrictions against rural workers seeking employment in cities*' (SCNPC, 2007). Nevertheless, Yang and Xiong's (2014) study show that compared to non-agricultural *hukou* holders, agricultural populations have experienced more *hukou*-status-related restrictions during their job-seeking. To promote the occupational mobility opportunities for RMWs, there should be an on-going project to ensure that *hukou*-related discriminations in workplaces should not exist.

As shown in our findings, the existence of nepotism in workplaces also works against fair competition and the promotion of occupational mobility for RMWs. Stories of URW participants' use of family social network resources to bypass a 'skill-meritocratic' selection system in recruitment in both the state and non-state sectors are documented in this study. Nepotism in the non-state sector is harder to challenge, since private firms are essentially the property of the owners. Whilst in the state sector, recruitment is supposed to go through a strict and un-biased examination system that aims to select the best candidate meritocratically (e.g., Jarrett and Huihan, 2009). The real problem that needs to be resolved in the state sector is not a lack of equal participation policies, as they have long existed, but the poor regulatory compliance of those rules in practice.

Whilst the removal of *hukou*-based discriminations and nepotism would certainly be beneficial for occupational attainment for RMWs, it is still controversial that a purely 'skill-meritocratic' recruitment could create a fair competition environment for RMWs. Firstly, when the conditions are unequal (e.g., URWs could access better educational and family economic resources during the early life course), it is arguable whether 'free competition' means 'fair competition'. Secondly, there is an intrinsic problem of meritocracy that the standard of 'merits' is always biased towards the advantaged, who 'monopolise' the definition of merits in their own interests (Littler, 2017). As shown in Chapter Six, the definition of 'skills' in the urban labour market could be biased, as the familiarity with urban culture and lifestyle can sometimes be regarded as 'professional knowledge' in the urban workplaces. The successful quantitative data analysis owes a debt of gratitude to the availability of useful data provided by the CFPS. Having said that, this study shares a common problem with other research projects using secondary data sets: the imperfection of the operationalisation of concepts.

9.4. Tackling inequality in UIL

Certainly, a big issue to be addressed is the inequality of participation in UIL between RMWs and URWs. As argued in Chapter Seven, UIL is not an outcome of completely free choice but a resource-dependent activity constrained by individuals' available economic, cultural, social and other kinds of resources. Between RMWs and URWs, differences in internet adoption, the first-level digital divide, still exist, even among those who are from similar educational backgrounds and with similar family earnings. Self-perceived poor digital skills were mentioned as a reoccurring theme explaining lack of active internet use, echoing CNNIC's (2019) findings that poor computer and internet skills (54.5%) are the primary reason for lack of internet use in China. The unequal educational resource distribution between rural and urban areas might have led to the digital skill differences between RMWs and URWs, since computer courses and digital skills support in educational institutions are still reported to be a major source of initial digital skills acquisition. Even for young people, it is problematic to assume that they automatically acquire digital skills without receiving any support (Eynon and Geniets, 2016). As such, among other possible measures (e.g., provision of affordable or free broadband, mobile network access, and digital devices to disadvantaged backgrounds individuals), the provision of digital skills training support to individuals from disadvantaged backgrounds should be considered as a crucial measure in tackling present-day inequality in internet use.

However, digital inequality is a multifaceted and evolving issue reflecting pre-existing inequalities (e.g., DiMaggio et al., 2004; van Dijk, 2005; Robinson et al., 2020). When some gaps have been closed (e.g., the first-level digital divide in some developed countries), other forms of digital inequality remained or have sprung up. One effective way of reducing digital inequalities is to address deep-rooted social inequalities in the first place (Norris 2001). For example, in the context of learner-content interaction, one's literacy and accumulation of professional knowledge (helping to select and decode the meaning of online information resources) plays a vital role in determining an individual's likelihood of participating in UIL. That is to say, to promote equal participation in learner-content interaction with the use of the internet, issues like educational inequalities must first be addressed. Whilst the learner-instructor mode of interaction is considered to be the most effective learning practice, the internet has not made a human instructor's service less scarce and therefore more affordable for the disadvantaged. This implies: to promote an equalised participation in online learner-instructor interaction, economic inequalities must be addressed as well.

One day, the difference in hours spent, or self-perceived activeness, in UIL between RMWs and URWs may disappear. However, as long as the underlying social inequalities between these two groups still exist, some forms of inequality in UIL will persist. Inequalities in UIL might evolve into some forms that are more difficult to be discerned by current measurement tools. In the literature on educational attainment, a theory called *effectively maintained inequality* (Lucas, 2001) can be applied to make sense of the possible evolvement of inequality in UIL. The theory argues that the advantaged will use their advantages to secure whichever learning opportunities are *qualitatively better* (Ibid.). In that sense, even when advantaged and disadvantaged individuals spend the same amount of time in UIL, structural inequalities might enable the advantaged to exclusively make better use of certain qualitatively better UIL activities in order to secure their advantages (e.g., professional individuals who spend time on advanced-level machine learning courses to secure scarce work skills).

9.5. The provision of educational opportunities for RMWs

To reduce the RMW group's skill-deficiency, more educational opportunities should be provided to individuals from rural backgrounds, as self-learning with the use of online information resources seldom reduces the knowledge and skills gap between RMWs and URWs. As shown in Chapter Five and Seven, the most popular form of UIL, the learner-content interaction, is heavily premised on individuals' previously accumulated professional knowledge, resulting in a situation where those who have more knowledge in a given area can easily learn more effectively by strategically making better use of the overload information resources online. In a relative sense, the learner-instructor interaction can guarantee a better learning outcome with less dependence on one's accumulation of professional knowledge, since an expert's interactive tutorial can instruct learners to develop new understandings more effectively. However, the use of the internet does not make an instructor's tutorial service less scarce and therefore more affordable and accessible. Without intervention, the availability of abundant information resources online will only enlarge the knowledge-gap between the well and poorly informed. The provision of educational programmes for the disadvantaged and the formal learning opportunities with instructors' instructions will be an effective measure to reduce knowledge and skill disparities between the advantaged and disadvantaged.

To reach the goal of knowledge and skills gap reduction, the educational programmes must be high-quality (i.e., ensuring good learning outcomes) and inclusive. First, it is essential to reduce unequal educational resource distribution between rural and urban areas, and to provide adequate economic and other forms of support to help pupils from disadvantaged backgrounds in rural areas to finish their education. Second, more high-quality and affordable adult education programmes should be available for low-skilled RMWs in cities. Government supported vocational education programmes for RMWs have long existed in urban areas. However, the supply has not been sufficient to meet the demand of a large population of RMWs in China (Xu, 2013). In the past, some government supported training schemes could not be offered for free, causing a low willingness among RMWs to participate in those schemes (Zhu, 2004). As such, it is essential to increase the spending on and the provision of free, or at least affordable, but high-quality adult education programmes for RMWs in cities. Furthermore, stipends could be introduced to increase employers' incentives to provide or invest training opportunities for RMWs. As mentioned in Chapter Seven, employers have a low incentive to invest in RMWs because, among other reasons, employers believe that investment in the already well-informed will bring more productivity returns to the organisation (Zhu, 2004; Xu, 2014). As such, a 'public-private partnership' solution, the government supplied stipends for employers to invest in RMWs' skill-training, could be introduced as a means of increasing employers' willingness to bring more investment in RMWs.

9.6. Beyond the consideration of social mobility?

The implications of this study force us to think beyond the promotion of social mobility as a way of improving economic well-being for RMWs. The findings of this study have demonstrated that it is technically problematic to consider providing learning opportunities and promoting opportunities for career development to resolve the issue of economic disadvantage. As discussed in 9.4., digital inequalities in learning are constantly evolving. When one form of inequality in UIL diminishes, the inequality might simply evolve into another form. Unless other aspects of social equality are reached between RMWs and URWs, some forms of inequality in UIL will always exist. Those forms of remaining inequality in UIL will still grant the privileged some advantages in the acquisition of scarce work skills. In other words, inequality of condition leads to unequal opportunities for development.

Yet, opportunities for development are often proposed to be the solution to tackle the issue of economic disadvantage by mainstream policies in industrial counties. That is, the consequence of equality of condition (i.e. equal opportunities for development) has been proposed to be the solution to tackle the issue of economic inequality. But when the condition is unequal, how could we create an equal environment for development? And when equality of condition is attained, why do we still bother to promote individuals' occupational mobility to tackle the issue of economic inequality, which has no longer existed? As discussed at the end of Chapter Eight, inequality of mobility and inequality of condition are always entangled. Inequality of condition makes sure some valuable and scarce opportunities or resources for occupational mobility always favours a few advantaged individuals. However, when inequality of conditions diminishes, there is no need to rely on social mobility engineering to improve disadvantaged populations' economic well-being. As such, policy attention should be shifted from the consideration of promoting occupational mobility to addressing social inequality more directly.

As such, reducing the RMW group's economic disadvantage relies on policies that should address the substantial issue of unequal distribution of resources to citizens. Three main aspects of reform are particularly relevant. Firstly, *hukou*-based discrimination in welfare benefit entitlement and access to social services should be completely abolished. For a long time, the lack of entitlement to benefits in cities has meant that RMWs remain solely reliant on their own labour to achieve economic security. On the one hand, working has become the only source of income for RMWs in cities. On the other hand, without the entitlement to benefits like health insurance and public-school education, they need to set aside extra money for these types of expenditures. Since 2013's *Comprehensively deepening reform* (CCPCC, 2013), the abolishment of *hukou*-based discrimination in welfare benefit entitlement and access to social services has been put on the agenda, but is still an on-going project. In particular, while big cities tend to put forward policies on equal benefit entitlement and access to social services between local residents and migrants, big cities also tend to restrict migration by creating a high threshold (e.g., purchasing a luxury apartment, initiating large investments, obtaining high-level qualifications) for migrants to obtain a local *hukou* status (Chen, 2018). That also makes the second aspect of the reform, the reduction of regional inequality, crucial. In 2014, the State Council (State Council of the People's Republic of China, 2014) issued *Opinions on Further Reform of the Hukou System* which publicises the idea of nationwide abolition of the agricultural and non-agricultural *hukou* distinction with 30 provinces having initiated local policies in 2016 to remove the distinction of agricultural and non-agricultural *hukou* types for new households' registration (*Xinhua*, 2016). While this is often interpreted by journalists as a sign of the end of the distinction between the agricultural and non-agricultural populations, Chan (2018) contends that the agricultural/non-agricultural equalization is far from being achieved as the essential distinction in welfare and service provision between rural and urban regions still persists. Furthermore, if differentiations in economic activities and earnings across regions have not substantially changed, agricultural populations will still suffer from economic disadvantages and will rely on migration-for-work to improve their economic life chances. Last, but probably the most difficult one, radical redistributive policies could be introduced to reduce nationwide earnings inequality between occupations. As introduced in Chapter Two, to a large extent, the economic inequality between RMWs and URWs is due to occupational segregation, with RMWs contributing to a massive labour force of unskilled manual workers in cities with low wages, poor working conditions, extended working hours and employment instability. Effective policy responses should directly address the earnings gap between individuals working in different industries, sectors, and roles, rather than promoting the idea of encouraging upskilling to change work positions in order to live a decent life.

9.7. Contributions and implications for future studies

This study has made some theoretical contributions. The temporarily scarce skills theory in Chapter Five contributes a new perspective to the field of social stratification by articulating the impact of the internet on the obsolescence of work skills in a rapidly changing world, and the routinisation of 'learning labour' to secure scarce work skills and economic life chances. The diligence dependence theory in Chapter Six provides a critical perspective to interpret the stronger 'learning-mobility' association for the disadvantaged as a sign of their resource-deprivation. The practical action theory of UIL in Chapter Seven articulates the 'resource-dependent' nature of UIL, which offers a new theoretical lens to understand inequalities in learning online. Regarding the found phenomenon of negative selection in UIL, this study offers a theoretical explanation of 'capital accumulation' to understand the negative selection in UIL as a way that advantaged populations constantly reproduce their advantages to secure resources and opportunities. As 'learning' has become a key form of routinised labour in the contemporary labour market, future theoretical works should pay more attention to its role in occupation-related social stratification and mobility in the contemporary world.

Empirically, this study updates evidence to show the ineffectiveness of merely relying on the internet as a new learning tool to equalise pre-existing unequal occupational mobilities. The findings from each chapter provide new empirical evidence to indicate the general landscape of inequality of occupational mobility between RMWs and URWs, the role of UIL in the contemporary labour market in urban China, the heterogeneity of the relationship between UIL and occupational mobility for RMWs and URWs, and issues of inequality in internet use and UIL between RMWs and URWs. As in this study UIL is defined in a broad way that includes all kinds of work-relevant learning activities with the use of the internet, future studies should go beyond this type of 'overall-picture' analysis and scrutinise each specific kind of learning activity with the use of the internet to gain some insights of idiosyncrasy. In the part of qualitative analysis, this study adopted Moore’s (1989) interaction-based learning activities typology to classify UIL into three types: learner-content interaction, learner-instructor interaction, and learner-learner interaction. Probably because the abundance of online information resources is a key benefit of using the internet, most of the UIL stories mentioned by participants were actually learner-content interactions in this study. Ideally, future studies should further explore the other two kinds of UIL: the learner-learner interaction and learner-instructor interaction. Furthermore, while the empirical findings in this study presents a phenomenon of negative selection in UIL among RMWs and URWs in urban China, as suggested by the above-mentioned theoretical works, the negative selection in UIL might well be a general pattern that links to structural inequality. Thus, future empirical works should further explore the phenomenon of negative selection in UIL in relation to other aspects of structural inequality, as well as its existence in different social contexts.

Appendix A Ethical approval documents

Appendix A1 ethical approval confirmation

Ethics Approval

JACKSON, FIONA S.F. <s.f.jackson@durham.ac.uk>

Wed 01/08/2018 11:41

To: ZHANG, CHOING <chong.zhang@durham.ac.uk>

Dear Chong

I am pleased to confirm that the Ethics Committee have approved your recent Ethics Application forms and

you are now permitted to undertake the aspect of the field work and data collection referred to within them.

Congratulations on reaching this exciting stage of your Research.

Unfortunately, at the time of writing a fully signed copy of your Ethics form is not available. A copy of this

email, when presented along with your Ethics documents, is a sufficient record to show you have fulfilled

Durham University’s Ethics processes.

Best Wishes

S.Fiona Jackson

S.Fiona Jackson |

Postgraduate Research Administrator

Durham University | ***School of Applied Social Sciences*** |

32 Old Elvet | Durham DH1 3HN

Tel: +44 (0) 191 334 1485| www.dur.ac.uk/sass

Appendix A2 Research Ethics and Risk Assessment Form

Section A: Introductory Information

A.1. Name of researcher(s):	CHONG ZHANG
A.2. Email Address(es) of researcher(s):	chong.zhang@durham.ac.uk
A.3. Project Title:	Abundant information resources, equal development?
A.4. Project Funder (where appropriate):	
A.5. When do you intend to start data collection?	2018.8
A.6. When will the project finish?	2018.9
A.7. ***For students only:*** Student ID: Degree, year and module: Supervisor:	000672355 PhD Applied Social Science Dr. Matthew David Dr. Keming Yang
A.8. Brief summary of the research questions: The central question is: To what extent can using the internet for learning transform the unequal occupational mobilities between rural migrant workers and urban resident workers in urban China? It is followed by three sub questions: 1, How does using the internet for learning possibly relate to occupational mobility? 2, Do rural migrant and urban resident workers divide in the involvement of using the internet for learning? 3, In the context that urban resident workers have other advantages in the urban labour market, does using the internet for learning appear to be more helpful for rural migrant workers' career progressions?	
A.9. What data collection method/s are you intending you use, and why? I am intending to conduct semi-structural interviews to collect data. Semi-structural interview provides convenience for comparison while allows openness for new ideas to be brought up. Interviews will include questions about participants' demographical information, career history in urban labour market and experiences of using the internet for learning. The interviews will be audio recorded and transcribed.	

SECTION B: ETHICS CHECKLIST

While all subsequent sections of this form should be completed for all studies, this checklist is designed to identify those areas where more detailed information should be given. Please note: It is better to identify an area where ethical or safety issues may arise and then explain how these will be dealt with, than to ignore potential risks to participants and/or the researchers.

	Yes	No

a). Does the study involve participants who are *potentially vulnerable*[28]?	☐	√
b). Will it be necessary for participants to take part in the study without their knowledge/consent (e.g. covert observation of people in non-public places)?	☐	√
c). Could the study cause harm, discomfort, stress, anxiety or any other negative consequence beyond the risks encountered in normal life?	√	☐
d) Does the research address a *potentially sensitive topic*[29]?	☐	√
e). Will financial inducements (other than reasonable expenses and compensation for time) be offered to participants?	☐	√
f). Are steps being taken to protect anonymity and confidentiality?	√	☐
g). Are there potential risks to the researchers' health, safety and wellbeing in conducting this research beyond those experienced in the researchers' everyday life?	☐	√

SECTION C: Methods and Data Collection

C.1. Who will be your research participants?

The plan is to interview 32 individuals (including both rural migrants and urban residents, males and females) in Guangzhou, China. 16 of them started their careers as manufacturing workers (as a most typical type of manual workers) in the urban labour market and 16 of their first or earlier stage occupations in the urban labour market are white-collar workers in office settings (as a typical type of the 'intermediate' occupational levels)

	First or earlier stage job as manufacturing workers (as a typical type of manual workers)	First or earlier stage job as white-collar workers in offices (as a typical type of intermediate workers)

[28] ***Potentially vulnerable groups*** can include, for example: children and young people; those with a learning disability or cognitive impairment; those unable to give informed consent or individuals in a dependent or unequal relationship.

[29] ***Sensitive topics*** can include participants' sexual behaviour, their illegal or political behaviour, their experience of violence, their abuse or exploitation, their mental health, or their gender or ethnic status. Elite Interviews may also fall into this category.

Rural migrant workers	Male	4	4
	Female	4	4
Urban resident workers	Male	4	4
	Female	4	4

C.2. How will you recruit your participants and how will they be selected or sampled?

First, leaflets about this research project will be distributed in industrial blocks in *Panyu* district and office building blocks in *Tianhe* district in Guangzhou, China. Individuals who show an interest in this project and meet the above criteria will be shortlisted. If there are excessive candidates, I will randomly select 4 candidates for each category (e.g. male rural migrant first job manual).

C.3. How will you explain the research to the participants and gain their consent? (If consent will not be obtained, please explain why.)

The information sheet contains a short introduction (in both English and Chinese) about my research project, the process of interview and the rights of being a participant in the research project. The information sheet will be given to participants before the interviews start. Participants are required to read the information sheet and sign the consent form (to make sure they fully understand what being a participant will involve) before they agree to participate in the research project. They have the right to ask me any question if they find they fail to understand any part of the information sheet and consent form and I will answer their questions as well as make sure they have well understood everything.

C.4. What procedures are in place to ensure the anonymity and confidentiality of your participants and their responses?

All files will be stored securely on a password protected Durham University server. The audio recordings will be transcribed with anonymity. All transcripts will contain no identifiable information about participants (by removing identifiable information and ascribing pseudonyms). And after the transcription, the audio recordings will be destroyed.

C.5. Are there any circumstances in which there would be a limit or exclusion to the anonymity/confidentiality offered to participants? If so, please explain further.

No

C.6. You must attach a **participant information sheet or summary explanation** that will be given to potential participants in your research.

Within this, have you explained (in a way that is accessible to the participants):	Yes	No

a). What the research is about?	√	☐
b). Why the participants have been chosen to take part and what they will be asked to do?	√	☐
c). Any potential benefits and/or risks involved in their participation?	√	☐
d) What levels of anonymity and confidentiality will apply to the information that they share, and if there are any exceptions to these?	√	☐
e). What the data will be used for?	√	☐
f). How the data will be stored securely?	√	☐
g). How they can withdraw from the project?	√	☐
h). Who the researchers are, and how they can be contacted?	√	☐

SECTION D: Potential Risks to Participants

You should think carefully about the risks that participating in your research poses to participants. Be aware that some subjects can be sensitive for participants even if they are not dealing explicitly with a 'sensitive' topic. Please complete this section as fully as possible and continue on additional pages if necessary.

What risks to participants may arise from participating in your research?	How likely is it that these risks will actually happen?	How much harm would be caused if this risk did occur?	What measures are you putting in place to ensure this does not happen (or that if it does, the impact on participants is reduced)?
1. Risk of participants feeling unhappy when talking about their unfortunate past experiences	Somehow likely. Especially for participants from disadvantaged backgrounds who may have low self-esteem about their life situations or feel emotional when talking about some unfortunate past experiences or stories.	If this risk were to occur, they could experience short-term emotional distress.	Participants have the right not to answer specific questions, stop their interview and withdraw their information at any point during the research. They will be notified of this prior to research being undertaken. When they appear to feel uncomfortable to talk about some of their experiences, the interviewer will remind them their rights again.

SECTION E: POTENTIAL Risks to Researchers

You should think carefully about any hazards or risks to you as a researcher that will be present because of you conducting this research. Please complete this section as fully as possible and continue on additional pages if necessary. Please include an assessment of any health conditions, injuries, allergies or intolerances that may present a risk to you taking part in the proposed research activities (including any related medication used to control these), or any reasonable adjustments that may be required where a disability might otherwise prevent you from participating fully within the research.

1.Where will the research be conducted/what will be the research site?

What hazards or risks to you as a researcher may arise from conducting this research?	How likely is it that these risks will actually happen?	How much harm would be caused if this risk did happen?	What measures are being put in place to ensure this does not happen (or that if it does, the impact on researchers is reduced)?
1.			

SECTION F: Other Approvals

	Yes, document attached	Yes, documents to follow	No
a). Does the research require ethical approval from the NHS or a Social Services Authority? If so, please attach a copy of the draft form that you intend to submit, together with any accompanying documentation.	☐		√
b). Might the proposed research meet the definition of a *clinical trial*[30]? (If yes, a copy of this form must be sent to the University's Insurance Officer, Tel. 0191 334 9266, for approval, and evidence of approval must be attached before the project can start).	☐		√
c). Does the research involve working data, staff or offenders connected with the National Offender Management Service? If so, please see the guidance at https://www.gov.uk/government/organisations/national-offender-management-service/about/research and submit a copy of your proposed application to the NOMS Integrated Application System with your form.	☐		√
d). Does the project involve activities that may take place within Colleges of Durham University, including recruitment of participants via associated networks (e.g.		☐	√

[30] ***Clinical Trials:*** Research may meet the definition of a clinical trial if it involves studying the effects on participants of drugs, devices, diets, behavioural strategies such as exercise or counselling, or other 'clinical' procedures.

social media)? (If so, approval from the Head of the College/s concerned will be required after departmental approval has been granted – see guidance notes for further details)			
e). Will you be required to undertake a Disclosure and Barring Service (criminal records) check to undertake the research?	☐	☐	√
f) I confirm that travel approval has or will be sought via the online approval system at http://apps.dur.ac.uk/travel.forms for all trips during this research which meet the following criteria: For Students travelling away from the University, this applies where travel is not to their home and involves an overnight stay. For Staff travelling away from the University, this applies only when travelling to an overseas destination.	Yes √		No ☐

SECTION G: Submission Checklist and Signatures

When submitting your ethics application, you should also submit supporting documentation as follows:

Supporting Documents	Included (tick)
Fully Completed Research Ethics and Risk Assessment Form	√
Interview Guide (if using interviews)	√
Focus Group Topic Guide (if using focus groups)	
Questionnaire (if using questionnaires)	
Participant Information Sheet or Equivalent	√

Consent Form (if appropriate)	√
For students only: Written/email confirmation from all agencies involved that they agree to participate, also stating whether they require a DBS check. If confirmation is not yet available, please attach a copy of the letter that you propose to send to request this; proof of organisational consent must be forwarded to your Programme Secretary before any data is collected.	

Please indicate the reason if any documents cannot be included at this stage:

(Please note that any ethics applications submitted without sufficient supporting documentation will not be able to be assessed.)

Signatures

Researcher's Signature: Chong Zhang

Date: 2018.6.29

Supervisor's Signature (PGR students only):

Date:

Please keep a copy of your approved ethics application for your records.

If you decide to change your research significantly after receiving ethics approval, you must submit a revised ethics form along with updated supporting documentation before you can implement these changes.

Appendix A3 Consent Form

Abundant information resources, equal development?

Consent form（合意表）

Everyone who takes part in this research project is required to give their informed consent.

This means that I have a responsibility to make sure that you fully understand what being a

participant will involve for you before you agree to do so. Please therefore familiarise

yourself with the attached information sheet, and don't hesitate to ask me if you have any

questions about the research project and your involvement in it.

(Translation: 每一位参加本次研究的受访者都要在知情的情况下表示同意参与本次研究方面。这意味着在您同意参与此项目前，我有义务向你解释并保证你清楚作为本次项目的参与者所涉及的内容。请通过阅读下表内容熟悉关于本次研究的相关内容。若您对本次研究项目及作为参与者相关的内容有任何问题，您可随时咨询我。)

	Yes (是)	No (否)
I have read the information sheet and been given the opportunity to ask questions about the research project, with satisfactory responses. （Translation:我已阅读项目信息单，并已被提供机会发问任何与本研究项目相关的问题，且已获得满意的答复）		
I agree to take part in this interview. （Translation:我同意参与本次采访）		
I understand that I have the right not to answer any question I do not feel comfortable with, and that I can leave or take a break from the interview at any time. （Translation:我清楚我有权拒绝回答任何我不想回答的问题，且可选择在任何时间点停止及终止采访）		
I give my permission for the interview to be audio recorded and transcribed into text. (Translation:我允许本次采访的内容将被录音记录并转录成文本)		
I understand that the audio recordings and all data will be stored securely，then when the recordings have been		

transcribed they will be destroyed, and that any identifiable information about myself will not be included in the transcripts. All files will be stored securely on a password protected Durham University server. (Translation:我清楚录音记录及所有信息将会被妥善保存。所有录音记录在转录完毕后将会被删除。所有可识别您个人身份的信息将不会出现在转录文本中。所有档案及资料会被加密保护在大学服务器里。)		
I am aware that my name will not be used and that my identity will be kept anonymous in any publications related to this research project. (Translation:我知道我的姓名及身份信息将不会出现与本研究相关的发表作品中)		
I understand that the collected data will be used for the research purpose only. ((Translation: 我清楚所有数据只会用作研究用途)		
I understand that I am free to choose whether or not to take part in this research project, and that I am also free to withdraw from it at any point both during and after the interview has been completed. (Translation:我清楚我有权随时选择是否继续参与本研究项目、在采访中或采访后随时可退出本研究项目)		
I understand that I can keep a copy of this consent form for my records.（Translation:我清楚我有权留一份本合意表作为记录）		

Having read the information sheet and consent form, I confirm that I understand what is

required of me for this research project and that I am happy to take part.

(Translation:在确认已阅读项目信息单及合意表后，我确认我已清楚本研究需要我做的事项，且我乐意参与本项目)

Signed: ___________________________________ (Participant)

Signed: ___________________________________ (Researcher)

Date: ___ / ___ /_______

Appendix A4 Information Sheet

Abundant information resources, equal development?

Participant Information Sheet (信息单)

Thank you for agreeing to take part in my research. The interview shouldn't take more than 45 minutes, but you can leave or take a break whenever you wish.

It will form part of my doctoral research project, which is an attempt to shed light on the issue of the differentiation of occupational mobilities and its relationship to using the internet for learning. In the urban labour market, not only do rural migrant workers find it harder to achieve well-paid and stable jobs, they also face less promising prospects in career progression. Professional skills have been considered as one of the most important factors determining waged-workers' prospects in career progression. We are living in an information age that online informational resources can be acquired easily and at a low cost. Therefore, I am interested in studying to what extent can using the internet for learning transform the unequal career progression patterns between rural migrant workers and urban resident workers in urban China. Thus, I intend to conduct interviews with both rural migrant and urban citizen workers in urban China, with the purpose of hearing your experiences of using the internet for learning purpose and career trajectories in the urban labour market. The interview will also contain questions about your demographical information (age, marital status, educational background., etc.). Your views and experiences will be very helpful for broadening our understanding about occupational mobility in this information age, and inequality between rural migrant and urban resident workers in the urban labour market.

It is possible that you may not very feel comfortable to talk about some of your live or work experience in the past. Please note that you do not have to answer specific questions if you don't want to. You can also leave the interview whenever you want, and you are free to withdraw from the research project at any point both during and after the interview has been completed. There will be no repercussions to this so please just let me know if you wish to do so. The interview will be audio recorded and transcribed. After the transcription, the audio recordings will be destroyed. All transcripts will contain no identifiable information about participants (by removing identifiable information and ascribing pseudonyms). Data will be used for the research purpose only. All files will be stored securely on a password protected Durham University server. No identifiable information about yourself will be appeared in any publications related to this research project in future.

If you would like to feedback on anything after the interview, please contact me using the details below:

Researcher Name: Chong Zhang

Phone: +86 18520300634

Email: chong.zhang@durham.ac.uk

全文中文翻译(Chinese Translation)：

非常感谢您同意参与本次研究。本次采访预计会占用您不超过45分钟的时间，但您可以随时选择暂停或终止。

本次采访会成为本人博士研究项目的一部分。本人的博士研究项目尝试去阐明职业流动分化与使用互联网学习间的关系。在城镇地区劳动力市场，农村流入就业人口不仅更难获得高收入及稳定的工作机会，且他们也相对更难获取职业晋升的机会。专业知识技能常常被认为是决定就业人员职业晋升机会的一个非常重要的因素。现今，我们生活在一个能通过使用互联网非常容易获取廉价的信息资源的信息时代。于是，我感兴趣于研究在多大程度上使用互联网学习能改变农村流入务工人口与城市户口务工人口职业流动不平等的情况。因此，我希望能对农村流动务工人口与城市户口务工人口进行采访，采访的内容包括一些基本的人口信息（年龄、婚姻状况、教育程度等）、使用互联网进行学习活动的经历及工作经历。您的意见及经历将会对我们的研究会有非常大的帮助。

有可能您会觉得谈及过去的某些生活或工作经历时你会觉得不舒服。请注意您可以选择不回答任何您不想回答的问题。您可以选择在任何时间点退出采访及提出退出本次研究项目（在采访中或采访结束后任何时间点）。您的退出不会对您造成任何不良影响，当您想退出时告知我们即可。采访将会被录音，该录音将会被转录成文本。录音将会在转录完成后被删除摧毁。所有记录及信息都会被匿名处理及保护。所有档案及资料会被加密保护在大学服务器里。所有信息只会被用作本次研究用途。（通过去除涵盖个人信息的数据及化名）不会有任何可识别您个人身份的信息会被出现在转录文本及将来相关的发表作品。

若你有任何意见想反馈，请使用以下方式联系本人：

姓名：张充

电话： +86 18520300634

Email: chong.zhang@durham.ac.uk

Appendix B Interview guide

Durham University
Department of Sociology

Opening

Thanks for your coming. This research project is an attempt to study to what degree using the internet for learning can transform the unequal career progression patterns between rural migrant workers and urban resident workers in urban China. For this interview, I would like to hear your personal experiences and stories on using the internet for learning and career trajectories. I will ask you questions about your demographical information, your practices of using the internet for learning purpose, your general labour market experience and your career trajectories.

Please note: you do not have to answer specific questions if you don't want to. You can also leave the interview whenever you want, and you are free to withdraw from the research project at any point both during and after the interview has been completed. The interview will be audio recorded and transcribed. All data will be stored anonymously and be protected securely on a password protected Durham University server. The data will be used for the research purpose only.

Demographical information

Basic demographical information

Age:

Gender:

Levels of education:

Current occupation, industry and sector:

If applicable, current income level:

Marital status:

If married, partner's occupation, levels of education and current household registration type:

Current household registration (*hukou*) type, and any changes in the past?

For RMW, experiences of migration:

Here I have some simple questions about your migration experience.

Originally, where were you from and what did you do there before migration?

What did you know about here before you came here?

What are the main motivations of migration?

Lengths of time you have stayed in cities:

Do you think you have achieved what you had expected through migration?

Questions for career trajectories:

The starting point of the story:

What job (in what industry and sector) did you do when you first entered the urban labour market?

How did you know and get this job?

Why did you decide to take this job?

The changes:

Subsequently, what kinds of changes have you experienced in your career history? (That could mean changing the positions within an organisation, changing employers or job-hopping, changing the salaries, changing jobs completely, being laid off, etc).

What were the important factors/events/elements that made these changes happen? Were they (the changes) somehow related to work-related skills?

In your opinion, what kinds of changes you have experienced can be viewed as career advancement/progression? Why do you think so?

To succeed career advancement/progression (salary rise/promotion/job hopping to a better job/others according to participants' definitions), what kinds of advantages and/or difficulties did you have?

In your opinion, why did you have such advantages and/or difficulties (prompts: related to household registration status?)?

Questions for using the internet for learning

Learning activities

By saying *Learning activities*, here I refer to the activities that you engaged in with the purpose of developing work-related professional knowledge and skills. Recently, have you been involved in any learning activities? If yes, what are they/what exactly have you been doing?

The starting point of the story:

When you first entered the urban labour market, had you been engaged in any learning activities regularly and why? If yes, what exactly did you do and why did you choose to do that?

The changes:

Subsequently, what kinds of changes did you have (on your learning activities) and why did you have such changes?

The internet usage

Do you have internet access? If yes, do you use the internet regularly?

(for internet users) Currently, what do you use the internet for?

The starting point of the story:

Do you remember when did you start to use the internet in the first place?

What did you use the internet for in the beginning?

Where did you learn the skills to use the internet in such ways?

The changes:

Subsequently, what kinds of changes did you have and why you changed your internet usage habits in such ways?

(for non-users) Have you tried to use the internet before? If you have, what made you stop trying to use the internet/why you do not use the internet anymore?

Using the internet for learning

By saying **using the internet for learning,** I refer to any kinds of learning activities with the help of using the internet, for the purpose of developing work-related professional skills and knowledge.

Currently, do you regularly use the internet to help your learning about work-related professional knowledge and skills? What exactly do you do? (Prompts: Like what websites do you often go to, what kinds of digital resources do you usually look for and how, and what do you do with the acquired resources? How often?)

The starting point of the story:

When you first entered the urban labour market, had you been engaged in using the internet for learning purpose regularly and why?

If yes, what exactly did you do and why did you choose to do that (prompts: are they related to your accumulated professional knowledge and digital skill at that time?)?

The changes:

Subsequently, what kinds of changes did you have (on using the internet for learning) and why did you have such changes (prompts: are the changes related to the changes of accumulated professional knowledge and digital skill?)?

Based on your experience, to develop work-related skills, how important is the use of the internet or Information Communications Technology in general?

And to what degree is using the internet for learning purpose helpful for your promotion/salary rise/ a better job position acquisition? Why?

Appendix C Demography of participants

Table C1. Demography of the recruited participants

	Group 1: *Hukou* type	Group 2: First job as manual or non-manual in the urban labour market	Internet user	Age	Gender	Ethnicity	Education	Started to work in the urban labour market	First Job in the urban labour market	Current Job in the urban labour market
R1	Agricultural	Non-manual	Yes	32	Female	Han	Currently, Higher Vocational Education (*Dazhuan*) certificate in accounting. Specialized Senior Secondary School (*Zhongzhuan*) in pre-school education when first started to work	2004	Nursery school teacher	A departmental manager in a preschool education centre
R2	Agricultural	Manual	Yes	33	Male	Han	General Senior Secondary School	2008	Assembly line operator (Junior) in a manufacturing factory	Assembly line operator (Junior) in a manufacturing factory
R3	Agricultural	Non-manual	Yes	34	Male	Han	When first started to work, Specialized Senior Secondary School (*Zhongzhuan*) in computer science. Later, got a bachelor degree in electronic commerce	2003	Broadband salesman in a telecom company	Manager in a construction company

R4	Agricultural	Manual	Yes	30	Male	Miao	General Senior Secondary School	2008	Assembly line operator (Junior) in a manufacturing factory	Technician in a manufacturing factory
R5	Agricultural	Manual	Yes	27	Male	Han	General Senior Secondary School	2008	Assembly line operator (Junior) in a manufacturing factory	Assembly line operator (Junior) in a manufacturing factory
R6	Agricultural	Manual	Yes	30	Female	Han	Junior Secondary School	2005	Assembly line operator (Junior) in a manufacturing factory	Assembly line operator (Junior) in a manufacturing factory
R7	Agricultural	Manual	Yes	34	Female	Han	Primary School	2002	Assembly line operator (Junior) in a manufacturing factory	Assembly line operator (Junior) in a manufacturing factory
R8	Agricultural	Non-manual	Yes	26	Female	Han	Vocational Senior Secondary School	2011	Nursery school teacher	Assembly line operator (Junior) in a manufacturing factory
R9	Agricultural	Manual	Yes	24	Male	Han	Junior Secondary School	2013	Assembly line operator (Junior) in a manufacturing factory	Assembly line operator in a manufacturing factory & headhunter in a HR company
R10	Agricultural	Non-manual	Yes	29	Female	Han	Higher Vocational Education (*Dazhuan*)	2014	Sales operation officer in an online marketing company	Manager in sales operation in an online marketing company
R11	Agricultural	Non-manual	Yes	38	Female	Han	Higher Vocational Education (*Dazhuan*) in accounting	2004	Accountant	Director of finance department in a real-estate company
R12	Agricultural	Non-manual	Yes	35	Male	Han	Higher Vocational Education (*Dazhuan*) in IT	2004	Programming technician in a medical technology company	Network Director in a medical technology company
R13	Agricultural	Non-manual	Yes	34	Male	Han	Higher Vocational Education (*Dazhuan*) in logistics	2006	Clerk and operator in a logistics company	Online marketing manager in a medical technology company

R14	Agricultural	Manual	No	46	Male	Han	Junior Secondary School	2010	Logistics staff in a construction company	Logistics staff in a construction company
R15	Agricultural	Manual	No	60	Male	Han	Junior Secondary School	2018	Logistics staff in a manufacturing factory	Logistics staff in a manufacturing factory
U1	Non-agricultural	Non-manual	Yes	26	Male	Han	Bachelor degree in computer science	2014	Web developer in a tech company	Web developer (a team leader) in a tech company
U2	Non-agricultural	Manual	Yes	31	Male	Han	Higher Vocational Education (*Dazhuan*) in education	2008	Assembly line operator (Junior) in a manufacturing factory	Refurbishment worker (Self-employed)
U3	Non-agricultural	Manual	Yes	22	Male	Han	General Senior Secondary School	2014	Apprentice in a car factory	Supervisor assistant in a manufacturing factory
U4	Non-agricultural	Non-manual	Yes	29	Male	Han	Higher Vocational Education (*Dazhuan*) in administrative management	2009	Project manager in a construction company	Regional director in a construction company
U5	Non-agricultural	Non-manual	Yes	28	Male	Han	Bechalor in Law	2014	Client manager in an advertisement company	Strategy director in an advertisement company
U6	Non-agricultural	Non-manual	Yes	26	Female	Han	Master degree in finance	2015	Administrative officer in an investment group (State sector)	Researcher in finance in an investment group
U7	Non-agricultural	Non-manual	Yes	29	Male	Han	Master degree in finance	2014	Sales manager in an investment bank	Owner of a start-up company in fashion
U8	Non-agricultural	Non-manual	Yes	27	Female	Han	Bachelor degree in human resource management	2014	Labour relation assistant in a trading company	Human resource manager in a market research company
U9	Non-agricultural	Non-manual	Yes	30	Female	Han	Bachelor in English	2010	Administrative clerk in a state-own publisher (State sector)	Administrative clerk in a state-own publisher (State sector)

Appendix D Comparison of samples (before and after listwise deletion)

Appendix D offers an analysis of samples' potential biasness after listwise deletion for the quantitative analysis in Chapter 4, 5 and 6, by making a comparison on demographic and socio-economic features of the samples before and after listwise deletion. For the quantitative analysis in Chapter 4, the 2010-2014 sample has a slightly smaller of percentage of higher managerial and professional origin cases (Before listwise deletion: 14.07%; After listwise deletion: 11.83%) after listwise deletion. Apart from that, there are no other noticeable changes in demographic and socio-economic characteristics of the 2010-2014 sample after listwise deletion. The 2014-2016 and 2010-2016 samples in Chapter 4 do not show any noticeable differences in demographic and socio-economic characteristics after listwise deletion. Presumably, no serious biases are created after listwise deletion for the complete case analysis in Chapter 4. For the 2010-2014 sample used in Chapter 5 and 6, there was a slightly higher proportion of male, older and semi-unskilled manual cases after listwise deletion. For the 2014-2016 sample in Chapter 5 and 6, there was a slightly higher proportion of male, older, agricultural, low educational level, and semi-unskilled manual cases after listwise deletion. Male, older, agricultural, low educational level, and semi-unskilled manual cases might be more likely to stay in the survey overtime and provide valid information for each survey question. However, the demographic and socio-economic differences in samples before and after listwise deletion might not only be related to the pattern of missing, it could also be related to the pattern of staying active in the labour market. It could be the case that individuals with the above-mentioned attributes are less likely to quit the labour market for reasons like further education, retirement and family duties. However, the difference is small. So even if those differences are due to missing data, presumably, the differences do not contribute to significant bias for our analysis.

Table D1. Comparison on sample characteristics before and after listwise deletion (Chapter 4 analysis)

		Sample used in Chapter 4					
		2010-2014		2014-2016		2010-2016	
		Before listwise deletion	After listwise deletion	Before listwise deletion	After listwise deletion	Before listwise deletion	After listwise deletion
Gender	Female	41.71%	40.79%	41.26%	40.68%	41.71%	39.94%
	Male	58.29%	59.21%	58.74%	59.325	58.29%	60.06%
	Missing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Age	Mean	38.74	38.95	39.97	40.28	38.74	38.69
	Missing	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Hukou	Agricultural	36.41%	37.75%	45.02%	46.08%	36.41%	38.92%
	Non-agricultural	63.51%	62.25%	54.25%	53.92%	63.51%	61.08%
	Missing	0.07%	0.00%	0.75%	0	0.07%	0.00%
Ethnicity	*Han*	95.55%	96.07%	93.83%	94.80%	95.55%	95.66%
	Minority	4.27%	3.73%	5.01%	5.01%	4.27%	4.21%
	Missing	0.18%	0.20%	1.16%	0.19%	0.18%	0.13%
Educational background	*Low*	18.25%	19.53%	22.87%	23.48%	18.25%	19.16%
	Medium	55.01%	55.25%	54.21%	55.03%	55.01%	55.46%
	High	26.74%	25.22%	21.89%	21.47%	26.74%	25.38%
	Missing	0.00%	0.00%	1.03%	0.02%	0.00%	0.00%
Occupational class	Higher managerial and professional	14.07%	11.83%	8.90%	8.97%	14.07%	13.57%
	Lower managerial and professional	14.86%	15.69%	12.40%	12.26%	14.86%	14.85%
	Routine non-manual	17.70%	17.19%	16.80%	16.48%	17.70%	15.61%
	Self-employed	15.37%	14.93%	17.19%	17.17%	15.37%	16.54%
	Manual supervisor	1.80%	1.90%	2.06%	2.01%	1.80%	1.76%
	Skilled manual	14.73%	15.96%	15.76%	15.81%	14.73%	16.56%
	Semi-unskilled manual	21.46%	22.49%	26.89%	27.30%	21.46%	22.06%
	Missing	0.00%	0	0.00%	0	0.00%	0
N		5457	3035	6226	4213	5457	2733

Table D2. Comparison on sample characteristics before and after listwise deletion (Chapter 5-6 analysis)

		Sample used in Chapter 5-6			
		2010-2014		2014-2016	
		Before listwise deletion	After listwise deletion	Before listwise deletion	After listwise deletion
Gender	Female	42.96%	38.70%	41.66%	37.60%
	Male	57.04%	61.30%	58.34%	62.40%
	Missing	0.00%	0.00%	0.00%	0.00%
Age	Mean	38.51	41.70	39.50	43.31
	Missing	0.00%	0.00%	0.00%	0.00%
Hukou	Agricultural	31.07%	32.20%	41.85%	45.20%
	Non-agricultural	68.84%	67.80%	56.01%	54.80%
	Missing	0.09%	0.00%	2.13%	0.00%
Ethnicity	*Han*	95.73%	95.70%	94.34%	95.80%
	Minority	4.05%	4.30%	4.40%	4.20%
	Missing	0.22%	0.00%	1.26%	0.00%
Educational background	*Low*	15.18%	16.50%	20.31%	24.10%
	Medium	54.11%	55.60%	53.14%	53.10%
	High	30.71%	28.00%	25.43%	22.90%
	Missing	0.00%	0.00%	1.12%	0.00%
Occupational class	Higher managerial and professional	16.63%	14.20%	10.74%	9.50%
	Lower managerial and professional	17.56%	18.45%	14.97%	14.10%
	Routine non-manual	20.92%	18.20%	20.29%	17.80%
	Manual supervisor	2.12%	2.80%	2.50%	2.60%
	Skilled manual	17.41%	18.80%	19.03%	19.80%
	Semi-unskilled manual	25.37%	27.60%	32.47%	36.10%
	Missing	0.00%	0.00%	0.00%	0.00%
N		4618	2279	5156	3187

Appendix E Brand test on proportional odds assumption

Table E1. Brand test results (Chapter 7 analysis）

	2014				2016			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Variables in the model	hukou type, occupation	hukou type x occupation	hukou type, occupation, education, family income, age, gender, ethnicity	hukou type x occupation, education, family income, age, gender, ethnicity	hukou type, occupation	hukou type x occupation	hukou type, occupation, education, family income, age, gender, ethnicity	hukou type x occupation, education, family income, age, gender, ethnicity
Brant test	X^2 (df=30, *N* = 4825) = 31.61, *p = 0.386*.	X^2 (df=55, *N* = 4825) = 52.37, *p = 0.576*.	X^2 (df=70, *N* = 4825) = 230.50, *p = 0.000*.	X^2 (df=95, *N* = 4825) = 252.40, *p = 0.000*.	X^2 (df=30, *N* = 6271) = 43.34, *p = 0.055*.	X^2 (df=55, *N* = 6271) = 1242.17, *p = 0.000*.	X^2 (df=70, *N* = 6271) = 282.17, *p = 0.000*.	X^2 (df=95, *N* = 6271) = 19.93, *p = 1.000*.

Null hypothesis: the location parameters (slope coefficients) are the same across response categories

Appendix F Full regression result tables

Table F1. Linear mixed models on occupational change score

	Occupational change score					
	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Year (ref=2010-2014)						
2014-2016	-0.038	-0.018	-0.002	0.000	-0.032	0.005
	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Occupation (t-1) (ref=Higher managerial and professional)						
Lower managerial and professional	0.896***	0.895***	0.787***	0.789***	1.059***	0.916***
	(0.059)	(0.057)	(0.059)	(0.059)	(0.106)	(0.103)
Routine non-manual	1.472***	1.559***	1.514***	1.515***	1.482***	1.539***
	(0.056)	(0.055)	(0.056)	(0.056)	(0.100)	(0.097)
Manual supervisor	0.637***	0.840***	0.973***	0.982***	0.563***	0.886***
	(0.108)	(0.106)	(0.106)	(0.106)	(0.176)	(0.171)
Skilled manual	1.662***	1.915***	2.017***	2.021***	1.701***	2.047***
	(0.060)	(0.060)	(0.061)	(0.061)	(0.095)	(0.094)
Semi-unskilled manual	2.418***	2.691***	2.771***	2.776***	2.388***	2.738***
	(0.057)	(0.058)	(0.058)	(0.058)	(0.090)	(0.089)
UIL (t-1) (ref=No internet use)						
Not active	0.331***	0.173**	0.137*	0.135*	0.343*	0.109
	(0.059)	(0.058)	(0.059)	(0.059)	(0.167)	(0.162)
Somewhat active	0.496***	0.265***	0.216***	0.213***	0.586***	0.289*
	(0.047)	(0.048)	(0.050)	(0.050)	(0.125)	(0.123)
Active	0.550***	0.295***	0.241***	0.237***	0.531***	0.220*
	(0.043)	(0.044)	(0.046)	(0.046)	(0.107)	(0.106)
Interaction (ref=Higher managerial and professional x No internet use)						
Lower managerial and professional x Not active					-0.269	-0.092
					(0.218)	(0.211)
Lower managerial and professional x Somewhat active					-0.369*	-0.318*
					(0.158)	(0.152)
Lower managerial and professional x Active					-0.140	-0.119
					(0.137)	(0.133)
Routine non-manual x Not active					0.117	0.098
					(0.205)	(0.198)
Routine non-manual x Somewhat active					-0.112	-0.136
					(0.155)	(0.150)
Routine non-manual x Active					0.005	-0.011
					(0.133)	(0.129)
Manual supervisor x Not active					0.050	0.054
					(0.379)	(0.366)
Manual supervisor x Somewhat active					0.403	0.444
					(0.284)	(0.274)
Manual supervisor x					-0.067	-0.013

Active					
				(0.255)	(0.246)
Skilled manual x Not active				-0.037	0.002
				(0.206)	(0.199)
Skilled manual x Somewhat active				-0.075	-0.027
				(0.168)	(0.162)
Skilled manual x Active				-0.145	-0.124
				(0.148)	(0.143)
Semi-unskilled manual x Not active				0.001	0.045
				(0.200)	(0.193)
Semi-unskilled manual x Somewhat active				0.006	0.046
				(0.162)	(0.157)
Semi-unskilled manual x Active				0.422**	0.389**
				(0.148)	(0.143)
Non-agricultural hukou		0.154***	0.151***		0.155***
		(0.039)	(0.039)		(0.039)
Educational background (t-1) (Ref=low)					
Medium	0.402***	0.347***	0.345***		0.327***
	(0.047)	(0.049)	(0.049)		(0.049)
High	1.035***	0.876***	0.891***		0.876***
	(0.061)	(0.066)	(0.066)		(0.066)
Age (t-1)		-0.006	-0.003		-0.003
		(0.010)	(0.010)		(0.010)
Age (t-1) Squared		-0.000	-0.000		-0.000
		(0.000)	(0.000)		(0.000)
Male		-0.133***	-0.132***		-0.137***
		(0.036)	(0.036)		(0.036)
Ethnic minority		0.117	0.118		0.128
		(0.086)	(0.086)		(0.086)
Non-state-sector (t-1)		0.106**	0.107**		0.110**
		(0.038)	(0.038)		(0.038)
Industry (t-1) (ref= Agricultural, forestry, animal husbandry)					
Energy and utility		-0.201	-0.201		-0.217
		(0.237)	(0.237)		(0.237)
Manufacturing, construction, transportation, storage, postal and delivery		0.021	0.021		0.017
		(0.058)	(0.058)		(0.058)
Public sector, organization and admin		0.085	0.087		0.091
		(0.066)	(0.066)		(0.066)
Real estate, rental, commercial service and finance		0.153*	0.155*		0.151*
		(0.062)	(0.062)		(0.062)
Residential service, hotel and catering		0.266***	0.264***		0.265***
		(0.066)	(0.066)		-0.066

Retail and wholesale			0.483***	0.476***		0.480***
			(0.070)	(0.070)		(0.070)
Scientific research, education, culture, sport and recreation			0.401***	0.396***		0.396***
			(0.055)	(0.055)		(0.055)
Others			0.110	0.108		0.119
			(0.082)	(0.082)		(0.082)
Higher level credential gained at the later wave				0.276**		0.277**
				(0.100)		(0.100)
Constant	-1.747***	-2.303***	-2.197***	-2.277***	-1.765***	-2.287***
	(0.053)	(0.066)	(0.219)	(0.221)	(0.084)	(0.229)
Observations	5,466	5,466	5,466	5,466	5,466	5,466
Number of pid	3,992	3,992	3,992	3,992	3,992	3,992
sigma u	0.740	0.718	0.706	0.705	0.741	0.705
sigma e	0.763	0.763	0.763	0.762	0.759	0.758
rho	0.485	0.470	0.461	0.461	0.488	0.464
Wald Chi-square	2075	2462	2632	2642	2127	2691
df	9	11	25	26	24	41
Prob > chi2	0	0	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F2 Mixed-effects logistic regression models on downward mobility

	Downward mobility					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Year (ref=2010-2014)						
2014-2016	0.990	0.955	0.910	0.906	0.983	0.902
	(0.076)	(0.077)	(0.078)	(0.078)	(0.076)	(0.078)
Occupation (t-1) (ref=Higher managerial and professional)						
Lower managerial and professional	0.357***	0.314***	0.420***	0.419***	0.244***	0.276***
	(0.049)	(0.047)	(0.066)	(0.066)	(0.058)	(0.076)
Routine non-manual	0.177***	0.119***	0.121***	0.120***	0.191***	0.131***
	(0.030)	(0.024)	(0.026)	(0.026)	(0.046)	(0.038)
Manual supervisor	2.447***	1.683*	1.124	1.094	2.411*	1.193
	(0.569)	(0.419)	(0.296)	(0.288)	(0.990)	(0.546)
Skilled manual	0.274***	0.142***	0.092***	0.091***	0.226***	0.074***
	(0.043)	(0.028)	(0.021)	(0.021)	(0.050)	(0.022)
Semi-unskilled manual	0.035***	0.015***	0.009***	0.009***	0.036***	0.009***
	(0.008)	(0.005)	(0.003)	(0.003)	(0.010)	(0.004)
UIL (t-1) (ref=No internet use)						
Not active	0.672**	0.850	0.910	0.915	0.748	1.171
	(0.100)	(0.134)	(0.152)	(0.153)	(0.259)	(0.460)
Somewhat active	0.465***	0.672**	0.733*	0.736*	0.393***	0.611
	(0.058)	(0.088)	(0.105)	(0.105)	(0.105)	(0.185)
Active	0.499***	0.758*	0.846	0.855	0.426***	0.719
	(0.054)	(0.087)	(0.108)	(0.109)	(0.096)	(0.186)
Interaction (ref=Higher managerial and professional x No internet use)						
Lower managerial and professional x Not active					1.938	1.395

				(0.901)	(0.732)
Lower managerial and professional x Somewhat active				2.094*	2.351*
				(0.727)	(0.920)
Lower managerial and professional x Active				1.520	1.649
				(0.454)	(0.558)
Routine non-manual x Not active				0.495	0.446
				(0.238)	(0.238)
Routine non-manual x Somewhat active				0.921	0.990
				(0.334)	(0.396)
Routine non-manual x Active				0.876	0.841
				(0.267)	(0.286)
Manual supervisor x Not active				1.189	1.034
				(1.060)	(1.001)
Manual supervisor x Somewhat active				0.602	0.446
				(0.377)	(0.310)
Manual supervisor x Active				1.453	1.329
				(0.833)	(0.839)
Skilled manual x Not active				0.954	0.858
				(0.425)	(0.425)
Skilled manual x Somewhat active				1.334	1.268
				(0.499)	(0.525)
Skilled manual x Active				2.125*	2.266*
				(0.675)	(0.808)
Semi-unskilled manual x Not active				0.252+	0.237+
				(0.204)	(0.201)
Semi-unskilled manual x Somewhat active				0.400	0.404
				(0.310)	(0.325)
Semi-unskilled manual x Active				0.176+	0.184
				(0.184)	(0.195)
Non-agricultural hukou		0.654***	0.660***		0.647***
		(0.072)	(0.072)		(0.072)
Educational background (t-1) (Ref=low)					
Medium	0.445***	0.511***	0.515***		0.530***
	(0.059)	(0.071)	(0.071)		(0.074)
High	0.152***	0.225***	0.219***		0.225***
	(0.030)	(0.045)	(0.044)		(0.046)
Age (t-1)		0.994	0.987		0.990
		(0.027)	(0.027)		(0.027)
Age (t-1) Squared		1.000	1.000		1.000
		(0.000)	(0.000)		(0.000)
Male		1.447***	1.447***		1.446***
		(0.141)	(0.141)		(0.142)
Ethnic minority		0.910	0.901		0.864
		(0.211)	(0.209)		(0.202)
Non-state-sector (t-1)		0.924	0.920		0.912
		(0.098)	(0.098)		(0.098)
Industry (t-1) (ref= Agricultural, forestry, animal husbandry)					

Energy and utility			1.040	1.031		1.086
			(0.632)	(0.626)		(0.661)
Manufacturing, construction, transportation, storage, postal and delivery			0.935	0.934		0.925
			(0.162)	(0.162)		(0.162)
Public sector, organization and admin			0.814	0.806		0.782
			(0.144)	(0.142)		(0.140)
Real estate, rental, commercial service and finance			0.582**	0.579**		0.557***
			(0.101)	(0.100)		(0.097)
Residential service, hotel and catering			0.501***	0.503***		0.490***
			(0.100)	(0.100)		(0.099)
Retail and wholesale			0.231***	0.234***		0.231***
			(0.049)	(0.049)		(0.049)
Scientific research, education, culture, sport and recreation			0.368***	0.373***		0.366***
			(0.061)	(0.061)		(0.061)
Others			0.984	0.985		0.970
			(0.232)	(0.232)		(0.229)
Higher level credential gained at the later wave				0.443*		0.447*
				(0.145)		(0.148)
Constant	1.611***	5.279***	6.308**	7.597***	1.774**	8.080***
	(0.200)	(1.100)	(3.802)	(4.625)	(0.322)	(5.095)
Observations	5,466	5,466	5,466	5,466	5,466	5,466
Number of pid	3,992	3,992	3,992	3,992	3,992	3,992
sigma u	0.808	0.992	1.071	1.064	0.820	1.075
rho	0.166	0.230	0.258	0.256	0.170	0.260
Wald Chi-square	228.5	210.1	205.1	206.1	228.2	208.7
df	9	11	25	26	24	41
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F3. Mixed-effects logistic regression models on upward mobility

	Upward mobility					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Year (ref=2010-2014)						
2014-2016	0.757***	0.782**	0.771**	0.775**	0.769***	0.782**
	(0.058)	(0.062)	(0.062)	(0.063)	(0.059)	(0.063)
Occupation (t-1) (ref=Semi-unskilled manual)						
Lower managerial and professional	0.172***	0.102***	0.129***	0.129***	0.291***	0.207***
	(0.030)	(0.022)	(0.028)	(0.028)	(0.065)	(0.053)
Routine non-manual	0.460***	0.329***	0.337***	0.336***	0.549***	0.440***
	(0.056)	(0.049)	(0.051)	(0.051)	(0.090)	(0.082)
Manual supervisor	0.181***	0.141***	0.155***	0.158***	0.118***	0.100***
	(0.057)	(0.048)	(0.051)	(0.052)	(0.076)	(0.066)
Skilled manual	0.484***	0.440***	0.448***	0.450***	0.473***	0.444***

	(0.057)	(0.056)	(0.055)	(0.055)	(0.068)	(0.066)
UIL (t-1) (ref=No internet use)						
Not active	1.537**	1.285	1.198	1.199	1.541+	1.250
	(0.223)	(0.197)	(0.183)	(0.182)	(0.360)	(0.299)
Somewhat active	1.737***	1.350*	1.203	1.196	1.996**	1.445+
	(0.211)	(0.175)	(0.159)	(0.158)	(0.426)	(0.319)
Active	2.204***	1.673***	1.515***	1.505***	3.337***	2.335***
	(0.254)	(0.204)	(0.188)	(0.186)	(0.734)	(0.529)
Interaction (ref=Semi-unskilled manual x No internet use)						
Lower managerial and professional x Not active					0.490	0.496
					(0.255)	(0.261)
Lower managerial and professional x Somewhat active					0.340**	0.351**
					(0.130)	(0.137)
Lower managerial and professional x Active					0.397**	0.438*
					(0.131)	(0.148)
Routine non-manual x Not active					1.140	0.984
					(0.412)	(0.362)
Routine non-manual x Somewhat active					0.725	0.627
					(0.221)	(0.196)
Routine non-manual x Active					0.500*	0.439**
					(0.142)	(0.128)
Manual supervisor x Not active					1.003	1.015
					(1.283)	(1.305)
Manual supervisor x Somewhat active					3.653	3.871+
					(2.940)	(3.152)
Manual supervisor x Active					0.700	0.755
					(0.581)	(0.631)
Skilled manual x Not active					0.986	1.004
					(0.366)	(0.375)
Skilled manual x Somewhat active					1.168	1.128
					(0.379)	(0.369)
Skilled manual x Active					0.796	0.786
					(0.245)	(0.244)
Non-agricultural hukou			1.072	1.066		1.068
			(0.101)	(0.100)		(0.100)
Educational background (t-1) (Ref=low)						
Medium		1.630***	1.569***	1.561***		1.491***
		(0.198)	(0.187)	(0.185)		(0.177)
High		3.517***	3.185***	3.226***		3.179***
		(0.633)	(0.566)	(0.573)		(0.564)
Age (t-1)			0.990	0.997		0.998
			(0.025)	(0.025)		(0.025)
Age (t-1) Squared			1.000	1.000		1.000
			(0.000)	(0.000)		(0.000)
Male			1.043	1.050		1.024
			(0.092)	(0.092)		(0.090)
Ethnic minority			1.336	1.335		1.351

			(0.262)	(0.261)		(0.265)
Non-state-sector (t-1)			1.445***	1.449***		1.478***
			(0.143)	(0.143)		(0.147)
Industry (t-1) (ref= Agricultural, forestry, animal husbandry)						
Energy and utility			1.305	1.308		1.273
			(0.850)	(0.848)		(0.826)
Manufacturing, construction, transportation, storage, postal and delivery			0.978	0.974		0.967
			(0.141)	(0.140)		(0.139)
Public sector, organization and admin			1.410*	1.408*		1.419*
			(0.239)	(0.238)		(0.241)
Real estate, rental, commercial service and finance			0.880	0.885		0.857
			(0.144)	(0.145)		(0.141)
Residential service, hotel and catering			1.227	1.216		1.220
			(0.213)	(0.211)		(0.212)
Retail and wholesale			0.719	0.715		0.708+
			(0.149)	(0.148)		(0.147)
Scientific research, education, culture, sport and recreation			1.787***	1.769***		1.746***
			(0.256)	(0.252)		(0.249)
Others			1.481*	1.475*		1.528*
			(0.288)	(0.285)		(0.296)
Higher level credential gained at the later wave				1.764*		1.779*
				(0.454)		(0.460)
Constant	0.459***	0.320***	0.366+	0.315*	0.430***	0.292*
	(0.039)	(0.041)	(0.195)	(0.169)	(0.040)	(0.157)
Observations	4,799	4,799	4,799	4,799	4,799	4,799
Number of pid	3,634	3,634	3,634	3,634	3,634	3,634
sigma u	0.774	0.949	0.779	0.758	0.789	0.751
rho	0.154	0.215	0.156	0.149	0.159	0.146
Wald Chi-square	119.9	126.7	152	154.7	127.5	162
df	8	10	24	25	20	37
Prob > chi2	0	0	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F4. Linear mixed models on occupational change scores

	Occupational change score	
	Model 1	Model 2
Year (ref=2010-2014)		
2014-2016	-0.023	-0.002
	(0.026)	(0.027)
Occupation (t-1) (ref=Higher managerial and professional)		
Lower managerial and professional	0.893***	0.787***
	(0.058)	(0.059)
Routine non-manual	1.463***	1.513***
	(0.056)	(0.056)
Manual supervisor	0.674***	0.983***

	(0.108)	(0.106)
Skilled manual	1.714***	2.024***
	(0.060)	(0.061)
Semi-unskilled manual	2.464***	2.778***
	(0.057)	(0.058)
Non-agricultural hukou	0.317***	0.189***
	(0.046)	(0.047)
UIL (t-1) (ref=No internet use)		
Not active	0.261*	0.144
	(0.107)	(0.106)
Somewhat active	0.437***	0.204*
	(0.083)	(0.085)
Active	0.663***	0.382***
	(0.076)	(0.078)
Interaction		
Non-agricultural hukou x Not active	0.031	-0.017
	(0.127)	(0.123)
Non-agricultural hukou x Somewhat active	0.021	0.007
	(0.099)	(0.097)
Non-agricultural hukou x Active	-0.208*	-0.194*
	(0.088)	(0.087)
Educational background (t-1) (Ref=low)		
Medium		0.337***
		(0.049)
High		0.888***
		(0.066)
Age (t-1)		-0.002
		(0.010)
Age (t-1) Squared		-0.000
		(0.000)
Male		-0.132***
		(0.036)
Ethnic minority		0.118
		(0.086)
Non-state-sector (t-1)		0.108**
		(0.038)
Industry (t-1) (ref= Agricultural, forestry, animal husbandry)		
Energy and utility		-0.207
		(0.237)
Manufacturing, construction, transportation, storage, postal and delivery		0.018
		(0.058)
Public sector, organization and admin		0.087
		(0.066)
Real estate, rental, commercial service and finance		0.153*
		(0.062)
Residential service, hotel and catering		0.261***
		(0.066)
Retail and wholesale		0.479***
		(0.070)
Scientific research, education, culture, sport and recreation		0.397***
		(0.055)
Others		0.116
		(0.082)

Higher level credential gained at the later wave		0.276**
		(0.100)
Constant	-1.951***	-2.332***
	(0.060)	(0.225)
Observations	5,466	5,466
Number of pid	3,992	3,992
sigma u	0.735	0.706
sigma e	0.762	0.761
rho	0.481	0.462
Wald Chi-square	2157	2652
df	13	29
Prob > chi2	0	0

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F5. Mixed-effects logistic regression models on downward and upward mobility

	Downward		Upward	
	Model 1	Model 2	Model 1	Model 2
Year (ref=2010-2014)				
2014-2016	0.943	0.913	0.766***	0.773**
	(0.075)	(0.079)	(0.059)	(0.062)
Occupation (t-1)				
Higher managerial and professional	ref	ref	/	/
Lower managerial and professional	0.341***	0.418***	0.166***	0.130***
	(0.048)	(0.066)	(0.030)	(0.028)
Routine non-manual	0.164***	0.118***	0.444***	0.337***
	(0.029)	(0.025)	(0.056)	(0.051)
Manual supervisor	2.338***	1.095	0.175***	0.158***
	(0.567)	(0.291)	(0.056)	(0.051)
Skilled manual	0.220***	0.088***	0.480***	0.451***
	(0.038)	(0.021)	(0.057)	(0.055)
Semi-unskilled manual	0.025***	0.008***	ref	ref
	(0.007)	(0.003)		
Non-agricultural hukou	0.457***	0.548***	1.224+	1.158
	(0.059)	(0.078)	(0.135)	(0.134)
UIL (t-1) (ref=No internet use)				
Not active	0.698	0.769	1.613+	1.309
	(0.183)	(0.221)	(0.419)	(0.348)
Somewhat active	0.478***	0.670+	1.932**	1.398
	(0.102)	(0.158)	(0.391)	(0.298)
Active	0.362***	0.534**	2.510***	1.754**
	(0.073)	(0.118)	(0.476)	(0.350)
Interaction				
Non-agricultural hukou x Not active	1.072	1.315	1.613+	0.872
	(0.341)	(0.452)	(0.419)	(0.273)
Non-agricultural hukou x Somewhat active	1.065	1.167	1.932**	0.790
	(0.268)	(0.318)	(0.391)	(0.195)
Non-agricultural hukou x Active	1.733*	1.924**	2.510***	0.798
	(0.389)	(0.473)	(0.476)	(0.176)
Educational background (t-1) (Ref=low)				
Medium		0.529***		1.534***

		(0.074)		(0.183)
High		0.218***		3.220***
		(0.045)		(0.570)
Age (t-1)		0.979		1.001
		(0.027)		(0.025)
Age (t-1) Squared		1.000		1.000
		(0.000)		(0.000)
Male		1.451***		1.048
		(0.142)		(0.092)
Ethnic minority		0.900		1.342
		(0.210)		(0.262)
Non-state-sector (t-1)		0.914		1.452***
		(0.098)		(0.143)
Industry (t-1) (ref= Agricultural, forestry, animal husbandry)				
Energy and utility		1.043		1.313
		(0.637)		(0.849)
Manufacturing, construction, transportation, storage, postal and delivery		0.944		0.971
		(0.165)		(0.139)
Public sector, organization and admin		0.806		1.408*
		(0.144)		(0.237)
Real estate, rental, commercial service and finance		0.578**		0.881
		(0.101)		(0.144)
Residential service, hotel and catering		0.501***		1.205
		(0.101)		(0.209)
Retail and wholesale		0.227***		0.718
		(0.048)		(0.148)
Scientific research, education, culture, sport and recreation		0.366***		1.770***
		(0.061)		(0.252)
Others		0.958		1.494*
		(0.228)		(0.289)
Higher level credential gained at the later wave		0.438*		1.776*
		(0.144)		(0.457)
Constant	2.830***	10.027***	0.412***	0.279*
	(0.467)	(6.319)	(0.044)	(0.152)
Observations	5,466	5,466	4,799	4,799
Number of pid	3,992	3,992	3,634	3,634
sigma u	0.937	1.094	0.802	0.750
rho	0.211	0.267	0.164	0.146
Wald Chi-square	219.7	203	118.9	155.6
df	13	29	12	28
Prob > chi2	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F6. Mixed-effects logistic regression models on weekly UIL and No UIL in a whole year among all working individuals

	Weekly UIL				No UIL in a whole year			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Year (Ref=2014)								

2016	0.993	0.993	1.052	1.050	0.722***	0.721***	0.640***	0.640***
	(0.057)	(0.057)	(0.062)	(0.061)	(0.045)	(0.045)	(0.040)	(0.040)
Occupation (ref=Higher managerial and professional)								
Lower managerial and professional	0.536***	0.363***	0.736**	0.574**	2.614***	3.876***	1.741***	2.225***
	(0.056)	(0.063)	(0.076)	(0.100)	(0.336)	(0.801)	(0.215)	(0.448)
Routine non-manual	0.325***	0.361***	0.460***	0.488***	4.341***	4.030***	2.909***	3.096***
	(0.034)	(0.064)	(0.048)	(0.086)	(0.562)	(0.848)	(0.360)	(0.635)
Manual supervisor	0.296***	0.394**	0.526**	0.625	3.977***	3.888***	1.912*	2.303*
	(0.073)	(0.132)	(0.129)	(0.206)	(1.117)	(1.483)	(0.508)	(0.835)
Skilled manual	0.099***	0.092***	0.242***	0.221***	17.017***	17.874***	5.526***	6.225***
	(0.013)	(0.017)	(0.030)	(0.040)	(2.577)	(3.847)	(0.760)	(1.255)
Semi-unskilled manual	0.060***	0.050***	0.205***	0.172***	34.143***	39.105***	7.072***	8.192***
	(0.007)	(0.009)	(0.023)	(0.030)	(5.168)	(8.407)	(0.929)	(1.615)
Non-agricultural hukou	1.884***	1.560**	1.584***	1.369+	0.480***	0.579**	0.534***	0.652*
	(0.129)	(0.260)	(0.117)	(0.229)	(0.037)	(0.120)	(0.043)	(0.133)
Interaction								
Lower managerial and professional x Non-agricultural		1.873**		1.475+		0.514*		0.672
		(0.401)		(0.315)		(0.133)		(0.169)
Routine non-manual x Non-agricultural		0.862		0.922		1.105		0.907
		(0.184)		(0.196)		(0.283)		(0.225)
Manual supervisor x Non-agricultural		0.477		0.615		1.143		0.718
		(0.236)		(0.301)		(0.636)		(0.380)
Skilled manual x Non-agricultural		1.112		1.138		0.960		0.840
		(0.258)		(0.262)		(0.257)		(0.216)
Semi-unskilled manual x Non-agricultural		1.391		1.333		0.785		0.792
		(0.297)		(0.285)		(0.195)		(0.190)
Educational background (Ref=low)								
Intermediate			3.472***	3.441***			0.256***	0.257***
			(0.402)	(0.398)			(0.029)	(0.029)
High			12.243***	12.115***			0.050***	0.050***
			(1.758)	(1.738)			(0.008)	(0.008)
Family income per capita (Ref: First quartile)								
Second quartile			1.163	1.158			0.830*	0.830*

			(0.107)	(0.107)			(0.078)	(0.078)
Third quartile			1.389***	1.384***			0.677***	0.677***
			(0.129)	(0.128)			(0.065)	(0.065)
Fourth quartile			1.895***	1.891***			0.486***	0.484***
			(0.179)	(0.179)			(0.049)	(0.049)
age			0.936***	0.936***			1.108***	1.107***
			(0.003)	(0.003)			(0.005)	(0.005)
Male			1.304***	1.307***			0.752***	0.753***
			(0.090)	(0.090)			(0.056)	(0.056)
ethnicity			0.937	0.940			1.063	1.061
			(0.102)	(0.103)			(0.128)	(0.128)
Constant	0.989	1.118	1.267	1.384	0.383***	0.342***	0.112***	0.098***
	(0.099)	(0.158)	(0.293)	(0.350)	(0.046)	(0.060)	(0.029)	(0.028)
Observations	11,096	11,096	11,096	11,096	11,096	11,096	11,096	11,096
Number of pid	8,153	8,153	8,153	8,153	8,153	8,153	8,153	8,153
sigma u	1.590	1.578	1.344	1.339	2.092	2.081	1.597	1.597
rho	0.434	0.431	0.354	0.353	0.571	0.568	0.437	0.437
Wald Chi-square	730.6	739.6	901.4	904.3	742.7	748.8	902	901.6
df	7	12	15	20	7	12	15	20
Prob > chi2	0	0	0	0	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F7. Mixed-effects logistic regression models on internet adoption among all working individuals

		Internet adoption			
		Model 1	Model 2	Model 3	Model 4
Year (Ref=2014)					
	2016	4.570***	4.592***	5.568***	5.585***
		(0.417)	(0.420)	(0.541)	(0.543)
Occupation (ref=Higher managerial and professional)					
	Lower managerial and professional	0.304***	0.238***	0.524***	0.521*
		(0.058)	(0.071)	(0.088)	(0.140)
	Routine non-manual	0.316***	0.415**	0.514***	0.571*
		(0.059)	(0.125)	(0.086)	(0.158)
	Manual supervisor	0.194***	0.329*	0.464*	0.547
		(0.074)	(0.172)	(0.154)	(0.254)
	Skilled manual	0.049***	0.063***	0.212***	0.249***
		(0.010)	(0.019)	(0.037)	(0.064)
	Semi-unskilled manual	0.020***	0.019***	0.174***	0.184***
		(0.004)	(0.006)	(0.029)	(0.046)
	Non-agricultural hukou	2.130***	2.328**	2.352***	2.662***
		(0.220)	(0.727)	(0.228)	(0.760)
Interaction					
	Lower managerial and professional x Non-agricultural		1.555		1.025
			(0.591)		(0.350)
	Routine non-manual x Non-agricultural		0.658		0.849

		(0.250)		(0.291)
Manual supervisor x Non-agricultural		0.309		0.726
		(0.232)		(0.476)
Skilled manual x Non-agricultural		0.569		0.722
		(0.214)		(0.239)
Semi-unskilled manual x Non-agricultural		1.101		0.924
Lower managerial and professional x Non-agricultural		(0.387)		(0.288)
Educational background (Ref=low)				
2.educim			4.008***	4.021***
			(0.465)	(0.467)
3.educim			15.659***	15.537***
			(2.957)	(2.941)
Family income per capita (Ref: First quartile)				
2.famincomeimQ			1.398**	1.399**
			(0.145)	(0.145)
3.famincomeimQ			2.363***	2.362***
			(0.264)	(0.264)
4.famincomeimQ			4.096***	4.080***
			(0.518)	(0.516)
age			0.837***	0.837***
			(0.006)	(0.006)
Male			1.268**	1.271**
			(0.110)	(0.110)
ethnicity			0.661**	0.664**
			(0.101)	(0.101)
Constant	11.714***	10.975***	645.817***	584.619***
	(2.171)	(2.874)	(246.209)	(245.780)
Observations	11,096	11,096	11,096	11,096
Number of pid	8,153	8,153	8,153	8,153
sigma u	3.063	3.053	1.804	1.802
rho	0.740	0.739	0.497	0.497
Wald Chi-square	605.5	605.6	651.7	652.5
df	7	12	15	20
Prob > chi2	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table F8. Mixed-effects logistic regression models on weekly UIL and No UIL in a whole year among those who use the internet

	Weekly UIL				No UIL in a whole year			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Year (Ref=2014)								
2016	0.621***	0.621***	0.660***	0.659***	1.512***	1.504***	1.328***	1.326***
	(0.039)	(0.039)	(0.042)	(0.042)	(0.110)	(0.109)	(0.098)	(0.097)
Occupation (ref=Higher managerial and professional)								
Lower managerial and	0.695***	0.473***	0.822+	0.611**	1.854***	2.833***	1.525**	2.113***

professional								
	(0.072)	(0.082)	(0.086)	(0.107)	(0.251)	(0.617)	(0.209)	(0.468)
Routine non-manual	0.394***	0.404***	0.518***	0.528***	3.635***	3.911***	2.737***	3.121***
	(0.041)	(0.070)	(0.055)	(0.094)	(0.491)	(0.858)	(0.374)	(0.698)
Manual supervisor	0.384***	0.451*	0.566*	0.663	2.640**	3.312**	1.650	2.186+
	(0.097)	(0.151)	(0.145)	(0.225)	(0.808)	(1.320)	(0.507)	(0.875)
Skilled manual	0.192***	0.163***	0.312***	0.273***	7.712***	9.180***	4.291***	5.215***
	(0.024)	(0.030)	(0.039)	(0.050)	(1.200)	(2.057)	(0.656)	(1.163)
Semi-unskilled manual	0.164***	0.141***	0.297***	0.244***	10.404***	11.503***	5.034***	6.110***
	(0.020)	(0.025)	(0.035)	(0.044)	(1.594)	(2.565)	(0.739)	(1.345)
Non-agricultural hukou	1.579***	1.273	1.230**	1.019	0.593***	0.775	0.725***	0.971
	(0.109)	(0.208)	(0.095)	(0.172)	(0.047)	(0.168)	(0.064)	(0.217)
Interaction								
Lower managerial and professional x Non-agricultural		1.850**		1.596*		0.488**		0.584+
		(0.396)		(0.347)		(0.134)		(0.163)
Routine non-manual x Non-agricultural		0.972		0.974		0.885		0.816
		(0.205)		(0.208)		(0.234)		(0.219)
Manual supervisor x Non-agricultural		0.599		0.599		0.648		0.581
		(0.303)		(0.307)		(0.407)		(0.365)
Skilled manual x Non-agricultural		1.309		1.232		0.743		0.732
		(0.307)		(0.293)		(0.210)		(0.209)
Semi-unskilled manual x Non-agricultural		1.282		1.387		0.867		0.737
		(0.280)		(0.307)		(0.229)		(0.198)
Educational background (Ref=low)								
Intermediate			2.241***	2.216***			0.404***	0.406***
			(0.279)	(0.276)			(0.051)	(0.051)
High			6.706***	6.592***			0.089***	0.091***
			(1.002)	(0.983)			(0.015)	(0.016)
Family income per capita (Ref: First quartile)								
Second quartile			1.001	0.996			0.997	0.997
			(0.099)	(0.098)			(0.108)	(0.108)
Third quartile			1.042	1.036			0.986	0.988
			(0.102)	(0.101)			(0.108)	(0.108)
Fourth quartile			1.295**	1.294**			0.827+	0.821+
			(0.128)	(0.128)			(0.093)	(0.093)
Age			0.983***	0.983***			1.038***	1.038***
			(0.004)	(0.004)			(0.005)	(0.005)
Male			1.290***	1.292***			0.757***	0.759***
			(0.091)	(0.092)			(0.062)	(0.063)
ethnicity			1.009	1.012			0.914	0.912

			(0.110)	(0.110)			(0.118)	(0.117)
Constant	2.362***	2.715***	0.918	1.044	0.103***	0.088***	0.189***	0.157***
	(0.246)	(0.392)	(0.218)	(0.271)	(0.016)	(0.018)	(0.053)	(0.049)
Observations	7,236	7,236	7,236	7,236	7,236	7,236	7,236	7,236
Number of pid	5,606	5,606	5,606	5,606	5,606	5,606	5,606	5,606
sigma u	1.216	1.204	1.175	1.167	1.544	1.528	1.444	1.438
rho	0.310	0.306	0.296	0.293	0.420	0.415	0.388	0.386
Wald Chi-square	390.7	398.4	484.7	488.8	348.1	353.2	435.4	437.1
df	7	12	15	20	7	12	15	20
Prob > chi2	0	0	0	0	0	0	0	0

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

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