Essays in Applied Microeconomics and Development

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Declaration

I, Luigi Minale, confirm that:

- The work presented in this thesis is my own and it has not been presented to any other university or institution for a degree;
- Where information has been derived from other sources, I confirm that this has been indicated in the thesis;
- Chapter 2 is based on conjoint work with Nicola Mastrorocco (London School of Economics).
- Chapter 3 is based on conjoint work with Christian Dustmann (University College London) and Francesco Fasani (Queen Mary University) and Xin Meng (Australian National University).

Luigi Minale

Abstract

In my thesis I address questions in applied microeconomics within two topic areas: the first is the effect of news media on perceptions and political outcomes; the second is labour allocation and internal migration decision making in developing country settings.

In the second chapter I exploit a unique natural experiment occurred in the Italian television market - the staggered timing of the digital TV signal introduction - to study the influence of information provided by partisan news media on the perceptions individuals hold, focusing on perceptions about crime. Combining unique data on each channel's crime news coverage and prime-time viewing shares, I find that reduced exposure to crime-related news decreased concerns about crime and did so mainly for older individuals who, on average, watch more television and use alternative sources of information less frequently. I also provide evidence of potential effects on voting.

In the third chapter I study the relation between household migration decisions and the distribution of risk attitudes within a household in a rural-developing country setting. I do so by developing and testing - with data from internal migrants and their family members left behind in rural China - a household model of migration decision with heterogeneous risk preferences. Findings suggest that risk attitudes of household members other than the migrant affect not only individual migrations but also whether a household sends a migrant at all.

In the fourth chapter I analyse if and in what measure individuals and households in rural China reallocate labour across sectors in response to agricultural productivity shocks. I match panel data of individual and household labour supply histories with detailed weather information, which I use to proxy agricultural productivity. Results suggest that farming is reduced and urban sector employment increased in response to negative rainfall shocks, both along the intensive and the participation margin; that responses are heterogeneous across age; and that land tenure insecurity might partially prevent households from freely reallocating labour away from farming.

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Chapter 1

1. Introduction

In my thesis I address questions in applied microeconomics within two topic areas: the first is the role of news media in shaping perceptions and political outcomes (chapter 2); the second is household and individual decision making about internal migration and labour allocation in developing country settings (chapters 3 and 4).

The first topic relates to the growing interest economists have in understanding the influence of media on beliefs, perceptions and behaviours. As Della Vigna and Gentzkow (2010) argue, the efficiency of democratic and economic systems ultimately depends on the accuracy of individual beliefs. Yet, such accuracy is often hindered because of many reasons, among them the fact that a large share of information is provided by intermediaries – such as television, newspaper, or Internet - who might themselves have some interest in the receivers' behaviour. The **second chapter** of this thesis (based on joint work with Nicola Mastrorocco) investigates precisely the *influence on news media on beliefs and perceptions individuals hold, with a focus on crime perceptions*. We do so by focusing on the case of Italy, a country where the majority of TV channels have been under the influence of the former Prime Minister Silvio Berlusconi for more than a decade. In the first part of the chapter we document the existence of a potential bias in the number of crime news reported by the Berlusconi-influenced TV channels. We then test if individuals revise their perceptions about crime once exposure to these channels is reduced. In order to identify the causal effect, we exploit a natural experiment in the Italian television market where the introduction of the digital TV signal led to a drastic and sudden drop in the viewing shares of partisan channels. Exploiting the staggered timing of such introduction, and combining unique data on each channel's crime news coverage and prime-time viewing shares, we find that reduced exposure to crime-related news broadcast by partisan channels decreased concerns about crime. The effect is mainly driven by older individuals who, on average, watch more television and use alternative sources of information (such as internet, radio and newspapers) less frequently. Such a change in perceptions is likely to be relevant for voting behaviour. We predict that the reduction in crime concern caused by the digital introduction might induce about 3% of those aged above 65 who voted for the centre-right coalition to change their vote. This chapter contributes to the literature on persuasive communication by producing causal evidence of the impact of information provided by motivated agents (partisan media) on the beliefs and perceptions individuals hold. Further, it adds to the growing literature that looks specifically at the effects of media on voting. First, it sheds light on one of the possible mechanisms through which media can persuade voters: influencing their beliefs and perceptions about topics that are relevant in the political debate. Second, the use of unique data on viewing shares and news content of the different TV channels allows us to improve upon some existing studies in the area, by measuring the effect of exposure to media more precisely.

In the second part of the thesis I look at household and individual decision-making about migration and labour allocation in rural contexts and I do so by focusing on China.

The **third chapter** (based on joint work with Christian Dustmann, Francesco Fasani and Xin Meng) studies *the relation between household migration decisions and the distribution of risk attitudes within a household*. Although there is a growing literature suggesting that individual's own risk aversion has an impact on a wide range of individual economic decisions (such as portfolio choices, occupational choices and migration), when decisions are taken at the household level preferences of all household members might matter as well. Migration, in particular internal migration in developing countries, is a good example of such types of decisions. We develop a simple model that, allowing for heterogeneous risk preferences within the household, implies that which member migrates depends on the distribution of risk attitudes among all household members, and that the risk diversification gain to other household members may induce migrations that would not take place in an individual framework. Using unique data for China on risk attitudes of internal (rural-urban) migrants and their family members left behind, we empirically test three key implications of the model: (i) that conditional on migration gains, less risk averse individuals are more likely to migrate; (ii) that within households, the least risk averse individual is more likely to emigrate; and (iii) that across households, the most risk averse households are more likely to send migrants as long as they have at least one family member with sufficiently low risk aversion. Our results not only provide evidence that migration decisions are likely to be taken on the level of the household, but also that risk attitudes of household members other than the migrant affect not only individual migrations but also whether a household sends a migrant at all. These findings have relevant implications for the selection of migrants; in fact our household level model predicts migration that would not take place in an individual framework of migration decisions.

In the **fourth chapter** I move from studying migration as an ex-ante risk-diversification strategy to analysing *if and in what measure individuals and households in rural China reallocate labour across sectors as an ex-post response to agricultural productivity shocks*. I propose a stylised framework where households can adjust their labour allocation across sectors - namely farm, local off-farm, and urban sector - according to the realised agricultural productivity, which is observed only after some months into each period. I employ various waves of a longitudinal survey of rural households to construct a panel of individual and household labour supply histories, and match them to detailed weather information, which I use to proxy agricultural productivity. For identification I exploit the year-by-county variation in rainfalls generated by the Chinese peculiar size and climatic heterogeneity to explain within-individual (and within-household) changes in days of work as well as participation in each of the sectors. Results suggest that farming is reduced by 4% while urban sector employment is increased by almost 6% in correspondence to mild negative rainfall shocks, i.e. rainfall realisation 1 standard deviation below the long term average. Individuals increase the number of days spent working in the city along both the participation and the intensive margin. While younger individuals tend to shift labour supply from farming toward working in the city, older ones generally shift labour from farming toward local off-farm work, without leaving the home village. Finally, I study the relationship between land tenure insecurity and the decision of households to reallocate labour toward rural-urban migration. Results suggest that the elasticity of rural-urban migration to agricultural productivity in villages with high risk of land reallocation is about half the size of that in other villages.

The **fifth chapter** concludes by providing a summary of the key findings together with some directions for future research.

Chapter 2

2. Information and Crime Perceptions: Evidence from a Natural Experiment

2.1. Introduction

A recent body of empirical literature suggests that media have a significant impact on political and public policy outcomes (see, among others: Della Vigna and Kaplan, 2007; Gerber et al., 2009; Enikolopov et al., 2011; Della Vigna et al., 2012; Barone et al., 2014). Yet, little is known about the mechanisms through which media concretely manage to influence collective decisions and policies. In this paper we explore one possible channel: influencing individuals' *beliefs* and *perceptions* about topics that are salient in the political debate. Understanding the role of information provided by the media on the formation of beliefs and attitudes is relevant for outcomes that go well beyond voting. Indeed, as Della Vigna and Gentzkow (2010) argue, the efficiency of democratic and economic systems ultimately depends on the accuracy of individual beliefs. One potential threat to the accuracy of belief steams from the fact that, although people base their beliefs partly on direct observation, a large share of information is provided by intermediaries - such as television, newspapers, or Internet - who might themselves have some interest in the behaviour of the receivers. In this case the communication is defined as persuasive[1] (Della Vigna and Gentzkow, 2010) and its effect on the receiver is uncertain. In this paper we focus on a particular type of, potentially persuasive,

[1] Della Vigna and Gentzow (2010) provide a theoretical definition of *persuasive communication* and present an extensive review of the empirical literature on the subject.

communication: the one provided by news media. More precisely, we investigate the influence of *news media* on beliefs and perceptions individuals hold, and we focus on *perceptions about crime*.

We do so in the context of Italy, a country where, for over a decade, a relevant share of traditional analogue TV channels has been under the influence of Berlusconi in his dual role of media tycoon and Prime Minister[2]. We study if and to what extent individuals revise their perceptions once their exposure to news provided by this group of channels is reduced. Estimating the causal effect of the exposure to specific media on individuals' perceptions poses difficult identification issues, as people self-select into TV channels according to their news content (Durante & Knight, 2012)[3]. To tackle endogeneity we exploit a natural experiment: the staggered introduction of digital TV in Italy. Between 2008 and 2012, Italy has gradually shifted from analogue to digital TV transmission: on specific dates, which varied by region, the analogue signal was switched off and substituted with the digital one. Around the digital switch dates the number of nationally available free TV channels increased from 7 to more than 50 within days. Such a supply shock was accompanied by a drastic drop in the viewing shares of the six main traditional analogue channels (Rai and Mediaset) from 82% in June 2008 to 60% in June 2012[4], mostly in favour of the newly available digital channels. We exploit the exogenous shift in viewing shares described above to study if and to what extent individuals revise their perceptions about crime when exposure to potentially biased news is reduced.

We focus on perceptions about crime for a number of reasons. First, not only have crime perceptions been proven to be relevant for several economic outcomes[5], but also crime is at the

[2] Three channels – Rai1, Rai2 and Rai3 - constituted the bulk of the Italian public broadcasting system, which has a long tradition of alignment with the parties in government (Larcinese, 2005). Other three channels – Rete4, Canale5 and Italia1 – were privately owned by Berlusconi through his media conglomerate Mediaset. Durante and Knight (2012) provide evidence of the bias in favour of the Berlusconi's coalition (centre-right) while he was Prime Minister on five out of six of the above TV channels.

[3] One of many sources of bias is generated by the fact that individuals, for example, tend to choose those sources of information that reinforce their pre-existing beliefs. One rare example of attempt to directly test the effect of the type of media individuals are exposed to on their beliefs and attitudes is provided by Gentzkow and Shapiro (2004).

[4] Source: AUDITEL data. http://www.auditel.it

[5] Crime perceptions and victimization have been proven to be relevant for outcomes such as house prices (Buonanno and Montolio, 2013) mental health (Dustmann and Fasani, 2014) and daily routines and behaviours (Braakman, 2014; Becker and Rubinstein, 2011).

top of people's concerns in many countries, and thus often at the centre of the political debate[6]. Second, and most importantly, thanks to unique data on the number of crime news broadcast in daily news programs, we are able to document how a specific group of traditional channels systematically over report crime news compared to other channels. Finally, it exists a puzzling mismatch between individual perceptions and actual data when it comes to crime rates.

Figure 2.1 provides evidence of such mismatch for Italy where despite a decreasing (or if anything stable) trend in actual crime rates over the period 2004 to 2012 (left panel) about 80% of respondents believe that crime is on the rise (right panel)[7]. These figures seem to reveal an information problem potentially deriving from the fact that people, by having little observational experience about crime, might tend to collect a relevant share of information about it through indirect and secondary sources. Thus the providers of such information (i.e. the media) are likely to play an important role in the formation of crime perceptions.

To identify the reduced-form effect of the expansion in the number of available channels on crime perceptions we exploit a specific feature of the digital introduction: the fact that the deadlines at which the signal switched from analogue to digital varied across regions, and did so for exogenous infrastructural reasons. In this way we recover an intention to treatment (ITT) parameter and find that the increase in the number of available TV channels - and the consequent lower exposure to news broadcast by partisan ones - led individuals to revise their perceptions about crime downward. The effect is mainly driven by individuals from older cohorts. For example, among those aged above 65, we estimate that the introduction of the digital TV caused the probability of mentioning crime as among the three priority problems in the country to drop by 5.2 percentage points, or about 8 percent with respect to the average value. To rationalise the differential effect across age groups we show that, on average, older individuals watch more TV and use alternative sources of information less frequently - i.e. internet, radio and newspapers – than their younger counterparts. They were therefore likely to

[6] As Appendix Figure A 2.1 shows, people rank consistently crime among the first five (out of 15) most important perceived problems in a number of European countries. Source: Eurobarometer.

[7] The gap between actual crime rates and people's perceptions is a feature common to other countries as well. Indeed, while crime levels have been decreasing in many western countries during the last decade (see for example "The curious case of falling crime" in The Economist, July 20th, 2013) a surprisingly large share of the population believes that crime is actually increasing. Dustmann and Fasani (2014) provide similar evidence for the UK.

be more exposed to the potential bias before, to place higher weight on information coming from television and to respond more to changes in its content.

We then estimate more precisely the change in the exposure to crime news induced by the digital reform. To do so, we combine unique data on: a) the monthly amount of crime-related news reported by each TV channel during prime-time news programs; and b) the region-specific monthly viewing shares of each TV channel during prime-time news programs. We use the switch to digital signals to predict exogenous changes in the exposure to crime news induced by the policy, and estimate the effect on crime perceptions through a two-step method. We find that the digital reform induced a reduction in exposure to crime news of about 12 percent of the average value and that a 1 standard deviation decrease in exposure to crime news is associated with a 9.2 percent decrease in people's concern about crime, among those aged above 65. In this case we recover a local average treatment effect (LATE) driven by those individuals who actually "changed" channel because of the digital reform.

In the last part of the paper we try to assess whether the change in crime perceptions induced by the lower exposure to crime news might be relevant for voting behaviour. Using data from an electoral survey collected just before the introduction of digital TV, we predict that the reduction in crime concern caused by the digital reform might have induced about 3% of those aged above 65 who voted for the centre-right coalition to change their vote. Since individuals aged above 65 represent about 1 out of 4 of Italian voters (and usually show higher turnout rate), the effect we detect is likely to be relevant for electoral outcomes.

This paper contributes to the growing literature on persuasive communication in economics, and in particular to the group of studies that focus on the effect of (biased) news media on political outcomes.[8] A number of papers within this literature provide empirical evidence that (biased) media influence voting outcomes. Della Vigna and Kaplan (2007) find that the introduction of Fox News has led to a significant increase in the share of votes for the Republican Party in the U.S. 2000 election. Enikopolov et al. (2011) adopts a similar empirical strategy to show that Russian voters with access to an independent TV channel were less likely

[8] See Pratt and Stromberg (2011) for an exhaustive review of the literature on media and electoral outcomes. A number of studies have also looked at the effect of persuasive communication in other context such as: advertisement (Simester et al., 2007); non-profits organisations (Landry et al., 2006); communication directed at investors by firms or financial analysts (Engelberg and Parsons, 2009) and non-informative communication provided by leaders (Bassi and Rasul, 2014).

to vote for Putin during the 1999 national election. Finally, Barone et. al (2014) measure the impact of media bias in favour of Berlusconi on his electoral support. Similarly to us, they exploit the introduction of the digital signal and, looking at the northern region of Piedmont, show how the availability of new digital channels caused a drop in Berlusconi's voting shares in the 2010 regional elections[9]. Our study differs from the papers above because, while most of the existing literature convincingly estimates some reduced-form effect of media on voting, we shed light on one of the possible mechanisms through which such effect might take place: the manipulation of individuals' perceptions with respect to politically salient topics. In fact, the paper is one of the first in producing causal evidence of the impact of information provided by potentially motivated agents (partisan media) on the beliefs and perceptions individuals hold. Moreover, by using unique data on TV viewing shares and news content of the different channels we are able to do better than just estimating an intention to treatment effect, thus improving upon some of the existing studies in the literature.

Our paper also contributes to a broader literature interested in the effect of media (mainly television) on beliefs, attitudes and behaviours. In particular our paper is close to those studies that look at how media affect perceptions and beliefs through their content (see, among the others Gentzkow and Shapiro (2004); La Ferrara et al. (2011); Della Vigna et al. (2014); Yanagizawa (2014); Olken (2009); and Jensen and Oster (2009)[10]. We add to this literature by providing a new field of evidence about the impact of media on perceptions, and we are the first to study the influence on crime perceptions.

The rest of the chapter is organized as follows: section 2.2 presents the institutional background on Italian television market and the intensity in crime news reporting on

[9] Barone et al (2014) exploit the fact that about half of Piedmont region introduced the digital TV signal before 2010 regional elections, and compare voting outcomes across municipalities within such region. They find that after more than ten years of exposure to biased television, voters have not completely filtered out the bias. Another recent working paper investigates the effect of Berlusconi's TV on voting behaviour, yet from a different perspective. Durante et al. (2013) analyse the long-term impact of early exposure to Berlusconi's commercial TV (Mediaset) and find that municipalities with a longer history of exposure to it did show greater electoral support for Berlusconi's party. They argue that this effect could not be explained by exposure to partisan news bias (since, prior to 1985, news programs were not broadcast on Mediaset channels) but instead by the decline in social capital and the diffusion of a culture of individualism promoted by Berlusconi's TV.

[10] Gentzkow and Shapiro (2004) study the effect of media use and Anti-American sentiment in the Muslim world; La Ferrara et al. (2011) the role of soap operas in reducing fertility in Brazil; Della Vigna et al. (2014) and Yanagizawa (2014) the effect of propaganda channeled through the radio on violence, respectively in Serbia and Rwanda; Olken (2009) the effect of television on trust in Indonesia; and finally Jensen and Oster (2009) the effect of cable TV and women's status in rural India.

traditional channels; section 2.3 discusses our identification strategy and presents the natural experiment; section 2.4 introduces the data and the estimating equations; section 2.5, 2.6 and 2.7 present different sets of results; section 2.8 concludes.

2.2. Background

2.2.1. The Italian TV market

Up until 2007 - the year before the switch from analogue to digital TV signal transmission started - Italy presented a particularly concentrated television market, with only seven national channels freely available to viewers through the analogue signal. Three channels – Rai1, Rai2 and Rai3 - constituted the bulk of the Italian public broadcasting system, which has a long tradition of alignment with the parties in government (Larcinese, 2005)[11]. Other three channels – Rete4, Canale5 and Italia1 – were privately owned by Berlusconi through his media conglomerate Mediaset. Finally, there was a seventh channel - LA7 - which is private and can be considered independent from political influences[12]. Until the digital reform the Italian TV market has been a de-facto duopoly with the six main traditional channels, those referring to either Rai or Mediaset, holding about 85% of total daily viewing shares. Silvio Berlusconi, in his double role of media tycoon and Prime Minister, was in the position to influence five out of seven national channels while in government, between 2001 and 2006 and between 2008 and 2011[13]. Durante and Knight (2012) provide evidence of the bias in favour of the Berlusconi's centre-right coalition while he was Prime Minister on five out of seven of the above TV channels. As Larcinese (2005) points out "*….for having the owner of a vast broadcasting corporation as the leader of one of the electoral coalitions, Italy is probably a unique example*

[11] Larcinese (2005) well explains the historical background. Initially there were two main public channels and just in a second moment a third one was added. This created the so call "*lottizzazione"* for which the two main channels went to the government coalition (which at the time was a coalition formed by *Democrazia Cristiana* and *Partito Socialista*) and the third one went to the communist opposition.

[12] LA7, previously called TeleMontecarlo, was owned since 1999 by Telecom Italia Media Spa, a telecommunication company specialized in television production and broadcasting, advertising and other multimedia activities.

[13] Durante and Knight (2012) find evidence of bias toward the centre-right coalition in Berlusconi privately owned channels. When it comes to the three public channels, Rai 1 and Rai 2 exhibit bias toward the centre-right while that coalition is at the government, whereas Rai 3 is generally closer to the opposition.

in having such extreme selective exposure to television news[14]". Such a concentrated television market, together with the link between an important share of TV channels with a single political party makes the introduction of digital TV a unique experiment for studying the effects of a change in the news content individuals are exposed to.

2.2.2. Crime news reporting on Italian television

In this section we study the intensity of crime news reporting in Italian TV channels and in particular in the six main traditional channels (Rai + Mediaset) in comparison with others. News programs in Italy (*telegiornali*) are usually broadcast between 6:00 and 8:30PM, the time slot labelled as prime-time. They last 30 minutes and contain between 10 and 15 news items. We have data on the number of crime news items (stories) broadcast by each TV channel per month.

In Figure 2.2 we compare the monthly averages of crime related news broadcast during prime-time news programs by the six main traditional channels with the same statistic for the only independent TV channel nationally transmitted through the analogue signal (LA7) for the years from 2007 to 2013. The difference in crime reporting intensity between the two groups is striking, with the Rai and Mediaset channels reporting a number of crime related news which is on average double that reported by the independent channel LA7. One could argue that LA7 might be underreporting crime news rather than Rai and Mediaset channels over reporting them. Because LA7 has no links with any political parties we expect it to have little incentive to under or over-report crime news. Nevertheless, we address such concern by comparing the monthly averages of crime related news broadcast by the main Italian public channel (RAI 1) with that of the main TV channels in a selected number of European countries. Such data are available for Spain (TVE), the UK (BBC), France (France 2) and Germany (ARD) from year 2010 onward and are presented in Figure 2.3. The main public Italian channel (RAI 1) broadcast an average of 73 crime related news per month during the period 2010 to 2013. The number is larger for a factor that ranges between 1.7 (Spain) to 18 (Germany) with respect to the same metric in the other European countries considered. As Figure 2.3 shows, such a large difference in the amount of attention dedicated to crime by news programs on specific Italian

[14] Larcinese (2005), p.4

channels is not justified by existing differences in crime rates (measured as murder rate) across countries.

We exploit such regularity in the broadcast of crime news together with the shift in viewing shares induced by the introduction of the digital TV signal to study the effect of a reduction in the exposure to crime news on crime perceptions. In the last section of the paper, while assessing the potential implications for voting, we will discuss to what extent it is plausible to consider the high amount of crime news reported in partisan channels as a rational strategy to gain electoral payoff.

2.3. Identification: Digital Reform as a Natural Experiment

2.3.1. The Digital Reform

In 2008 Italy began introducing terrestrial digital TV. On specific deadline dates, which varied by region, the analogue signal was substituted by the digital one. Terrestrial digital TV technology enhances transmission efficiency and allowed Italian households to receive more than 50 new digital channels previously not available through the analogue signal[15]. Terrestrial digital TV has a low set-up cost (lower than cable or satellite TV) as it uses existing analogue infrastructures. In order to receive the newly available digital channels people needed a specific *decoder* (similar to a modem). The price of such decoders was 50 euros, and its cost was 100% subsidized by the government through vouchers. The switch over was initiated in 2006 by the centre-left government as per a compulsory European Union Directive (2007/65/EC). Indeed many other European countries have gone through the same technological change, and switched-over from analogue to digital TV signal during the last decade. What is peculiar in the Italian case is that the deadlines to switch off differed across regions, allowing us to analyse the effect of the policy using a difference-in-difference type of strategy. Identification relies on the exogeneity of such switch-off deadlines, after conditioning on region fixed effects, time fixed effects and time varying region characteristics.

[15] E-media Institute, DGTVi

Area-specific deadlines were based on similarity of 1950s infrastructures and could not be manipulated by local politicians or interest groups once set[16]. Italy was divided into sixteen areas, to each of which a precise date for the switch off of the analogue signal was assigned. The switch over for the entire country was completed over 4 years from November 2008 to June 2012 (Appendix Figure A 2.2). To test the orthogonally of switch-off deadlines to regional characteristics we perform a balancing test and compare two groups of regions: *early* switchers (those that passed to digital before or at December 2009) and *late* switchers (those that passed to digital from January 2010 onwards). Table 2.1 shows that *late* and *early* switcher regions are similar in dimensions such as unemployment and employment rates, GDP per capita, share of tertiary educated, of immigrant residents and of internet users, persons cited for crimes and murder rates per 100,000 people, suggesting that area-specific deadlines seem to be largely idiosyncratic to the purpose of our analysis.

2.3.2. The induced change in TV viewing shares and in exposure to biased news

Treatment induced by the digital reform. The switch from analogue to digital TV signal caused an unprecedented increase in the offer of channels. Such increase was accompanied by a drastic drop in the viewing shares of the six traditional channels (Rai + Mediaset) mainly in favor of the newly available digital ones. The viewing shares during prime-time (the period between 6:00 and 8:30 pm when most news programs are aired) of the six main traditional channels went down from about 82% in June 2008 to 60% in June 2012[17]. At the same time, viewing shares of the new digital channels jumped from 2% to 17% (see Figure 2.4). Because the two platforms are characterized by different intensities of crime news reporting, such shift generates arguably exogenous variation in exposure to crime news. As shown above, the six main traditional channels broadcast higher number of crime related news than that broadcast by independent Italian TV channel and by most important channels in main European countries. On top of that, as we will show below, even among the six traditional channels,

[16] Please refer here for the EU directive legislation summary and here for the official Italian Law on the introduction of digital television

[17] We focus on prime-time, as we are interested in capturing the time of the day when most news programs are aired but, as we will show later, the drop in the viewing shares of traditional channels shares is homogeneous across all time slots during the day.

those characterized by higher crime news reporting intensity are those that lost relatively more viewing shares because of the Digital Reform.

Ultimately, for those who reacted to the introduction of digital TV by "changing" channel from traditional analogue channels to the new digital ones, we can think of two alternative possibilities. The first is to switch from news programs on traditional channels to news programs on digital ones. In this case people would now be exposed to a different (it could be lower or higher) amount of crime news. The second possibility is to switch from news programs on traditional channels to full-entertainment programs on digital ones. In this case, people would not receive any information about crime through that specific channel anymore and the exposure to potentially biased news is reduced. Data about the content of new digital channels indicate that the latter case is indeed most common. Figure 2.5 plots the increase in the viewing share of new digital channels, split into those that broadcast some news programs (News Channels) and those that are full-entertainment (Other Channels). About 95% of the viewing shares of new digital channels are of channels that do not broadcast news at all[18]. As Figure 2.6 shows the most common programs broadcast by digital channels are TV-shows, movies and programs for kids, and to a lower extent sport programs, educational/history programs and life-style programs.

Importantly for our analysis, as we show in detail in the Appendix, the switch to digital signal did not induce any change in the total amount of time spent by people watching television (see Table A 2.1). Thus, people did not watch more or less television in response to the digital reform; instead they simply switched from some channels to others. We therefore can conduct our analysis without worrying about possible substitution effects between TV watching time and other alternative activities being possibly contaminating the results.

In the next paragraphs we will show how the shift in viewing shares is clearly triggered by the new technology introduction and takes place precisely in correspondence of the region-specific switch-off deadlines, thus providing evidence of its exogeneity.

[18] Such data confirm the descriptive evidence presented by Barone et al. (2014) who also show that the vast majority of people watching digital TV channels in Italy sort themselves into full-entertainment programs.

Descriptive evidence. In order to further support the effectiveness of our identification strategy, we would like to observe jumps in the region-specific shares of the six main traditional and new digital channels in correspondence with the region-specific switch-off deadlines. Figure 2.7 plots the evolution of prime-time viewing shares, for respectively the six main traditional and new digital channels, in selected regions around switch-off dates. The plotted regions are Campania (switch-off deadline December 2009), Lombardy (switch-off deadline October 2010), Umbria (switch-off deadline November 2011) and Sicily (switch-off deadline June 2012). For all of them it is possible to observe a large and sudden increase (decrease) in the viewing shares of new digital channels (traditional analogue channels) in precise correspondence with the deadlines to switch off the analogue signal (indicated by the vertical dashed lines). To better show the variation we exploit in our empirical exercise, Figure 2.8 plots the evolution of the prime-time viewing shares of new digital channels in two pairs of neighbouring regions that switched off the analogue signal at different times. In Panel A we compare Campania with Calabria (in the south) while in panel B Emilia Romagna with Tuscany (in the center-north). Focusing on Panel A, the trend in digital channels viewing shares is remarkably similar before November 2009, when none of the two regions had switched off yet, and after May 2012, when both regions have already switched to the digital signal. In between switch-off deadlines (indicated by the dashed vertical lines) individuals who happened to live in either of the two neighbouring regions have been exposed to a different mix of TV channels. We exploit precisely such differential exposure, which we argue is as good as random.

Evidence from regression analysis. In order to provide a more systematic evidence of the effect of the digital introduction on TV watching behaviour we make use of unique data on TV viewing shares collected for each channel at the month by region level and estimate the TV viewing share during prime-time for various groups of channels (labelled as c) in region r and month t as a function of the introduction of digital signal as follows:

$$Share^{c}_{rt} = \gamma_0 + \gamma_1 Digital\_Switch_{rt} + \gamma_r + \lambda_t + u_{rt} \qquad (1)$$

We group channels into four groups: main traditional channels (RAI + Mediaset), New Digital Channels, Satellite Channels and Residual Channels[19]. In equation (1) above $Digital\_Switch_{rt}$ is an indicator for the region having switched to digital signal in month t or before, while γ_r and λ_t are region and time fixed effects respectively. Panel A of Table 2.2 reports estimates from equation (1) for the group of main traditional channels. The switch-over induces a decrease in the viewing shares of these channels between 8.1 and 8.7 percentage points, depending on the specification. This corresponds to more than a 10% decrease on the baseline value. In Panel B, C and D we look at viewing shares of New Digital, Satellite, and Residual Channels respectively. The switch-over is associated with an increase in the viewing shares of New Digital channels that ranges between 6.2 and 7.2 percentage points depending on the specification, while, as expected, has only a tiny positive effect on the viewing shares of Satellite and Residual Channels. In the table we deal in different ways with the potential confounding effect due to time trends by including linear time trends (column 1), year fixed effects (column 2), month*year fixed effects (column 3) and month*year plus region-specific linear trends (column 4). The switch to digital signal is very powerful in predicting values of TV viewing shares with an F-stat equal to 89.9 and 110.8 in our most restrictive specification (column 4) for respectively viewing shares of main traditional and new digital channels.

Viewing shares during slots other than prime-time. Although most of the news programs are aired during prime-time (between 6:00 and 8:30pm), some news are also broadcast during other time of the day, for example at lunch-time: between 12:00 and 15:00. One concern is that people might watch fewer news programs on traditional analogue channels during prime-time, but more of them during other times of the day. Such substitution across time-slots could potentially offset the decrease in crime news exposure measured during prime-time. It is therefore important to test whether TV viewing shares during other times of the day responded to the switch-over in the same way as they did during prime-time. Table A 2.2 presents estimates where we replicate, for all other time-slots available and for the entire day, the same exercise as in Table 2.2. Reassuringly, the effect of the switch-over on the viewing shares of traditional analogue channels (negative effect) and on new digital ones (positive effect) goes in

[19] Satellite Channels are pay-per-view ones to which terrestrial digital TV does not automatically provide access. The forth group, Residual Channels, include other digital and satellite channels whose viewing shares are not recorded individually, as well as some minor local channels.

the same direction in all and every time slot and estimates for all of them are very similar to those we found for prime-time.

2.4. Data and Estimating Equation

2.4.1. Data

To conduct our empirical analysis we draw on various sources of data.

Individual perceptions of crime. Our primary data source is the Multipurpose Household Survey, collected yearly by the Italian National Statistical Agency (ISTAT). One of its several modules gathers information about individual and household daily life[20]. The survey is carried out yearly (around March) and is a repeated-cross section representative at the regional level of the entire Italian population. In addition to the usual demographic, labour market, and education information, the survey asks a set of questions about the use of TV, Internet and radio, as well as about beliefs and perceptions regarding a number of issues. From this survey, we employ two measures of perceptions about crime. The first is the answer to the question that asks "*What do you think are the priority problems of the country*?". Respondents can choose three topics from the following list of ten: unemployment, crime, tax evasion, environment/pollution, public debt, inefficiency of health sector, inefficiency of school sector, inefficiency of judicial sector, immigration, poverty, others. Individuals are free to mention fewer than, but no more than three topics. We construct an indicator variable for the individuals reporting crime as one of the three priority problems in Italy and we call it *Crime_Concern*. This variable captures individuals' concern about crime, or, in other words, the level of salience of crime as a priority problem to be tackled at the national level. In our estimating sample 57% of individuals report crime as being among the three priority problems in Italy, making crime the second most reported problem after unemployment (mentioned by 72% of individuals) throughout the entire period. The average of *Crime_Concern* by sub-group of population, alongside other descriptive statistics for our main estimating sample, is reported in Appendix Table A 2.3. The share of people particularly concerned about crime is higher among those aged above 65 than among those aged 65 or less, and is equal to 62 and 55

[20] The module is called Aspects of Daily Life. http://siqual.istat.it/SIQual/visualizza.do?id=0058000

percent respectively. The survey contains a second measure of crime perception, which derives from the question "*What level of crime risk does your area of residence present?"*. Respondents can choose from four categories that range from "absent" to "very high". We therefore construct a categorical variable that goes from 1 to 4 and is increasing in the perceived level of crime in the area of residence and call it *Crime_Risk_Local*. This variable is less suited to our purpose as a) it refers only to the local area while we are interested in attitudes toward crime at the national level, and b) it is reported only at the household level. However, the question, unlike the previous one, has also been asked in year 2011 and 2012.

TV viewing shares. To measure the shift in audience shares induced by the digital reform we gathered unique data about monthly, region-specific, viewing shares for each TV channel available from year 2007 until 2013. The data have been extracted from the official Auditel[21] dataset. Auditel is an independent third party agency responsible for television audience measurement in Italy. Viewing shares data are based on a sample of about 5200 households and 14000 individuals that is representative at the regional level of the entire Italian population[22]. We have information about viewing shares for five different time slots during the day: slot1, from 07:00 to 11:59; slot2, from 12:00 to 14:59; slot3, from 15:00 to 17:59; slot4 (prime-time) from 18:00 to 21:30 and slot5, from 20:31 to 24:00.

Crime related TV news items. To measure the number of crime news items reported by each TV channel we use data on primetime newscasts collected by the "Pavia Observatory". The Pavia Observatory is an independent research institute specializing in media analysis that works in collaboration with the University of Pavia. We obtained data on the monthly number of crime-related news items broadcast during prime-time news programs for each one of the main traditional TV channels and some others, from 2007 until 2013.

Crime committed and other control variables. Data about the number of crime committed in each region by month and type of crime have been provided by the Italian Home Office Ministry. Crimes are split into the following categories: violent and drug related crimes,

[21] http://www.auditel.it
[22] More information on Auditel procedure is available at http://www.auditel.it/come-lavora/. Auditel has selected a sample of 20000 households. Every year they conduct a face to face interview with each of them to check the type of technology they use (Satellite, DG, DVD, etc) and they install the so called *people meter*. The *meter* is based on the advanced technology Unitam / CTS (content tracking system) and collects data everyday on the number of TV minutes watching per all the existing channels.

property crimes, and other types of crimes. A number of regional level time varying characteristics, such as employment and unemployment rate, GDP per capita, share of tertiary educated, and age structure, are provided by the Italian National Institute of Statistics (ISTAT).

2.4.2. Estimating Equation

In this section we present our empirical strategy to estimate the reduced-form effect of the increase in the number of available TV channels on individual perceptions about crime. In order to identify the intention to treatment effect (ITT), i.e. the effect of the switch-over from analogue to digital TV signal and the subsequent increase in number of available channels, we exploit region specific idiosyncratic deadlines to switch and implement a difference-in-difference design that compares crime perceptions of individuals within the same region, before and after the switch to digital signal occurred. More formally, we estimate various versions of the following linear probability model:

$$Crime\_Concern_{irt} = \alpha_0 + \alpha_1 Crime_{rt} + \alpha_2 Digital\_Switch_{rt} + \boldsymbol{X}'_{irt}\delta + \boldsymbol{Z}'_{rt} + \gamma_r + \lambda_t + \varepsilon_{irt} \quad (2)$$

where i indexes individuals, r regions and t time periods. The variable $Crime\_Concern_{irt}$ is an indicator for the individual mentioning crime among the three priority problems in the country. $Digital\_Switch_{rt}$ is a dummy that equals 1 if region r experienced the switch-off to digital signal at time (year) t or before. The switch-off might occur at any point in time during the year previous to the annual household survey collected in March. Indeed, switching to digital TV just one month before the survey is likely to induce different treatment than switching 11 months before it, as the share of time between two surveys during which individuals have access to more TV channels differs. In order to take such heterogeneity in (intention to) treatment intensity into account we also consider an alternative measure for *Digital_Switch*, which is the fraction of months (over the 12 previous to each annual survey) after the switch-off occurred. The coefficient of interest is α_2, which captures the impact of the increase in available TV channels on individual crime perceptions. For our purpose it is crucial to control for region-specific crime rates that are likely to be an important determinant of crime perceptions. $Crime_{rt}$ is the (log) crime rate, defined as number of crimes over 10’000 population, in region r during the calendar year previous to the collection of year t survey.

The coefficient on crime rates is of interest on its own as it will tell us whether, and to what extent, crime perceptions respond to actual crime rates. Vector $\mathbf{X'}_{irt}$ denotes a set of individual and household level characteristics including gender, age, age squared, marital status, education, set of dummies of occupational status, family size, family structure, and major source of household income. Vector $\mathrm{Z'}_{\mathrm{rt}}$ includes a series of region time-varying covariates that might affect crime perception directly or indirectly, such as unemployment rate, GDP per capita, share of population with tertiary education, and share of immigrants. The γ_r are region fixed effects meant to capture any unobserved time-invariant characteristics that affect crime perceptions and may also be correlated with the timing of the switch-over to digital TV. The λ_t are year fixed effects meant to allow for very flexible trend in crime perception common to all regions. Finally, ε_{irt} is an idiosyncratic error term. Our identifying assumption is that, conditional on region and year fixed effects and on the time-varying controls, the timing of the switch-over to digital TV is orthogonal to the error term. We will attempt to test the plausibility of this assumption in the reminder of the paper. Finally, throughout the empirical analysis, we cluster standard errors at the region level to allow for an arbitrary correlation of residuals within regions.

After having estimated the reduced-form effect of the digital TV introduction on crime perceptions, we will attempt to get a more precise estimate of the relationship between exposure to crime news and crime perceptions. To do so we will make use of unique data on TV news content and measure the effect of the switch-over on the exposure of individuals to crime news.

2.5. The Effect of the Digital Reform on Crime Perceptions

2.5.1. Estimates

Overall effect. Here we discuss results from the estimation of the reduced form effect of the switch-over to digital TV on individual crime perceptions. Table 2.3 summarizes the results from our estimation of equation (2): a linear probability model of *Crime_Concern* on a post switch-over indicator *Digital_Switch* and controls. *Crime_Concern* is an indicator for the individual reporting crime as being among the three priority problems in the country at the moment of the survey. The coefficient on *Digital_Switch*, an indicator taking value 1 if the region has switched-off in period t or before, captures the effect of the increase in the number of available TV channels on crime perceptions. When we look at the effect on the overall population (column 1) we find a negative coefficient, suggesting that the Digital Reform induced a lower concern about crime. The coefficient is not statistically significant though. However, we do not expect all groups of the population to a) be exposed in the same way to the pre-existing bias, and b) to respond in the same way to the partial removal of it. Indeed, individuals of different cohorts are likely to gather information from different combinations of media; for example, older individuals are likely to rely more on television and less on new technologies such as internet, as we will show in more detail later.

Heterogeneity of the effect across age groups. We therefore turn and study the heterogeneous effect of the Digital Reform for five different age groups of the population (results reported in column 2). We do so by interacting *Digital_Switch* with a set of five age group indicators. While estimates for individuals below age 41 are equal to zero, they are negative for older individuals. Estimates get larger as we move from younger to older groups and are significantly different from zero at conventional levels for the group formed by individuals above age 65. These results suggest that elderly individuals' crime perceptions respond more to the decreased exposure to potentially biased news programs broadcast by the six main traditional TV channels. We will investigate the possible reasons for this result in the reminder of this section.

New specification: accounting for the length of treatment. From column 3 onward we employ a more precise version of *Digital_Switch:* the share of months the region has spent under the new digital regime during the year previous to the survey. Such specification takes into account the length of the (intention to) treatment we are interested in. Our estimates (all negative) get larger, and are now significant also for the second oldest group of individuals, those aged 52-65. The fact that when we account for the intensity of the treatment estimates are larger suggests that in our empirical analysis we are not likely to be picking up just some spurious correlation between year of switch-off and changes in crime perceptions. We consider this specification more appropriate to the purpose of our analysis and will use it from this point forward.

Robustness of estimates and magnitude of the effect. The coefficients are very stable across specifications, suggesting that the introduction of digital TV is not correlated with any individual characteristic (included from column 4) or region time-varying characteristics (included from column 5). In Column 5 and 6 we also add region-specific crime rates that, very importantly, do not affect the estimates on the *Digital_Switch*. It is interesting to note that crime perceptions respond to actual crime rates, but only to specific crime categories; column 6 shows that people become more concerned about crime only when violent and drug related crimes increase, while property crimes and other crimes do not seem to affect individual concerns in any significant way. In our most complete specification the increase in TV channels, or better, having access for the entire pre-survey year to an increased number of TV channels, is associated with a statistically significant decrease in crime concern for individuals aged above 51. The effect estimated is economically relevant: if we focus on the older group of individuals, those aged above 65, the digital reform is associated with a decrease in the probability of reporting crime as one of three priority problems of 5.2 percentage points, corresponding to about 8.4 percent change with respect to the average probability for that specific age group (equal to 0.62). These results are consistent with the increase in the number of channels available - and the induced lower exposure to partisan ones over-reporting crime news - leading individuals to revise their crime perceptions downward.

Estimates of the group-specific *Digital_Switch* coefficients from the most complete specification (column 6) together with 90% confidence intervals are also plotted in Figure 2.9. The figure shows clearly how the effect of the reform gets larger as we move from left to right of the age distribution. In Figure 2.10 we also report estimates from regressions of the type in column 6 but estimated separately for males and females. Among females the effect is negative and statistically significant for those aged above 40 and gets more precisely estimated as age increases. The effect is negative and significant for males above age 65. As for interpreting the coefficients, for females aged above 65 the switch-off is associated with a decrease in the probability of reporting crime as priority problem of 3 percentage points, which represents a decrease of about 5 percent with respect to the average probability for that specific group of individuals. Similarly the effect of the switch-off on males above age 65 corresponds to a decrease of about 6.5 percent on their average probability[23].

2.5.2. Interpreting heterogeneous effects across age groups

TV watching time. The increase in the number of available TV channels, and the induced lower exposure to partisan ones over-reporting crime news, led to a decrease in the share of people who consider crime as a priority problem, particularly among older cohorts. Why do elderly people revise their perceptions more than other groups? One possible reason is that elderly individuals were more exposed to potentially biased traditional channels before the introduction of digital TV. Figure 2.11 shows the average daily TV watching time for individuals in our estimating sample, by gender and along the distribution of age. TV watching time is lowest for individuals between 25 and 45, when people are in the middle of their labour market participation. Then it starts increasing around age 40-50, in correspondence with the age group from which the reduced-form coefficients become negative and increasingly significant. Females tend to watch more TV than males, and this is true at almost every age. On average, individuals aged 65 watch TV for almost 3.5 hours per day, while individuals aged 35 do so for little more than 2 hours. By watching more television elderly individuals were more likely to be exposed to news programs in partisan channels before the introduction of the digital signal and this could be a reason why they revised their perceptions to a higher extent. The stronger response for the group of elderly individuals confirms findings from previous studies (for example Barone et al., 2014) that while looking at the effect of media on voting also found a stronger effects in town with higher share of elderly individuals.

Differential access to other sources of information. Television is not the only source of information people use; indeed we expect the access to other media to matter as well. Let us suppose that individuals collect information about the level and the salience of crime from two main different sources: direct observation and indirect channels, such as television, Internet, newspapers and the radio. We can think of individuals using a simple Bayes rule to update their perceptions once a new piece of information is received, and to do so according to the weight they attribute to the source of such information. If many sources of information are

[23] Average probability of reporting crime as a major problem is 0.62 and 0.61 for female and males respectively above age 65.

available each one will have little weight and contribute only marginally to the update of perceptions. Hence, we can expect the weight attached to information coming from television to be higher for individuals who have only limited access to other sources. To explore this hypothesis we examine data available for our estimating sample about the use of Internet, radio and newspapers. Individuals aged above 65 use information sources other than TV much less frequently in comparison with individuals aged below 65 **(**Figure 2.12**)**. More precisely, 94% of those aged above 65 have never used the Internet, 50% do not read any newspaper, and 63% never listen to the radio. On the contrary, among individuals below age 65 such shares are much lower: 39% have never used the Internet, 36% do not read any newspaper, and 29% never listen to the radio. Thus, older individuals appear to have a much less diverse set of sources from which they gather indirect information and the prominence of one single source could reveal why in their case changes in the content of television are more strongly reflected into changes in perceptions.

Effect on concerns about other topics. If elderly individuals are less concerned about crime after the introduction of digital TV, we might be interested in knowing what problems have substituted crime as priorities in their opinion[24]. We therefore look at the effect of the digital introduction on the likelihood of mentioning any of the other problems suggested by the question *"What do you think are the 3 priority problems of the country?"*, and there are nine of them apart from crime. The Appendix Table A 2.4 reports estimates for individuals aged above 65 of the effect of the switch-over for each of the other topics plus crime. In the table, problems are ranked from left to right from the most (unemployment) to the least mentioned (inefficiency of education system). The lower concern about crime seems to be compensated for by higher concern about most of the other problems, such as poverty, tax evasion, inefficiency of health sector, inefficiency of judicial system and public debt. However, estimates are statistically significant at conventional level only for inefficiency of health sector and judicial system though. The introduction of digital TV is also associated with lower concern about unemployment, but standard errors are quite large.

[24] Our outcome variable is a relative measure of concern as people are asked to report the three priority problems. Given such relative nature we are not able to test whether the increase in TV channels, and the consequent lower exposure to Berlusconi-influenced news programs, induced a lower general concern about every problem.

2.5.3. Further robustness checks

Effect of switch-over on unemployment and crime. The first robustness check we perform is to test if, in correspondence with the switch-off deadlines, regions have experienced changes in economic outcomes that are themselves relevant for crime perceptions. We test such hypothesis by estimating, in a similar fashion as above, the effect of the Digital Reform on unemployment and crime rates. The unit of observation is the region*year. Estimates suggest (Table A 2.5) that the Digital Reform is not statistically significantly associated with any change in unemployment or crime rates at the regional level, regardless of whether we use a specification with an indicator for Digital_Switch (columns 1 and 3) or the share of months (columns 2 and 4). In the case of unemployment share estimates even change signs when adopting the share of months as explanatory variable.

Effect of switch-over on individuals not watching TV. Some individuals in our sample do not watch TV at all. We should expect not to find any effect of the introduction of digital TV on them. As a robustness check we thus estimate the same reduced-form regressions presented in Table 3 on the sample of those individuals who report not to watch TV at all, i.e. about 5% of the total. This exercise is only valid under the assumption that these people did not pass from not watching TV to watching it (and vice versa) in response to the digital TV introduction. The Appendix Table A 2.6 reports results from such exercise, estimates on *Digital_Switch* are small and never significant (for any of the five age groups) across all the four specifications.

Timing of the switch-over effect: perceptions about local level crime. We now run a placebo test to check if we can detect any effect of the switch to digital signal before it actually occurred. To do so we employ the second measure of crime perceptions included in our dataset that refers to the level of crime risk in the area of residence. The questionnaire asks to rate the risk of crime in the local area of residence on a scale from 1 to 4 (highest level of crime) and we use answers to such question to construct a measure of perception of the level of crime in the local area called *Crime_Risk_Local.* Such variable is only reported at the household level but is available until year 2012 enabling us to look at the effect of the increase in the number of TV channels available also 1, 2 and 3 years after the switch-off. Exploiting the fact that different regions switched from analogic to digital TV transmission at different points in time between 2008 and 2012 we are able to run a regression with both lags and leads of the switch-off year indicator. The estimated leads and lags running from two years prior to two years after the switch-off are plotted in Appendix Figure A 2.3. Estimates show no effect of the switch-off before it actually occurred and such result is reassuring. They start to become negative right after the switch-off, and keep decreasing with time (becoming statistically significant two years after it). This might be an indication of individuals adjusting their viewing behavior gradually. Furthermore, it could be that perceptions about the level of local crime might take longer to adjust. Perhaps because individuals put larger weight on direct information when forming their perceptions about the crime level in the local area, while relying more on secondary sources of information, such as television, when forming perceptions at the national level.

Strategic editorial response to the change in market shares. The interpretation of our results would be hindered if the amount of crime news items broadcast by Berlusconi-influenced media changed with the introduction of digital television. This would be the case if the editors of news programs responded to the change in the television market's structure by strategically increasing or decreasing the amount of crime stories reported. To explore such possibility we plot (Appendix Figure A 2.4) the average number of crime news reported on channels directly owned by Berlusconi against the viewing shares of new digital channels, from 2007 until the end of 2012. Despite the significant increase in digital channels viewing shares (dashed blue line), the amount of crime news reported in Berlusconi's channels (red line) fluctuates around an average of about 100, and does not show any clear trend during the period. In particular, the number of crime news reported does not seem to change in any systematic way in correspondence with the various waves when the digital signal is introduced (indicated in the figure by the grey shaded areas).

2.6. Assessing the Effect of Crime News Exposure on Perceptions

Our reduced-form estimates indicate that (older) individuals tend to revise their concern about crime downward once they less exposed to news programs in partisan TV channels that are likely to over report crime news. In this section we try to measure to what extend such reduced-form effect can be linked to the change in crime news exposure induced by it. In other words, we now attempt to answer to the question about what happens to people's concern about crime when we vary the amount of crime news they are exposed to. As discussed earlier, in our setting the decrease (increase) in exposure to crime news comes also together with the decrease (increase) in exposure to other types of news, and with an increase (decrease) in exposure to full-entertainment contents. Therefore our measure of exposure to crime news will naturally capture those additional elements as well.

2.6.1. Measuring exposure to crime news

The first step toward estimating the effect of the amount of crime news on crime perceptions is to construct a measure of individual *exposure to crime news.* To do so, we combine unique data on: a) region-specific monthly viewing shares of each TV channel during prime-time news programs; and b) the monthly amount of crime-related news items reported by each TV channel during prime-time news programs. With these two pieces of information we construct the following region*time specific measure of *exposure to crime news*:

$$\sum_{c=1}^{C} CrimeNews_t^c * Share_{rt}^c$$

where $\mathrm{CrimeNews}_t^c$ represents the number of crime news items reported during prime-time news programs on channel c during period t; while Share_{rt}^c is the prime-time viewing share of channel c in region r during period t. The measure, that we call *Crime_News_Exposure,* is the summation, over all TV channels, of the number of crime news items broadcast during the period t weighted by the region-specific viewing share in the region r during the period t. This weighted average delivers us the actual number of crime news items the average individual who lives in region r is exposed to at each point in time (during each month or year). Between two months, the exposure to crime news of individuals living in a specific region can vary either because the average amount of crime news broadcast changes or because of some reallocation of viewing shares between TV channels characterised by different crime news reporting intensity takes place.

2.6.2. Estimating changes in crime news exposure induced by Digital Reform

We now estimate the effect of the Digital Reform on individuals' *exposure to crime news* and we do so by estimating the following first-stage equation:

$$\left(\sum_{c=1}^{C} CrimeNews_t^c * Share_{rt}^c\right) = \gamma_0 + \gamma_1 Digital\_Switch_{rt} + \boldsymbol{Z}'_{rt}\theta + \gamma_r + \lambda_t + v_{rt} \quad (3)$$

Where t can be either month or year and *Digital_Switch* is an indicator for the regions having switched to digital at time t or before[25]. While we always include region fixed effects, from columns 1 to 4 we account for possible confounding factors due to the time dimension in different ways. More precisely, in column 1 we only include a linear time trend; in columns 2 year fixed effects; in column 3 year*month fixed effects to allow for maximum flexibility in the (common) time trend; finally, in column 4, we estimate our tighter specification where we include both year*month fixed effects and region-specific linear time trends. In our context TV news programs are broadcast nationally, so any change over time in the amount of crime news reported is absorbed by time fixed effects. Instead, the variation in *Crime_News_Exposure* that is generated by the digital switch has to do with the reallocation of viewing shares away from traditional analogue channels and in favour of those with fewer or no crime news. In fact it is important to underline that if we look within the six main traditional channels, we can observe (Figure 2.13) how channels characetised by higher crime news reporting intensity are those that lost most viewing shares during the period of digital TV introduction. Thus, because of this differential effect of the Digital Reform on viewing shares of different traditional channels, even the group of individuals who keep watching those traditional channels is, after the reform, on average exposed to lower crime news intensity. Estimates (reported in Table 2.4) suggest that the digital introduction induced a decrease in the exposure of individuals to crime news. The coefficients on the *Digital_Switch* indicator are always negative, remarkably stable across specifications, and very powerful in predicting changes in

[25] In this part of the analysis we to use the dummy measure of the digital switch rather than the fraction of months after the switch-off occurred.

Crime_News_Exposure. They are all significant at the 1% level and the F-statistic associated with *Digital_Switch* always scores above 35 in our most complete specifications, from column 4 onward. In column 5 we exclude from the analysis the residual TV channels, which we cannot label as either digital, or satellite; while in column 6 we estimate the equation collapsing the data into a yearly dataset. Estimates are in both cases very similar to those in the main specification. According to these results in column 3 the switch to the digital TV caused a reduction in the exposure to crime news equal to 8.4 crime news items per month. This number corresponds to about 12% of the average amount of crime news individuals are exposed to during a month, thus suggesting a sizable effect.

2.6.3. Quantifying the effect of crime news exposure on crime perceptions

We then move on and use the predicted values of *Crime_News_Exposure* to get a better measure of the effect of the digital reform on crime perceptions. We do so by estimating the following second-stage equation:

$$Crime\_Concern_{irt} = \beta_0 + \beta_1 Crime_{rt} + \beta_2 \left(\sum_{c=1}^{C} \widehat{CrimeNews_t^c} * Share_{rt}^c\right) + \boldsymbol{X}'_{irt}\beta_3 + \boldsymbol{Z}'_{rt}\beta_4 + \eta_r + \kappa_t + u_{irt} \tag{4}$$

where the variable *Crime_Concern*$_{irt}$ is the same as the one used in equation (2) and described above. $\sum_{c=1}^{C} CrimeNews_t^c * Share_{rt}^c$ is our measure of *Crime_News_Exposure*. Vectors $\mathbf{X}'_{irt}$ and $\mathbf{Z}'_{rt}$ are the same as in equation (2). As usual robust standard errors are clustered at the regional level in all regressions.

In our first stage the change in *Crime_News_Exposure* is driven by the compliers, i.e. those individuals who decide to change channel in response to the digital reform. We identify a local average treatment effect (LATE) for those individuals who changed their viewing habits because of the digital introduction. In particular, because we observe *Crime_News_Exposure* at a higher than individual level, the estimates delivered by our model are a mixture of a zero effect for individuals in treated regions who did not change channel and a possibly non-zero effect for those who did change channel.

OLS estimates as well as IV ones of equation (4) are reported in Table 2.5. These are year level regressions where the exposure variable is calculated as the average monthly number of crime news broadcast during the year before each survey. Both OLS and IV estimates on *Exposure* are positive. OLS are just slightly larger than IV ones. This is due a first stage almost perfectly predicting *Crime_News_Exposure*. In fact, once we account for region and time fixed effects, almost the entire variation in the exposure to crime news is explained by the shift in viewing shares across TV channels induced by the digital TV introduction.

When we allow the effect to vary across age groups our IV estimates (column 6) indicate that, similarly to the reduced-form case, the effect gets stronger (more negative) with age, and estimates are significant for individuals aged above 65. According to these estimates a one standard deviation decrease in the exposure to crime news (equivalent to 13 fewer news items per month) is associated with a 5.7 percentage point decrease in the probability of reporting crime as priority problem for individuals aged above 65. That is about a 9.2 percent drop with respect to their average likelihood of being concerned about crime of 0.62. These results suggest that, over and above actual crime levels (crime rates is included as control in all specifications), people do respond to changes in the number of crime news they are exposed to in the intuitive way. That is, they are more concerned about crime when TV broadcasts higher number of crime news, regardless of the actual amount of crime.

2.7. Crime Perceptions and Voting Behaviour

In this section we want to analyse the potential implications that the change in perceptions induced by the introduction of digital TV might have for voting behaviour.

Issue bias and agenda setting. To do so we need to discuss whether reporting a particularly high number of crime news might be a rational strategy for TV channels under the influence of Berlusconi with the objective to increase people’s concern about crime and eventually gain electoral advantage (increase voting for the centre-right coalition). Such strategy, called issue selection or agenda setting within the political economy literature (Larcinese, Puglisi and Snyder, 2011), is realised when media choose which type of information to report (for example crime events) in order to influence the perception of citizens about which issues are relevant and to what extent. Indeed, quoting Larcinese et al. (2011) "editors and journalists have a large degree of freedom in deciding what is newsworthy and what is not, and these choices influence the perception of citizens about which issues are relevant and to what extent ". If this applies, a coalition that can influence or partially control the media might be incentivised to make a particular topic a salient one in the electorate's mind if the topic is perceived by the electorate as an area of specific expertise of the coalition. When, in other words, the coalition is said to "own" that specific topic. In the USA, for example, the majority of people believe that the Republican Party is better suited at dealing with national security issues while the Democratic Party is better at dealing with health care and social issues (Larcinese et al. 2011).

To gather evidence on whether crime is an issue "owned" by the centre-right coalition in Italy we use data from the Italian National Election Study Survey (ITANES), a survey similar in content to the American National Election Study Survey in the US and representative of the entire Italian population. It turns out that to the question "What coalition would be better able to face the problem: crime?", 51% of the respondents report the centre-right coalition, only 20% the centre-left and the remaining 29% say that is indifferent. These numbers suggest that making the topic crime a salient one in the electorate's mind might be a rational strategy for the Italian centre-right coalition, which indeed has often based its past electoral campaigns around issues such as crime and security.

During the period of digital TV introduction no national elections took place. Yet, we can look at the 2008 national election and use survey data to: a) study the relationship between crime concern and the probability of voting for the centre-right coalition; and b) use those estimates to, under some assumptions, predict the potential effect of the lower exposure to partisan TV channels on the likelihood to vote for the centre-right coalition.

We employ data from the post-2008 election wave of the Italian National Election Study Survey (ITANES) introduced above. Apart from the usual socio-demographic characteristics, the survey asks which party the person voted for in the 2008 national elections as well as the perceived most important problem in the country at the time of the elections. We regress an indicator for the individual reporting having voted for the centre-right coalition (*CR_Vote*) on a dummy equal one if the person reports *crime* as the most important problem in the country (*Crime_Concern*). Table 2.6 reports linear probability estimates from such regression.

Individuals who consider crime as the most important problem are almost 25 percentage point more likely to vote for the centre-right coalition that those who do not think so. These results are in line with the evidence shown above that the majority of Italian citizens believe that the centre-right coalition has a competitive advantage, over the centre-left one, in tackling crime. Estimates of the coefficient are stable to the inclusion of individual characteristics and region fixed effects. Although we cannot give causal interpretation to these results, they do point in the direction of a relationship in the Italian context between having crime as a major concern and the likelihood of voting for the centre-right coalition.

Predicting changes in voting behaviour. We use these estimates to run an illustrative exercise of the potential effect of the change in crime concern induced by the lower exposure to partisan channels on the probability of voting for the centre-right coalition. We focus on individuals aged above 65, the population group for which we found stronger effect of the Digital Reform. The estimated coefficient of the effect of the switch-off on crime concern was -0.052 (Table 2.3, column 6). Let us suppose a decrease of the same magnitude for the variable *Crime_Concern* from the regression above. Using the estimated relationship between considering crime as most important problem in the country (*Crime_Concern*) and the propensity to vote for the centre-right Berlusconi's coalition (*CR_Vote*) we obtain that the induced change in the latter likelihood would be equal to 1.3 percentage points, or 2.83 percent with respect to the average probability of centre-right vote (0.46). According to these numbers about 3% of 2008 national election centre-right voters aged above 65 could have been induced to change their vote by the decrease in crime concern caused by digital TV introduction. Individuals aged above 65 represent about one out of four of the Italian population entitled to vote and they have on average higher turnout rates than younger individuals. For such reasons we argue that the change in crime perceptions induced by the decreased exposure to partisan channels linked to Berlusconi might have relevant effects on voting outcomes.

2.8. Concluding Remarks

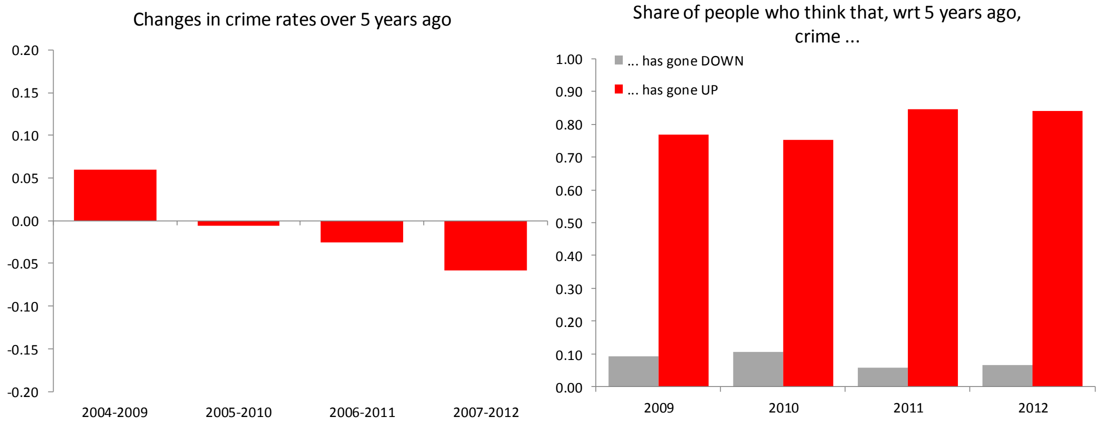
People base a good part of their behaviours on beliefs and perceptions. Thus, studying the role played by media in the formation of such beliefs and perceptions is particularly relevant for our understanding of individual and collective behaviours. In this paper we investigate the influence of news media, and in particular partisan ones, on crime perceptions and voting behaviour. To do so, we exploit a natural experiment in the Italian television market where the staggered introduction of the digital TV signal across regions led to a drastic drop in the viewing shares of partisan channels and, as a consequence, to a lower exposure to potentially biased news about crime.

We find that the lower exposure to partisan news channels led individuals to revise their perceptions about crime as one of the priority problem in Italy downward. The effect is mainly driven by individuals from older cohorts. Older individuals watch more TV and use alternative sources of information less frequently - i.e. internet, radio and newspapers – than their younger counterparts. They were therefore likely to be more exposed to the potential bias before the digital introduction and to place a higher weight on information coming from television. We then attempt to estimate the effect of exposure to crime news on crime perceptions. To do so, we combine unique data on: a) region-specific monthly viewing shares of each TV channel during prime-time news programs; and b) the monthly amount of crime-related news reported by each TV channel during prime-time news programs. After using the switch to digital signals to predict exogenous changes in the exposure to crime news we attempt to estimate the effect on crime perceptions through a two-step method. Findings suggest that the digital reform induced a reduction in exposure to crime news of about 12 percent of the average value and that a 1 standard deviation decrease in exposure to crime news is associated with a 9.2 percent decrease in crime concern, among those aged above 65. Finally, we assess whether the change in crime perceptions induced by the lower exposure to partisan channels might be relevant for voting behaviour. Using data from an electoral survey collected just before the introduction of digital TV, we predict that the reduction in crime concern caused by the digital reform might induce about 3% of those aged above 65 who voted for the centre-right coalition to change their vote.

This paper contributes to the literature on persuasive communication in economics by providing causal evidence of the impact of information provided by motivated agents (partisan media) on the beliefs and perceptions individuals hold. Further, using unique data on TV viewing shares we identify both an intention to treatment effect of the increase in the number of TV channels and a local average treatment effect driven by those individuals who actually "change" channel in response to the increase in their number. Finally, we contribute to the growing literature that looks at the effect of (biased) news media on political outcomes by shedding light on one of the possible mechanisms through which media manage to influence voting decision and policies: the manipulation of individuals' perceptions with respect to politically salient topics. We provide evidence of this phenomenon by studying the Italian case where a specific group of media tends to over-report crime news. As a consequence, individuals' perceptions of crime as a priority problem might be distorted, and indeed we find that people consistently over-estimate crime rates. We show that once the exposure to such news programs is reduced, the level of crime concern decreases, and does it in particular for those individuals, the elderly, who are likely to base a larger amount of their beliefs on information coming from television. Since new digital channels are mostly full-entertainment, our results suggest that, in this specific case, people's beliefs might have become more accurate once exposed to a lower amount of information. Finally it is worth noticing that individuals aged above age 52, for which we find a significant effect, make up about 30 percent of Italian voting population. Hence, for an office-seeking politician, being able to influence their beliefs about politically salient issues might have relevant implications in terms of voting outcomes.

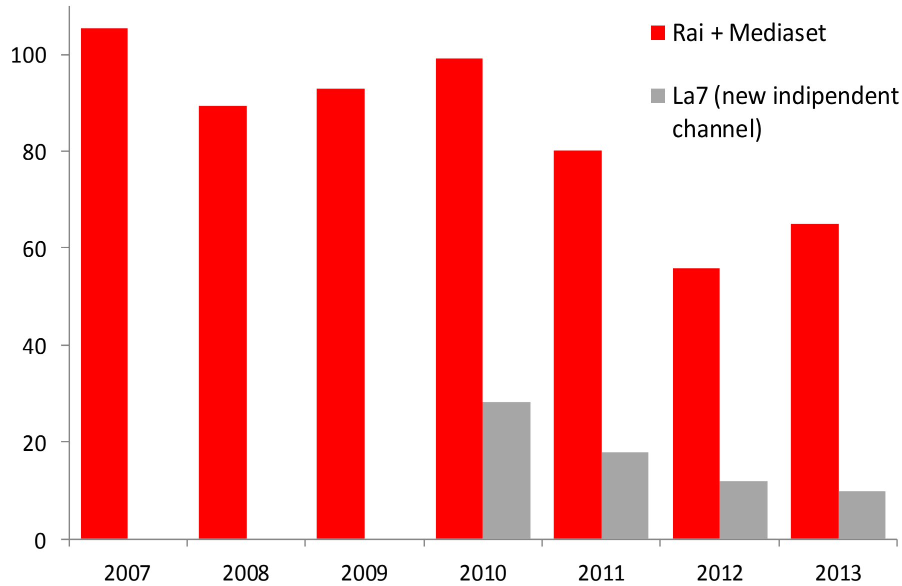
Figures

Figure 2.1 - Actual crime vs crime perceptions in Italy: 2004-2012



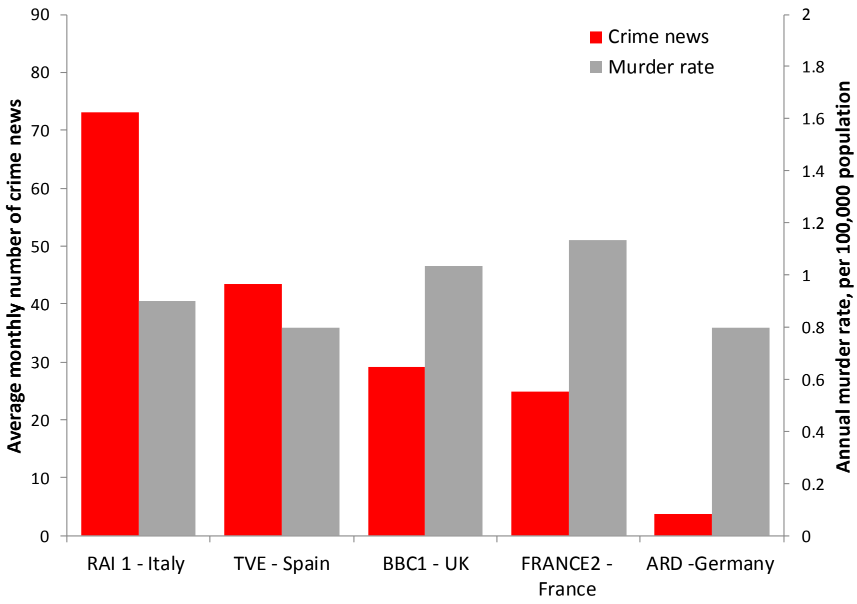
Note. The left panel of the figure reports changes in crime rates between 2004 and 2012. Source: Authors' elaboration on Italian Home Office Data. The right panel reports the share of people by answer to the question "Do you think that, with respect to five years ago, crime has gone up/gone down/ stayed the same/ do not know" from 2009 to 2012. The shares referring to the answers "stayed the same" and "do not know" are not reported. Source: Eurostat (left panel) and UNIPOLIS Foundation (right panel).

Figure 2.2 - Intensity of crime news reporting: Main Traditional Channels (Rai + Mediaset) vs New Independent Channel (La7)



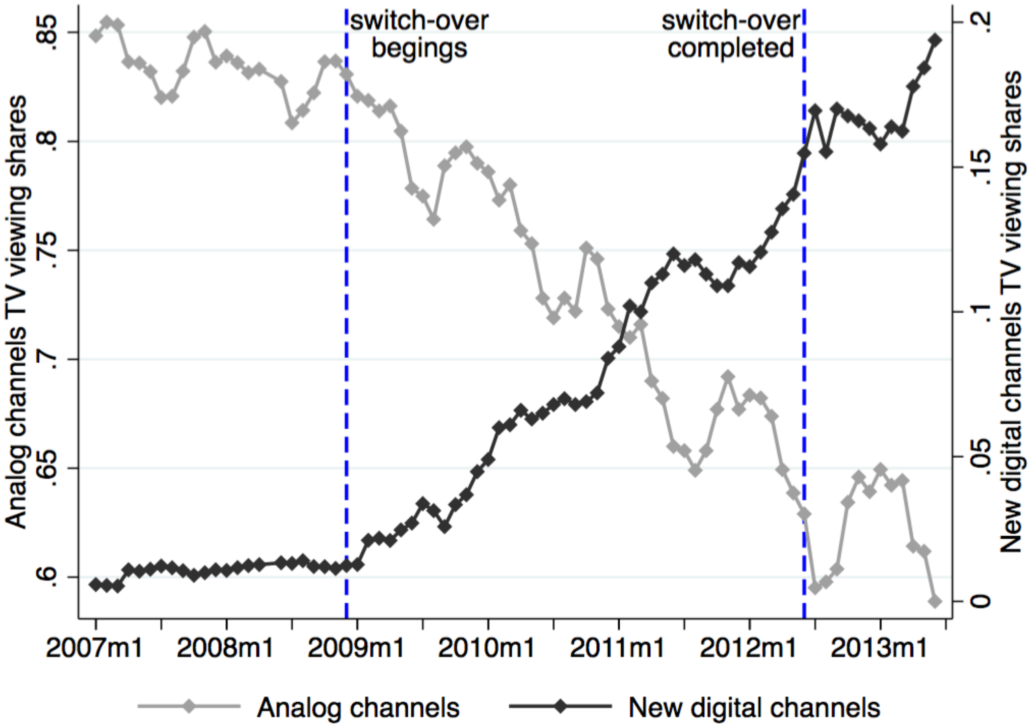
Note. The graph shows the average monthly number of crime news broadcast during prime-time news programs respectively by main traditional channels (Rai + Mediaset) and the new independent channel (La7). Data for LA7 channel are available only from year 2010 onwards.
Source: Authors' elaboration from Pavia Observatory data.

Figure 2.3 - Intensity of crime news reporting and murder rates: selected countries



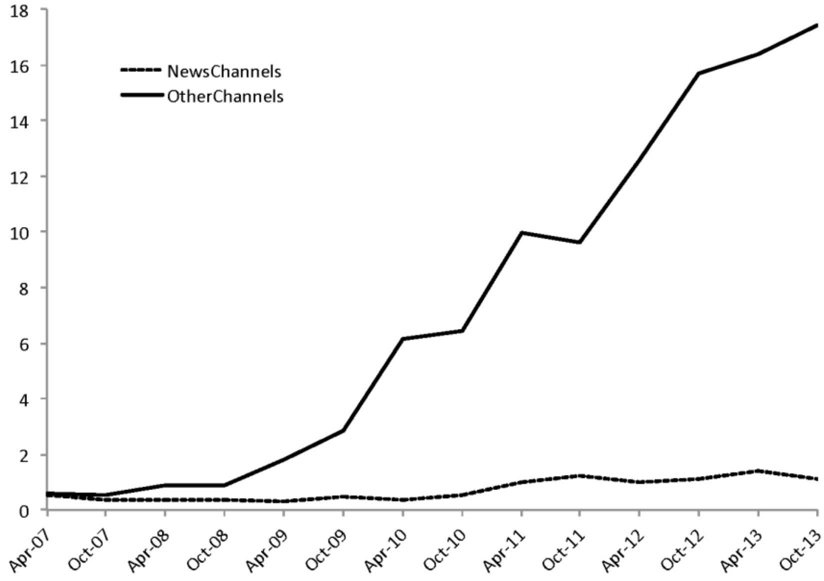
Note. The graph compares the average monthly number of crime news broadcast during prime-time news programs by the main public TV channel with the annual murder rate in a selected number of European countries.
Sources: Pavia Observatory (crime news data) and Eurostat (murder rates). Years: 2010-2012.

Figure 2.4 - Viewing shares during prime-time (18:00-20:30): Main traditional analogue channels (Rai + Mediaset) vs new digital channels



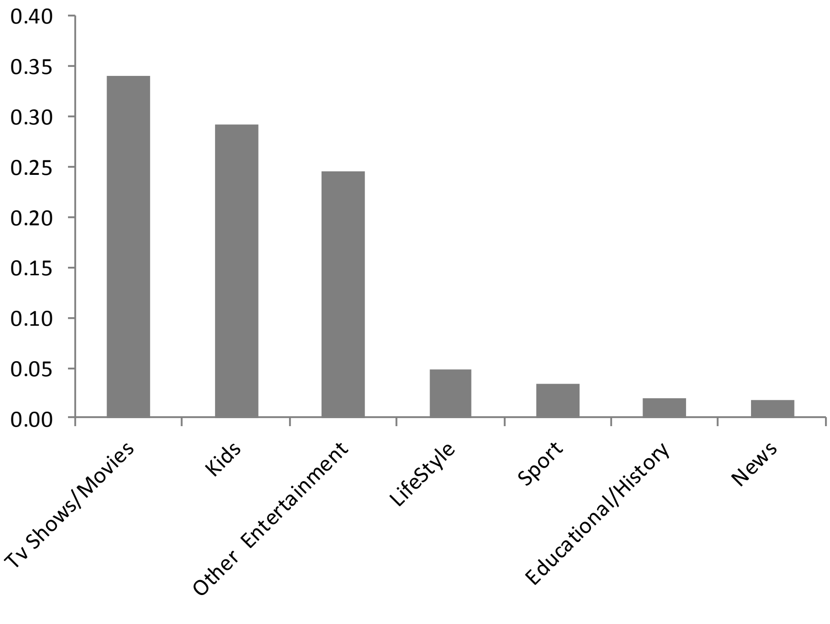
Note. The figure plots monthly TV viewing shares during prime-time for main traditional analogue channels (Rai and Mediaset) and new digital channels between 2007 and 2013. Source: authors' elaboration on AUDITEL data.

Figure 2.5 - Viewing shares: new digital channels also broadcasting news programs vs full-entertainment digital channels



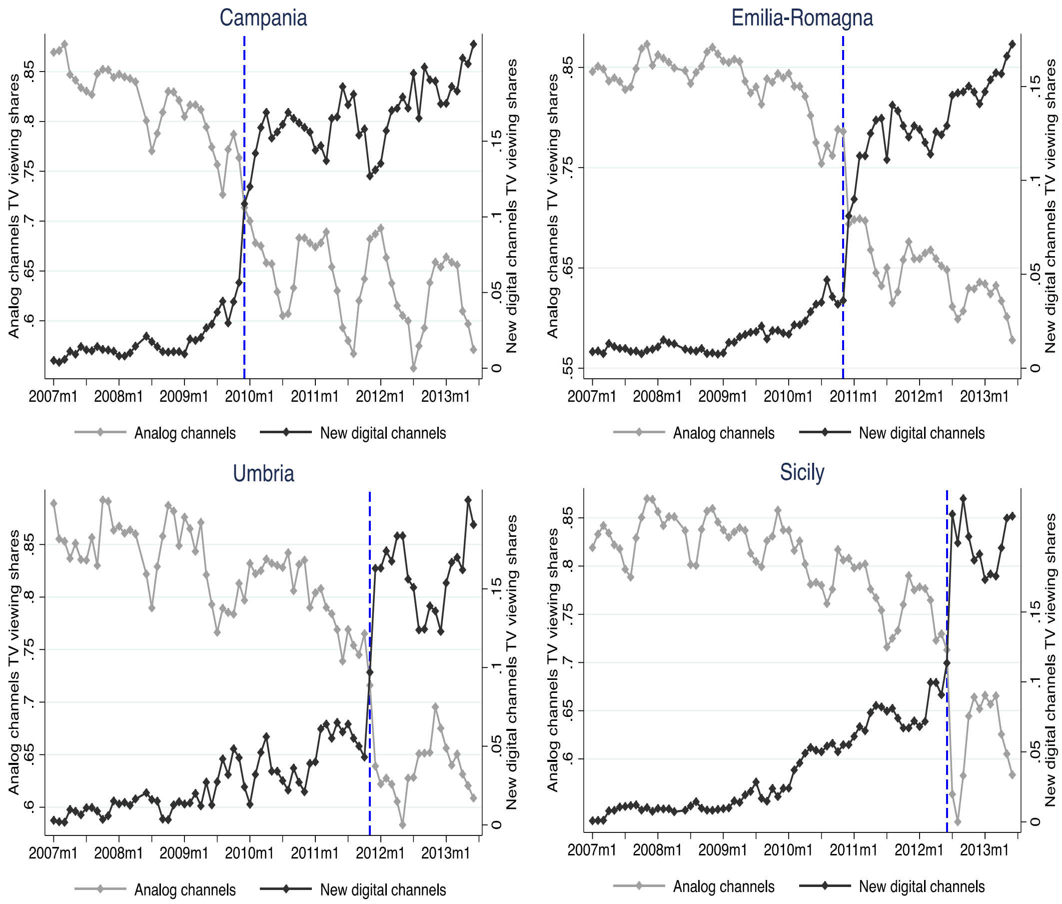
Note. The figure shows the evolution of viewing shares (prime-time) for new digital channels split into channels also broadcasting news programs (news digital) and full-entertainment (other digital channels). Source: authors' elaboration on AUDITEL data.

Figure 2.6 - Content of new digital channels: composition of total viewing shares



Note. The figure reports the total viewing of new digital channels divided by type of channel, for year 2010. The interpretation of the y axis scale is that, for example, almost 35% of the entire digital viewing share during year 2010 refers to digital channels broadcasting TV shows or movies.

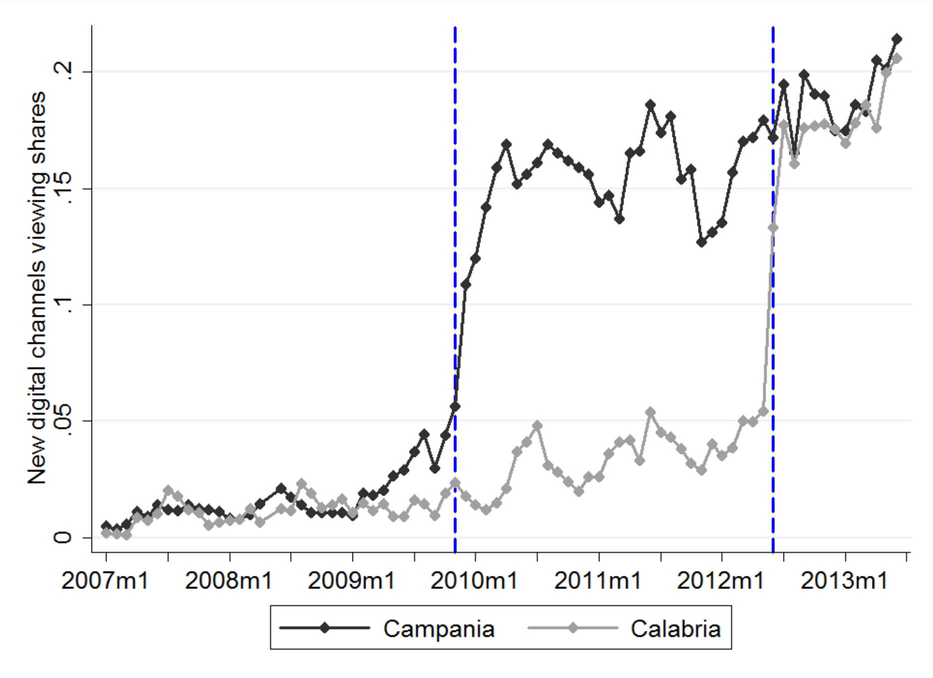
Figure 2.7 - Viewing shares (prime-time) around switch-over to digital signal deadlines in selected regions



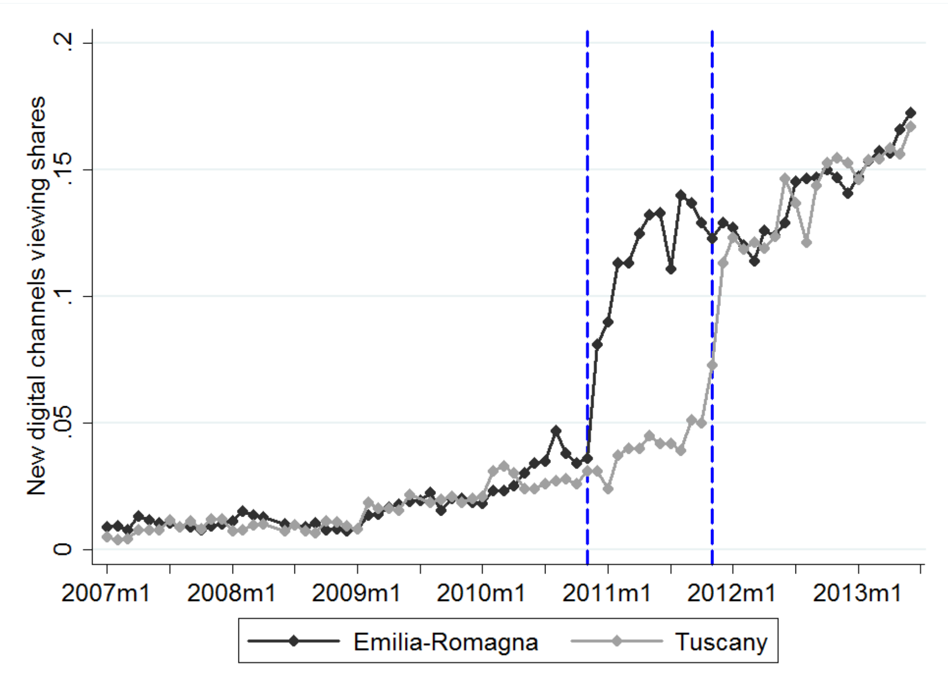
Note. The figure reports the evolution of monthly viewing shares (prime-time) before and after the switch-over to digital TV signal in 4 selected regions. The light grey lines indicate viewing shares of main traditional analogue channels while the dark grey ones indicate those of new digital channels. The dashed vertical lines indicate switch-off dates for each specific region. Source: authors' elaboration on AUDITEL data.

Figure 2.8 - Discontinuity in digital channels viewing shares (prime-time) around switch-over to digital signal deadlines: selected pairs of neighboring regions

Panel A

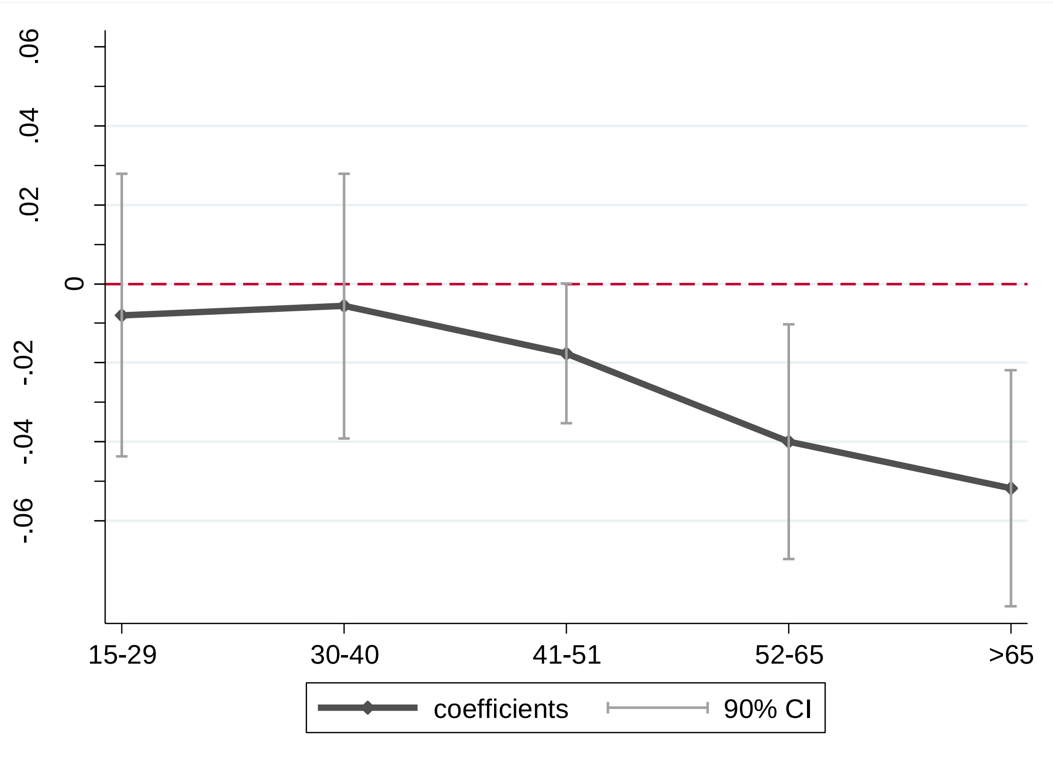


Panel B



Note. The figures show the evolution of monthly TV viewing shares (prime-time) of new digital channels in 2 pairs of neighboring regions, before, during, and after the switch to digital signal. The dashed vertical lines indicate switch-off dates. In particular in Panel A the first line corresponds to the deadline in region Campania (12/2009) while the second to the deadline in region Calabria (06/2012). In Panel B the first line corresponds to the deadline in region Emilia-Romagna (11/2010) while the second to the deadline in region Tuscany (11/2011). Source: authors' elaboration on AUDITEL data.

Figure 2.9 - Reduced-form effect of the Digital Reform on crime perceptions: heterogeneity across age groups

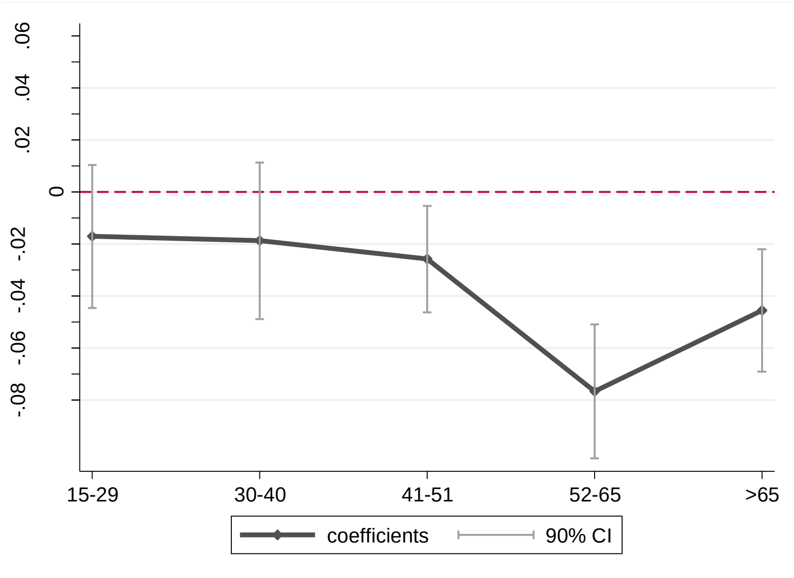


Note. The figure plots estimates and 90% confidence intervals by age groups from a LPM regression of *Crime_Concern* on a post digital switch variable (*Digital_Switch)* and controls. *Crime_Concern* is an indicator for the individual reporting crime as one of the 3 priority problems in Italy. *Digital_Switch* equals the number of months (as fraction of the 12 before each survey) elapsed since region *r* experienced the switch to digital signal. The specification is the same used in column 6 of Table 3. Individual and family controls include: gender, age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.

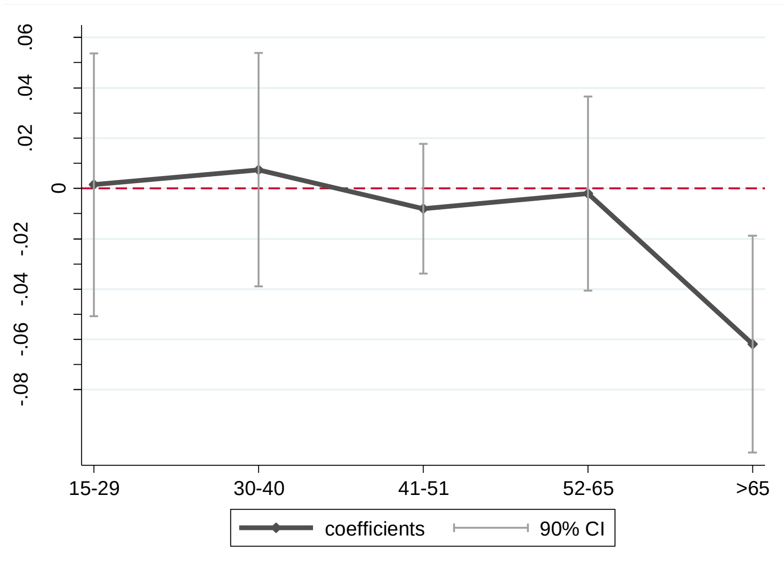
90% confidence intervals based on robust standard errors clustered by region are reported.

Figure 2.10 - Reduced-form effect of the Digital Reform on crime perceptions: heterogeneity by gender and age groups

Panel A: Females



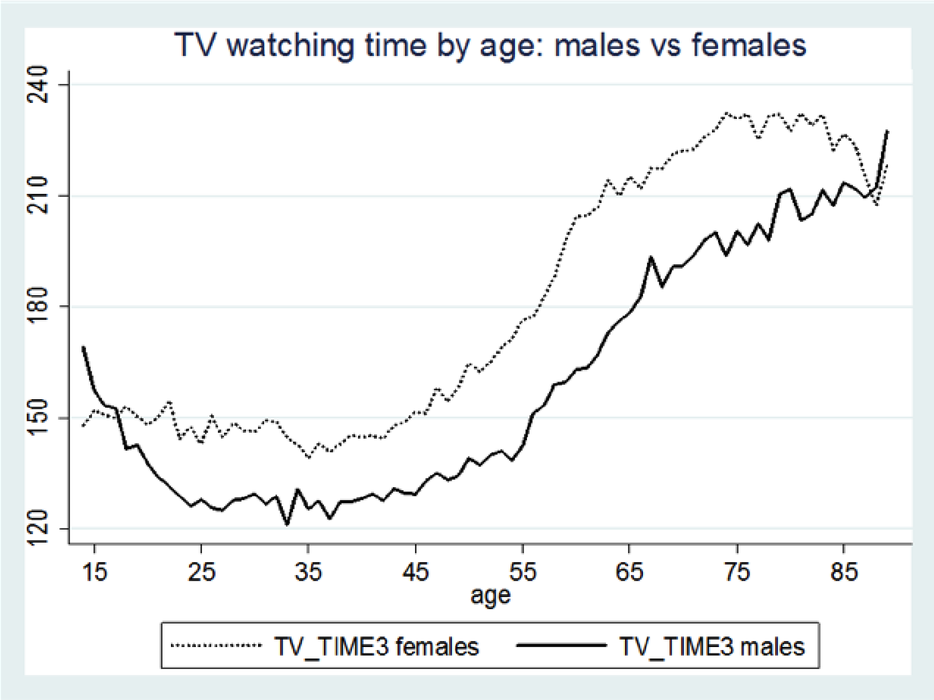
Panel B: Males



Note. The figure plots estimates and 90% confidence intervals by gender and age groups from a LPM regression of *Crime_Concern* on a post switch-over variable (*Digital_Switch)* and controls. *Crime_Concern* is an indicator for the individual reporting crime as one of the 3 priority problems in Italy. *Digital_Switch* equals the number of months (as fraction of the 12 before each survey) elapsed since region *r* experienced the switch to digital signal. The controls included are the same as those in column 6 of Table 3. In particular, individual and family controls include: age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.

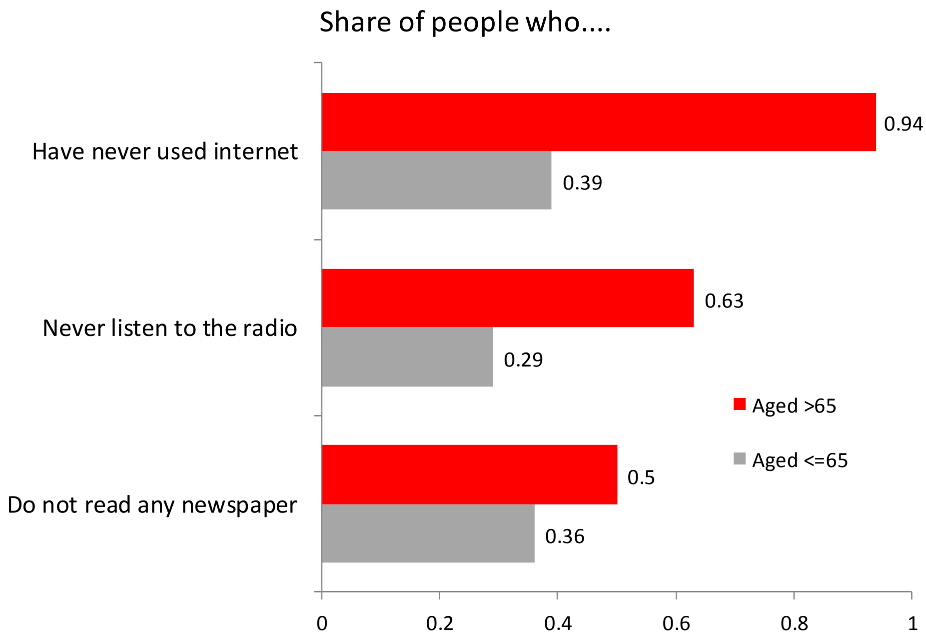
90% confidence intervals based on robust standard errors clustered by region are reported.

Figure 2.11 - Average daily TV watching time: by gender and age



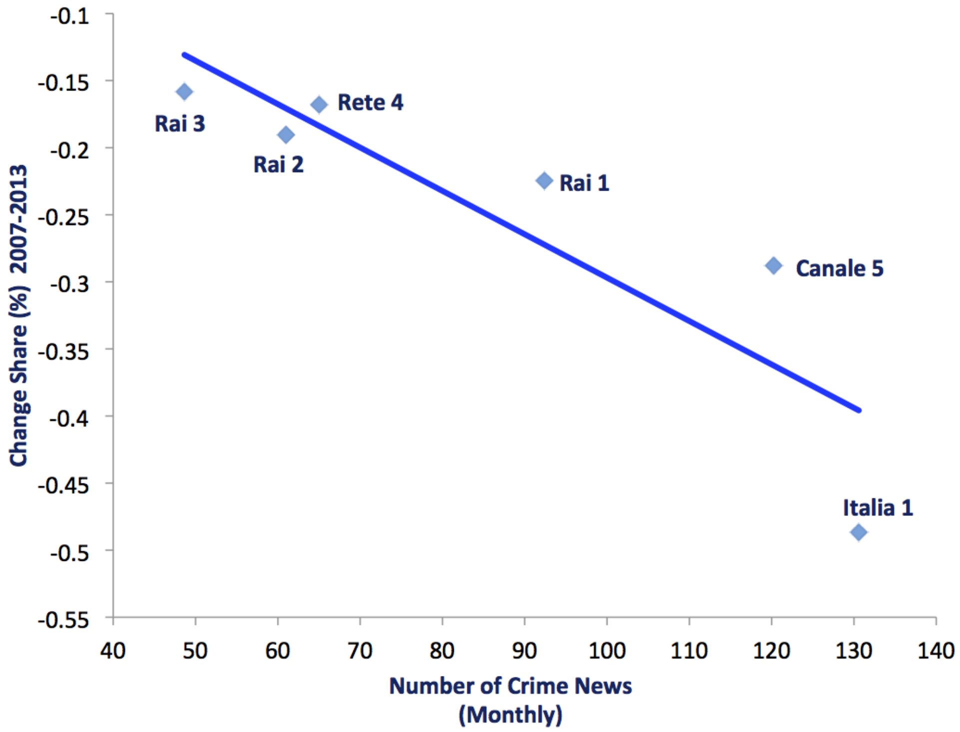
Note. The figure plots average (reported) daily TV watching time (in minutes) for males and females along the age distribution. The estimates are obtained by pooling various waves of the Multipurpose Household Survey (ISTAT).

Figure 2.12 - Use of alternative sources of information



Note. Source: authors' elaboration on data from the Multipurpose Household Survey (ISTAT).

Figure 2.13 - Crime news reporting intensity and viewing share drop during Digital Reform



Note. The figure plots monthly average number of crime news against the change in TV viewing shares (both between 2007-2013) for each of the six main traditional channels.
Source: authors' elaboration on AUDITEL data.

Tables

Table 2.1 - Balancing test: *early* vs *late* switcher regions

	Early Switchers	*Late Switchers*	Difference	p-value
Unemployment rate	0.063	0.064	-0.002	0.923
Employment rate	0.636	0.629	0.008	0.866
Share of tertiary educated	0.084	0.085	-0.001	0.121
Share of immigrant residents	0.039	0.042	-0.004	0.756
Share of internet users	0.388	0.355	0.033	0.213
GDP per capita (euros)	25,900	23,976	1924	0.550
Population density (people by square km)	186.3	182.9	-3.4	0.950
Persons cited for crimes (per 100,000 people)	1,149	1,137	-13	0.933
Murder rate (per 100,000 people)	1.010	0.881	0.129	0.546

Note. The table reports means of various characteristics for two groups of regions: those that switched to digital before or at December 2009 (*early switchers*) and those that switched to digital from January 2010 onwards (*late switchers*). Column 4 reports the p-values for tests of the difference between means in the two groups.

Table 2.2 - Effect of the Digital Reform on TV viewing shares

	(1)	(2)	(3)	(4)
Panel A: Traditional Channels				
Digital Switch	-0.087***	-0.086***	-0.085***	-0.081***
	(0.010)	(0.010)	(0.010)	(0.008)
F-stat: Digital Switch	79.25	74.09	73.42	89.93
Panel B: New Digital Channels				
Digital Switch	0.072***	0.067***	0.064***	0.065***
	(0.007)	(0.006)	(0.007)	(0.006)
F-stat: Digital Switch	103.4	116.5	94.45	110.8
Panel C: Satellite Channels				
Digital Switch	0.007	0.009**	0.009*	0.007
	(0.004)	(0.004)	(0.005)	(0.005)
F-stat: Digital Switch	2.732	4.559	3.473	2.370
Panel D: Other Channels				
Digital Switch	0.012***	0.012***	0.014***	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)
F-stat: Digital Switch	8.728	9.352	11.83	7.513
Region fixed effects	X	X	X	X
Linear time trend	X			
Year fixed effects		X		
Month*Year fixed effects			X	X
Region-specific linear trends				X
Observations	1,519	1,519	1,519	1,519

Note. The table reports estimates from regressions of TV viewing shares (during prime-time) on *Digital_Switch* The level of observation is the viewing share by channel*month*region. *Digital_Switch* equals one if the region r experienced the switch-over to digital signal at time (month) t or before. Each panel reports estimates of the TV viewing shares (prime-time) of a different group of channels. Rai and Mediaset channels are indicated as Traditional Channels.

Robust standard errors clustered at the region level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.3 - Reduced-form effect of the Digital Reform on crime perceptions

	Digital: Indicator of switch-off occurred		Digital: Share of months after switch-off			
	(1)	(2)	(3)	(4)	(5)	(6)
DigitalSwitch	-0.014					
	(0.010)					
DigitalSwitch * Aged 15-29		-0.000	-0.006	-0.008	-0.008	-0.008
		(0.015)	(0.020)	(0.020)	(0.018)	(0.022)
DigitalSwitch * Aged 30-40		0.001	-0.006	-0.005	-0.005	-0.006
		(0.015)	(0.021)	(0.020)	(0.022)	(0.020)
DigitalSwitch * Aged 41-51		-0.009	-0.015	-0.016	-0.016	-0.018
		(0.009)	(0.014)	(0.013)	(0.011)	(0.011)
DigitalSwitch * Aged 52-65		-0.025	-0.040*	-0.039*	-0.039*	-0.040**
		(0.017)	(0.022)	(0.022)	(0.020)	(0.018)
DigitalSwitch * Aged >65		-0.035***	-0.050***	-0.051***	-0.050***	-0.052**
		(0.012)	(0.012)	(0.011)	(0.011)	(0.018)
Crime rate: all					0.097	
					(0.091)	
Crime rate: violent & drug						0.205**
						(0.075)
Crime rate: property						0.035
						(0.081)
Crime rate: other						-0.025
						(0.057)
Individual & family controls				X	X	X
Region time-varying controls					X	X
Region fixed effects	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X
Observations	139,165	139,165	139,165	139,165	139,165	139,165

Note. The table reports estimates of the reduced-form effect of the introduction of digital TV on perceptions about crime. Estimates are from a linear probability model of *Crime_Concern* on a post switch-over variable (*Digital_Switch*). *Crime_Concern* is an indicator for the individual reporting crime as one of the 3 priority problems in Italy. In order to take into account the effective time passed since the region has switched to the digital signal we employ two alternative versions of the variable *Digital_Switch.* The first, which we employ in column 1 and 2, is a dummy that equals one if the region r experienced the switch-over to digital signal at time t or before. The second, which we employ from column 3 onwards, is the number of months (as fraction of the 12 before each survey) elapsed since region *r* experienced the switch to digital signal. Crime rates are calculated as logs of crimes per 10'000 individuals. Individual and family controls include: gender, age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4 - First-stage estimates: effect of Digital Reform on crime news exposure

					No residual channels	Yearly data
	(1)	(2)	(3)	(4)	(5)	(6)
Digital Switch	-15.895***	-8.306***	-8.436***	-8.130***	-7.783***	-8.154***
	(4.515)	(1.632)	(1.388)	(1.172)	(1.083)	(1.319)
F-stat: Digital Switch	12.39	25.92	36.92	48.16	51.64	38.23
Region fixed effects	X	X	X	X	X	X
Linear time trend	X					
Year fixed effects		X				X
Month*Year fixed effects			X	X	X	
Region-specific lin. trends				X	X	X
Observations	1,406	1,406	1,406	1,406	1,406	133

Note. The table reports estimates of the effect of the switch to digital signal on the exposure to crime news. Estimates are from regressions of *Crime_News_Exposure* on a post switch-over indicator *Digital_Switch.* The unit of observation is the TV viewing share by TV channel, month and region. *Crime_News_Exposure* is the summation, over all TV channels, of the number of crime news items broadcast during period t weighted by the region-specific viewing share in the region r during period t. *Digital_Switch* is a dummy that equals one if the region r experienced the switch-over to digital signal at month t or before. F-stats of the excluded instrument are reported.
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5 - OLS and IV estimates of the effect of crime news exposure on crime perceptions

	OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)	IV (6)
Exposure	0.0028**	0.0028*		0.0025	0.0022	
	(0.0013)	(0.0015)		(0.0019)	(0.0017)	
Exposure * Aged 15-29			0.0014			0.0013
			(0.0015)			(0.0024)
Exposure * Aged 30-40			0.0018			0.0011
			(0.0013)			(0.0020)
Exposure * Aged 41-51			0.0024*			0.0021
			(0.0014)			(0.0019)
Exposure * Aged 52-65			0.0033**			0.0035
			(0.0015)			(0.0026)
Exposure * Aged >65			0.0041**			0.0044**
			(0.0015)			(0.0019)
F-stat (excluded instr.)				29.80	29.29	18.76
Individual & family controls		X	X		X	X
Region time-varying controls		X	X		X	X
Region fixed-effects	X	X	X	X	X	X
Year fixed-effects	X	X	X	X	X	X
Observations	139,165	139,165	139,165	139,165	139,165	139,165

Note. The table reports OLS and IV estimates of regressions of *Crime_Concern* on *Crime_News_Exposure* (simply *Exposure* in the table). *Crime_Concern* is an indicator for the individual reporting crime as one of the 3 priority problems in Italy. *Crime_News_Exposure* is the summation, over all TV channels, of the number of crime news items broadcast during period t weighted by the region-specific viewing share in the region r during period t. Regressions are estimated on yearly data. In column 4, 5 and 6 we employ the switch to digital signal as an instrument for *Crime_News_Exposure.* In column 6 the digital switch is interacted with each of the age group dummies. F-stats of the excluded instrument are reported in columns 4, 5 and 6. Crime rates are calculated as logs of crimes per 10'000 individuals. Individual and family controls include: gender, age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

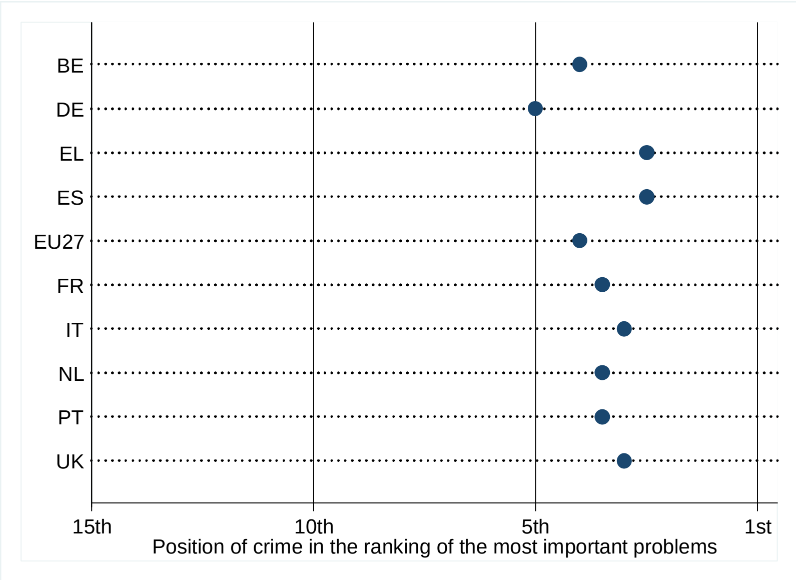
Table 2.6 - Concern about crime and likelihood of voting for the centre-right coalition

	Voted for the centre-right coalition		
	(1)	**(2)**	**(3)**
Crime Concern	0.249***	0.248***	0.246***
	(0.028)	(0.030)	(0.029)
Individual controls		X	X
Region fixed effects			X
Observations	1,652	1,637	1,637
R-squared	0.030	0.071	0.098

Note. The table reports estimates from a linear probability model of an indicator for the individual having voted for the centre-right coalition in 2008 election on a dummy for reporting crime as most important problem in the country at the moment of the elections. Individual controls include: age, male dummy, level of education, dummy for married and a set of dummies of occupational status. Sample: ITANES Survey (2008)
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

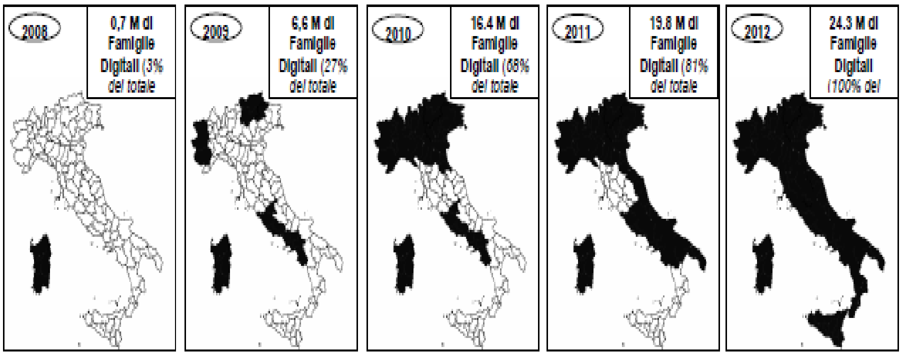
Appendix
Appendix Figures

Figure A 2.1 - Concern about crime in selected European countries (2008-2010)



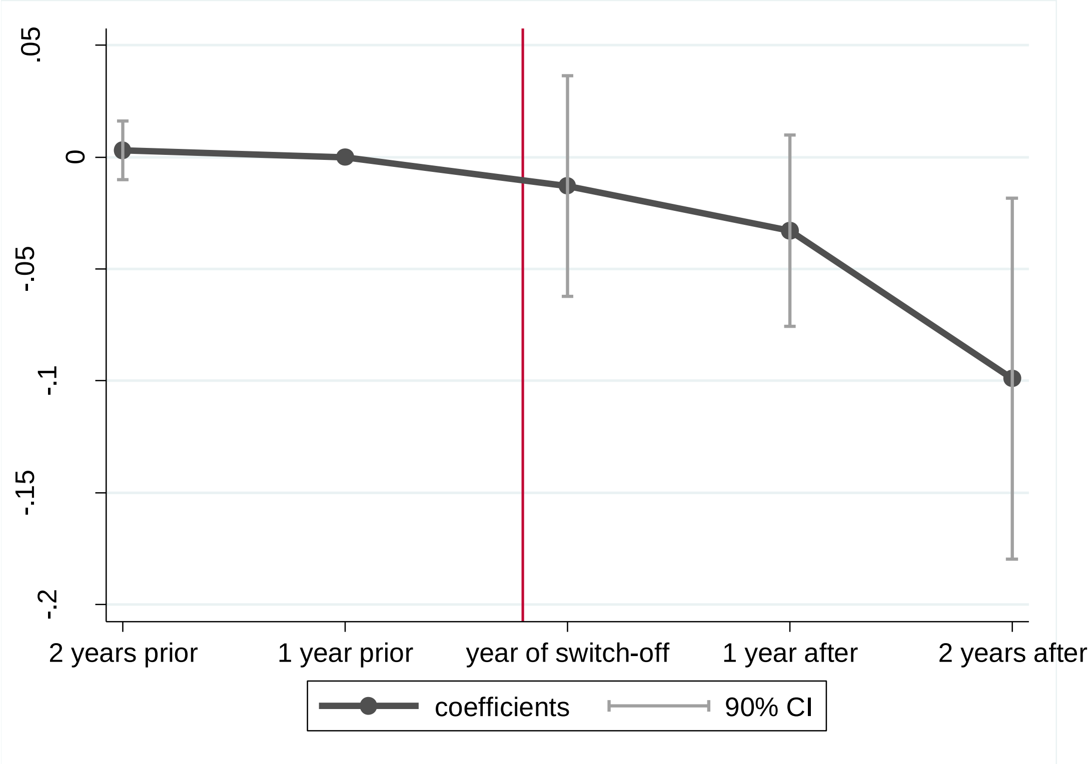
Note. This figure presents how crime is ranked, from 1st to 15th, among a list of major problems in selected European countries. The ranking goes from 15th, indicating the least mentioned topic, to 1st, indicating the most mentioned topic. Sources: Authors elaboration from the 2008 and 2010 waves (pooled) of the Eurobarometer Survey.

Figure A 2.2 - Timing switch-over Italian Regions



Note. Sources: Italian Ministry of Communication.

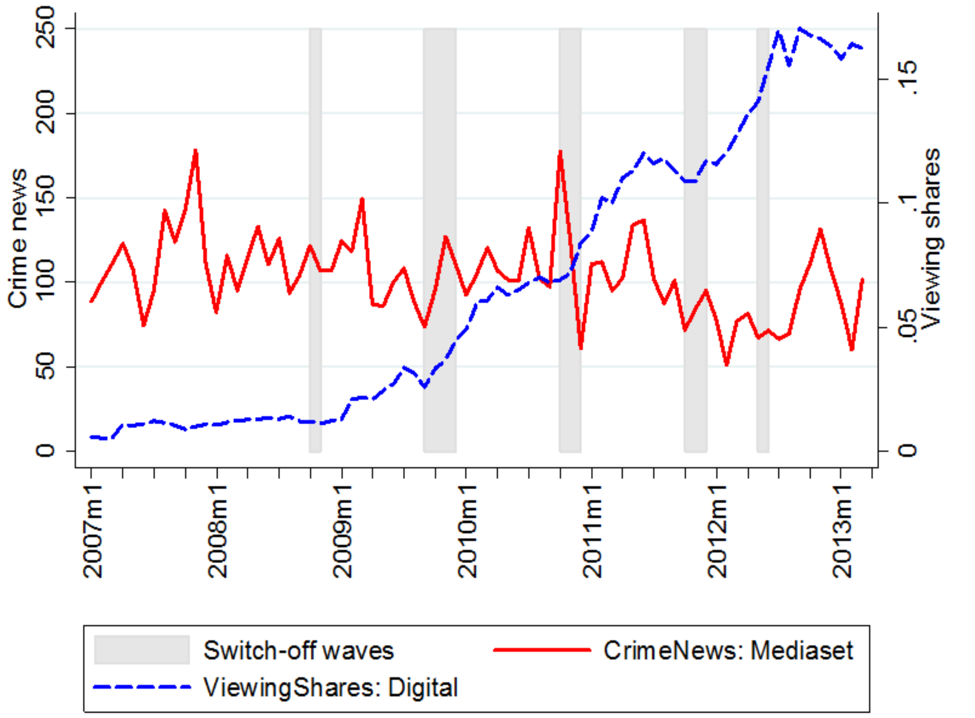
Figure A 2.3 - Timing of change in perceptions of local area crime after the switch-over to digital TV signal.



Note. The figure plots estimated coefficients and 90% confidence intervals from regression of the perception of crime level in the local area (*Crime_Risk_Local*) on a set of dummies from t-2 to t+2, where t=0 is the year when the switch-over to digital signal has occurred. The outcome variable ranges from 1 (crime absent) to 4 (crime level very high) and is collected at the household level. Family controls include: family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regression include year and region fixed effects.

90% confidence intervals based on robust standard errors clustered by region are reported.

Figure A 2.4 - Crime news reporting in Berlusconi-owned channels and viewing shares of new digital channels



Note. The figure plots the average number of crime news (per month) on TV channels owned by Berlusconi (Mediaset) against the viewing shares (prime-time) of new digital channels, from 2007 to 2013. The grey shaded areas indicate different waves of switch from analogue to digital signal.
Source: authors' elaboration on AUDITEL data and Pavia Observatory data.

Appendix Tables

Table A 2.1 - Effect of Digital reform on total TV watching time

	Do watch TV		Average viewing time per day	
	(1)	**(2)**	**(3)**	**(4)**
DigitalSwitch * Aged 15-29	-0.007	-0.008	2.672	1.532
	(0.005)	(0.005)	(2.801)	(2.790)
DigitalSwitch * Aged 30-40	-0.013	-0.012	1.105	-0.117
	(0.010)	(0.009)	(2.623)	(2.195)
DigitalSwitch * Aged 41-51	-0.003	-0.002	-2.073	-3.138
	(0.007)	(0.008)	(2.982)	(2.635)
DigitalSwitch * Aged 52-65	-0.005*	-0.003	-3.881	-0.647
	(0.003)	(0.002)	(3.028)	(2.487)
DigitalSwitch * Aged >65	0.001	0.002	-1.296	0.146
	(0.004)	(0.004)	(4.591)	(4.891)
Individual and family controls		X		X
Region time-varying controls		X		X
Region fixed effects	X	X	X	X
Year fixed effects	X	X	X	X
Observations	140,349	140,349	114,103	114,103

Note. The table investigates whether the switch to digital signal induced any change in the total amount of time people spend watching TV by regressing two measures of TV watching behavior on a post switch-over variable. *DigitalSwitch* is the number of months (as fraction of the 12 before each survey) elapsed since region *r* experienced the switch to digital signal. Column 1 and 2 report estimates from regressions where the outcome is an indicator for the individual watching at least some TV (columns 1 and 2), while columns 3 and 4 report estimates where the outcome is the average daily TV viewing time for those who watch at least some TV. Individual and family controls include: age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.

Estimates show no evidence of individuals from any of the age groups varying their total TV watching time after the introduction of the digital signal.

Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.2 - Effect of Digital Reform on TV viewing shares: all time-slots

Time slot:	18:00-20:30 Prime-time news	All day	12:00-14:59 Lunch-time news	7:00-11:59	15:00-17:59	20:31-23:59
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Traditional Channels						
Digital_Switch	-0.085***	-0.085***	-0.064***	-0.120***	-0.103***	-0.078***
	(0.010)	(0.010)	(0.010)	(0.019)	(0.014)	(0.010)
F-stat: Digital Switch	73.42	68.97	43.92	41.06	52.13	62.04
Panel B: New Digital Channels						
Digital_Switch	0.064***	0.068***	0.057***	0.094***	0.086***	0.062***
	(0.007)	(0.005)	(0.005)	(0.010)	(0.006)	(0.006)
F-stat: Digital Switch	94.45	154.1	140.5	90.33	179.1	110.3
Panel C: Satellite Channels						
Digital_Switch	0.009*	0.010*	0.010*	0.009	0.009	0.009
	(0.005)	(0.006)	(0.005)	(0.008)	(0.008)	(0.008)
F-stat: Digital Switch	3.473	3.177	3.613	1.406	1.401	1.222
Panel D: Other Channels						
Digital_Switch	0.014***	0.013***	0.006	0.025**	0.020***	0.011**
	(0.004)	(0.004)	(0.004)	(0.010)	(0.006)	(0.004)
F-stat: Digital Switch	11.83	9.460	1.677	6.504	10.77	7.251
Month*year fixed effects	X	X	X	X	X	X
Region fixed effects	X	X	X	X	X	X
Observations	1,519	1,519	1,519	1,519	1,519	1,519

Note. The table reports estimates from regressions of TV viewing shares on *Digital_Switch* for different time slots during the day. The level of observation is the viewing share by channel*month*region. *Digital_Switch* equals one if the region r experienced the switch-over to digital signal at time (month) t or before. In each panel the TV viewing shares of a different group of channel is adopted as outcome variable. Month-by-year and region fixed effects are included in all regressions, as in column 3 of Table 2. Rai and Mediaset channels are indicated as Traditional channels.
Robust standard errors clustered at the region level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.3 - Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
	Individuals				
Male	0.48	0.50	0	1	139,165
Age	49	19	15	95	139,165
Married	0.60	0.49	0	1	139,165
Tertiary education or more	0.10	0.30	0	1	139,165
Employed dummy	0.43	0.49	0	1	139,165
Retired dummy	0.22	0.41	0	1	139,165
Dummy for not watching TV at all	0.05	0.21	0	1	139,165
Average daily TV watching time (minutes)	165	114	0	930	136,382
Family size	2.98	1.30	1	12	139,165
***Crime_Concern:* dummy for reporting crime as one of 3 main problems in the country**	0.57	0.49	0	1	139,165
Individuals aged <= 65	0.55				
Individuals aged > 65	0.62				
Females	0.57				
Males	0.56				
***Crime_Risk_Local:* perception of crime level in the local area**	2.01	0.90	1	4	201,923

Note. Descriptive statistics of the main estimating sample from the Multipurpose Household Survey (ISTAT) for the years 2007 to 2010. The variable *Crime_Risk_Local* is available also for the years 2011 and 2012.

Table A 2.4 - Effect of Digital Reform on concern about other topics

	Unemployment	Crime	Poverty	Tax evasion	Inefficiency of health sector	Immigration	Environment / Pollution	Inefficiency of judicial system	Public debt	Inefficiency of education sector	Others
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
Effect of digital on aged >65	-0.063	-0.050***	0.031	0.018	0.028*	0.003	-0.001	0.031*	0.011	-0.010	-0.001
	(0.075)	(0.011)	(0.022)	(0.013)	(0.017)	(0.018)	(0.026)	(0.018)	(0.022)	(0.006)	(0.007)
Individual & family controls	X	X	X	X	X	X	X	X	X	X	X
Region time-varying controls	X	X	X	X	X	X	X	X	X	X	X
Region fixed effects	X	X	X	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X	X	X	X	X
Mean of outcome	0.72	0.57	0.3	0.22	0.22	0.21	0.16	0.15	0.14	0.07	0.02
Observations	139,165	139,165	139,165	139,165	139,165	139,165	139,165	139,165	139,165	139,165	139,165

Note. The table investigates the effect of the switch to digital signal on the likelihood for individuals aged above 65 of mentioning each of the other problem suggested by the question *"What do you think are the 3 priority problems of the country?"*. Suggested problems are ordered from left to right from the most to the least mentioned. The independent variable is the number of months (as fraction of the 12 before each survey) elapsed since region *r* experienced the switch to digital signal. Individual and family controls include: gender, age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.

Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.5 - Effect of Digital Reform on crime and unemployment

	Unemployment share (*100)		log (Crime rate)	
	(1)	(2)	(3)	(4)
Digital Switch (indicator)	-0.245		-0.019	
	(0.340)		(0.016)	
Digital Switch (fraction)		0.118		-0.022
		(0.302)		(0.018)
Region fixed effects	X	X	X	X
Year fixed effects	X	X	X	X
Observations	114	114	114	114

Note. The table investigates whether the timing of the switch to digital signal is associated with any changes in economic variables that might themselves explain crime perceptions. We regress the unemployment rate (multiplied by 100) and the crime rate in a specific region and year on *Digital_Switch.* Crime rates are calculate as logs of crimes per 10’000 individuals. We use two versions of the variable *Digital_Switch:* a dummy that equals one if the region r experienced the switch-over to digital signal at year t or before (columns 1 and 3); and the number of months, in the calendar year to which the outcomes refers, elapsed since region *r* experienced the switch to digital signal. Observations are at the region by (calendar) year level. The regressions include year and region fixed effects.
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.6 - Effect of Digital Reform on individuals who do not watch TV

	(1)	(2)	(3)	(4)
DigitalSwith * Aged 15-29	-0.011	-0.006	-0.006	0.006
	(0.082)	(0.081)	(0.081)	(0.071)
DigitalSwith * Aged 30-40	-0.011	-0.014	-0.014	-0.000
	(0.039)	(0.038)	(0.038)	(0.032)
DigitalSwith * Aged 41-51	-0.052	-0.057	-0.057	-0.039
	(0.056)	(0.052)	(0.053)	(0.042)
DigitalSwith * Aged 52-65	-0.018	-0.016	-0.016	-0.003
	(0.042)	(0.040)	(0.041)	(0.034)
DigitalSwith * Aged >65	-0.061	-0.071	-0.071	-0.061
	(0.088)	(0.087)	(0.088)	(0.080)
Individual & family controls		X	X	X
Region time-varying controls			X	X
Region & year fixed effects	X	X	X	X
Observations	5,822	5,822	5,822	5,822

Note. The table investigates the effect of the Digital Reform on those individuals who do not watch TV. It reports estimates from a linear probability model of an indicator for the individual reporting crime as one of the 3 main problems in Italy (*Crime_Concern*) on a post switch-over dummy. The sample includes individuals who report to never watch television. Individual and family controls include: age, education, set of dummies of occupational status, family size, family structure, major source of household income. Region time-varying controls include: unemployment rate, crime rate, GDP per capita, share of immigrants, share of population with tertiary education. The regressions include year and region fixed effects.
Robust standard errors are clustered by region and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

3. Risk Attitudes and Household Migration Decisions

3.1. Introduction

A recent and growing body of empirical literature suggests that individual risk aversion has a significant impact on a wide range of individual choices, including portfolio diversification, engagement in healthy behaviours, occupational choices, wealth accumulation, technology adoption and migration decisions (see, among others, Barsky et al., 1997; Bonin et al., 2007; Guiso & Paiella, 2008; Dohmen et al., 2011; Liu, 2013; Jaeger et al. 2010). All these papers explore the relationship between *individual* decision making and the individual's *own* risk aversion. However, when decisions are taken at the household level, the benefit of risk diversification to the more risk averse household members may also influence the decisions of one particular member. One context in which other household members' risk aversion may affect the behaviour of one focal individual is rural-urban migration in developing countries.[26]

[26] There exists a mainly theoretical body of literature suggesting that migrations in this context may be driven by motives of risk diversification (see e.g. Rosenzweig & Stark, 1989). However, these papers do not speak to the question as to how the *distribution* of risk attitudes within the household affects migration decisions.

In this paper, therefore, we analyse how the probability of a household sending a migrant depends on the distribution of risk attitudes within the household. In doing so, we focus on three aspects. First, we re-examine whether migrants are indeed less risk averse than non-migrants. Second, we investigate whether the risk aversion of other household members affects *who* emigrates from a particular household. Finally, we analyse *which households* send migrants and how this choice depends on the distribution of risk aversion among household members, as well as on the individual risk aversion of the potential emigrants.

To structure our empirical investigation, we develop a theoretical framework of household migration decisions from which to derive a set of testable implications. Our model draws on an earlier literature on household migration decisions and risk (e.g. Stark & Levhari, 1982; Hoddinott, 1994), but is most closely related to Chen et al. (2003). We add to this work by introducing heterogeneous risk preferences among family members in a setting in which the family chooses not only whether to send a migrant but also whom to send.[27] Our model provides us with testable implications on migrant selection at the individual level, both within households and across households. We test the model predictions using survey data on internal migration in China, a country that has experienced massive migration flows from rural to urban areas in recent years.[28] As explained in section 3.3.1, the Chinese institutional setting makes household decision models a particularly appropriate tool for analysing internal migration in this country (see also Taylor, Scott, & de Brauw, 1999, 2003).[29] We base our analysis on a unique dataset that includes responses to a set of items designed to elicit risk aversion from both migrants and non-migrants in their areas of origin. The reliability of this measure has been experimentally validated.

We find that in the context of internal migration in a large developing country (in this case, China), individuals who migrate are less risk averse than those who do not migrate. This result

[27] Only few papers study risk sharing when preferences are heterogeneous across households (Mazzocco and Saini, 2012; Chiappori et al., 2014) or within households (Mazzocco, 2004), but none of them study migration decisions.
[28] According to the Chinese National Bureau of Statistics, the number of internal immigrants in China increased from about 30 million in 1996 to over 150 million in 2009; that is, from 2.5 to more than 11% of the total resident population.
[29] China provides an ideal context for our study: under the *houku* residence system (see Section 3.3.1 for more details), migrants in urban areas have limited access to public services such as health, unemployment benefits, and child education in cities. They therefore leave the rest of the family behind while still keeping strong ties to the origin community in the expectation that they will eventually be returning.

lends further support to the findings of Jaeger et al. (2010) and Gibson and McKenzie (2011); our findings further imply that migrations are considered to be risky.[30] We then investigate how migration decisions of one household member are affected by the risk aversion of other household members. In line with our model assumptions, we show that individuals who are the least risk averse in their households are more likely to migrate than those with identical risk aversion but who are not the least risk averse in their household. At the household level, we find that more risk averse households are more likely to send migrants, but only if they have at least one household member who is sufficiently risk loving. These results suggest that internal rural-urban migration in China is a household decision and that the distribution of risk aversion within households is an important additional factor determining the selection of individuals and households into migration.

This role of risk diversification in migration decisions has been previously explored in the migration literature both when the migration decision is an individual choice (e.g. Dustmann, 1997) and when it is made at the household level (see e.g. Stark & Levhari, 1982; Rosenzweig & Stark, 1989; Chen et al., 2003; Morten, 2013).[31] Nevertheless, although these papers pinpoint risk diversification as a key element in a household's decision problem, they do not investigate the relation between risk attitudes and migration choices within and across household units nor do they discuss how the distribution of risk attitudes within households may affect the migration decision. Yet understanding who emigrates, how emigrants compare with other household members, and which households send migrants is crucial for assessing determinants and consequences of migration. Such an understanding is central, for example, to the issue of migrant selection based on unobservable characteristics determining productivity, which has important economic consequences for both receiving and sending communities (see e.g. Borjas, 1987; Borjas and Bratsberg, 1996; Chiquiar & Hanson, 2005; McKenzie & Rapoport 2010; Dustmann, Fadlon & Weiss, 2011). To date, however, such selection has been addressed primarily using models of individual migration decisions. Our analysis, in contrast,

[30] In line with that, Bryan et al. (2014) provide strong evidence for Bangladesh that migration is perceived to be risky and that for this reason individuals refrain from migrating despite large gains and small costs.

[31] The importance of household migration decisions as mechanisms to cope with unexpected negative shocks is illustrated by Jalan and Ravallion (1999) for rural China, who show the poorest households passing up to 40% of income shocks onto current consumption. Further, Giles (2006) and Giles and Yoo (2007) show that the liberalization of internal migration flows in China in the early '90s provided rural household with a new mechanism to hedge against consumption risk.

employs a household-level migration decision model to show that the risk preferences of *other* household members and their distribution within the household may not only determine who and how many emigrate but may also influence the level of risk aversion of the migrant population. This latter point is especially important in the face of recent findings that risk aversion is negatively correlated with both cognitive ability (Dohmen et al. 2010) and the probability of engaging in entrepreneurial activity (Ekelund, Johansson, & Lichtermann, 2005; Levine & Rubinstein 2014), which point to it being a key factor determining immigrant success.

The remainder of the paper is organized as follows. Section 3.2 outlines our theoretical framework for the relation between individual risk aversion and the household decision of whether to send a migrant and whom to send, and then develops the empirical implications of this relation. Section 3.3 describes the institutional background and data, and section 3.4 explains our empirical strategy. Section 3.5 reports the estimation results, and section 3.6 concludes the paper.

3.2. A Model of Household Migration Decision with Individual Heterogeneity in Risk Aversion

3.2.1. *Setup*

We denote individual earnings by y_j, where $j = S, D$ for source (*S*) and destination (*D*) region, and assign earnings a deterministic component $\bar{y}_j$ and a stochastic component ϵ_j, with $E(\epsilon_j) = 0$; $V(\varepsilon_j) = \sigma_j{}^2$ for $j = S, D$.[32] We further assume that shocks in source and destination regions are uncorrelated: $Cov(\varepsilon_S \varepsilon_D) = 0$.[33] Migration to region D incurs a

[32] In the context of rural-urban migration in China, the variance in earnings of urban migrations stems primarily from unemployment risk, while wages for rural migrants are fairly compressed around the subsistence level).
[33] Allowing for a non-zero correlation between shocks in source and destination regions does not change any of our conclusions (see Appendix section A.I.C) but does complicate our analysis.

monetary cost c that is heterogeneous across households but homogenous within households.[34] Earnings in the two regions are thus

$$y_S = \bar{y}_S + \varepsilon_S \tag{1}$$

$$y_D = \bar{y}_D - c + \varepsilon_D \tag{2}$$

Here, each household consists of two members who can perfectly pool their income only if they are both residing in the same origin region S.[35] We use $\tilde{Y}$ to denote total pooled household income and $\tilde{y}$ to represent the amount each individual receives from the pooled income. If both members stay in S, the total pooled household income is given by $\tilde{Y}_{SS} = 2y_S$, and each individual receives exactly $\tilde{y}_{SS} = y_S$.

If one individual migrates, distance and frictions will only allow imperfect income pooling. In particular, the member who remains in region S will pool her entire income y_S and receive a full quota of the total pooled income, while the member who migrates to region D will only contribute a fraction α of his earnings y_D and will receive the same fraction α of the full quota. Hence, total pooled income if one household member has emigrated is given by $\tilde{Y}_{SD} = y_S + \alpha y_D$. Defining $\tilde{y}^{NM}$ and $\tilde{y}^{M}$ as the individual disposable income of the non-migrant (NM) and migrant (M) household member, respectively, yields:

$$\tilde{y}^{NM} = \tilde{Y}_{SD}/(1+\alpha) \tag{3}$$

$$\tilde{y}^{M} = \alpha[\tilde{Y}_{SD}/(1+\alpha)] + (1-\alpha)y_D \tag{4}$$

It is thus parameter α that determines the extent to which the household engages in risk diversification across its members and the level of insurance the migrant receives against uncertainty in the destination region. If α equals zero, the migrant is fully exposed to uncertainty in region D (which is equivalent to the case of an individual migration decision). If instead, α equals one, migration can reduce the overall household variance in income, and the migrant and non-migrant members face the same exposure to uncertainty.

[34] This assumption reflects the fact that households may differ in their wealth, access to credit, distance from the destination region, etc. but that, within each household, the cost of financing the migration of one member or the other does not differ.

[35] Our theoretical framework can be straightforwardly extended to N household members. For example, in the subsequent simulation (see Appendix section AII), we use four household members, reflecting the average household size in our data.

3.2.2. Household migration decision

The household's decision to send a migrant to the destination region *D* is made by comparing the household utility of no migration with that of sending one household member to region *D*. We assume that household members differ only in their degree of risk aversion *k*, have a mean-variance utility function, and jointly maximize the sum of their utilities to act as a coherent unit.[36]

If both members remain in the source region *S*, the household utility is given by

$$U_{SS} = [E(y_S) - k_1 V(y_S)] + [E(y_S) - k_2 V(y_S)] = 2\bar{y}_{\mathrm{S}} - (k_1 + k_2)\sigma_S^2 \tag{5}$$

If instead one household member remains in region *S* (individual 1) and one migrates to region D (individual 2), the household utility is given by

$$U_{SD} = [E(\tilde{y}^{NM}) - k_1 V(\tilde{y}^{NM})] + [E(\tilde{y}^{M}) - k_2 V(\tilde{y}^{M})] =$$

$$= \underbrace{\left[\left(\frac{\bar{y}_{\mathrm{S}}+\alpha(\bar{y}_{\mathrm{D}}-c)}{1+\alpha}\right) - k_1\left(\frac{\sigma_S^2+\alpha^2\sigma_D^2}{(1+\alpha)^2}\right)\right]}_{NM} + \underbrace{\left[\left(\frac{\alpha\bar{y}_{\mathrm{S}}+(\bar{y}_{\mathrm{D}}-c)}{1+\alpha}\right) - k_2\left(\frac{\alpha^2\sigma_S^2+\sigma_D^2}{(1+\alpha)^2}\right)\right]}_{M} \tag{6}$$

The household will send a migrant whenever $\mathrm{U_{SD}} - \mathrm{U_{SS}} > 0$:

$$\mathrm{U_{SD}} - \mathrm{U_{SS}} = \underbrace{\left(\frac{\bar{y}_{\mathrm{S}} + \alpha(\bar{y}_{\mathrm{D}} - c)}{1+\alpha} - \bar{y}_{\mathrm{S}}\right)}_{\Delta\, E(\tilde{y}^{NM})} - k_1 \underbrace{\left(\frac{\sigma_S^2 + \alpha^2\sigma_D^2}{(1+\alpha)^2} - \sigma_S^2\right)}_{\Delta\, V(\tilde{y}^{NM})} +$$

$$+ \underbrace{\left(\frac{\alpha\bar{y}_{\mathrm{S}}+(\bar{y}_{\mathrm{D}}-c)}{1+\alpha} - \bar{y}_{\mathrm{S}}\right)}_{\Delta\, E(\tilde{y}^{M})} - k_2 \underbrace{\left(\frac{\alpha^2\sigma_S^2+\sigma_D^2}{(1+\alpha)^2} - \sigma_S^2\right)}_{\Delta\, V(\tilde{y}^{M})} > 0 \tag{7}$$

These terms thus characterize the change in expected earnings and earnings variance from migration (with respect to non-migration) for both the migrant and the non-migrant household member.

[36] The assumption that the family acts as a coherent unit can be justified either (a) based on the existence of a dominant head of household or (b) by a family utility function that is the aggregate of individual utility functions (assuming all household members have the same preferences, including risk aversion) (see Chen et al., 2003). In our case, household members do not have homogenous preferences (i.e. they differ in risk aversion), so we assume that a dominant head of household makes the decision of who migrates on behalf of the household.

We now identify the conditions under which expression (7) (i.e. the household gains from the migration of one of its members) is positive.[37] We first consider the changes in the expected earnings of the non-migrant and migrant, $\Delta E(\tilde{y}^{NM})$ and $\Delta E(\tilde{y}^{M})$. Both these will be positive as long as the migrant's expected earnings in the destination region (net of migration costs) are larger than in the source region ($\bar{y}_{\mathrm{D}} - c > \bar{y}_{\mathrm{S}}$). We then consider the changes in the earnings variances for the non-migrant and the potential migrant, $\Delta V(\tilde{y}^{NM})$ and $\Delta V(\tilde{y}^{M})$. In this model, risk diversification alone may lead the household to choose to send a migrant, even if the earnings differential between source and destination regions is zero (i.e. $\Delta E(\tilde{y}^{NM}) = \Delta E(\tilde{y}^{M}) = 0$). FIGURE 3.1 shows the relation between σ_D^2 (horizontal axis) and the change in earnings variance (vertical axis) for the migrant ($\Delta V(\tilde{y}^{M})$) and non-migrant ($\Delta V(\tilde{y}^{NM})$), respectively. Although both terms are increasing functions of σ_D^2, $\Delta V(\tilde{y}^{M})$ is steeper than $\Delta V(\tilde{y}^{NM})$, with slopes of $1/(1+\alpha)^2$ and $\alpha^2/(1+\alpha)^2$, respectively, which reflects the higher exposure of the migrant to risk in the destination region.[38] The non-migrant's earnings variance is reduced by migration ($\Delta V(\tilde{y}^{NM}) < 0$) if the variance in destination region D is not excessively larger than in source region S: $\sigma_D^2 < \frac{2+\alpha}{\alpha}\,\sigma_S^2$. Similarly, the migrant will experience a reduction in earning variance for sufficiently low values of σ_D^2: $\Delta V(\tilde{y}^{M})$ is negative for $\sigma_D^2 < (1+2\alpha)\sigma_S^2$. It should also be noted that $\Delta V(\tilde{y}^{M})$ crosses the zero line before $\Delta V(\tilde{y}^{NM})$: the threshold for σ_D above which a migration leads to *higher* earnings risk than non-migration is always higher for the non-migrant than for the migrant ($\frac{2+\alpha}{\alpha} > 1 + 2\alpha$). Obviously, the lower the share α of the migrant's earnings that is re-distributed to the non-migrant, the higher (lower) the earnings variance in region D that still reduces the overall earnings variance for the non-migrant (migrant) household member. Finally, if $\sigma_D^2 = \sigma_S^2$, the change in earnings variance is identical (i.e. $\Delta V(\tilde{y}^{M})$ and $\Delta V(\tilde{y}^{NM})$ cross), and both individuals benefit from the diversification of income risk.

[37] We do not consider the case in which both household members migrate because in the context we empirically analyse entire households do not emigrate.

[38] The difference in the slope of the two lines is inversely related to the parameter α, which determines the degree of income pooling: when income pooling is perfect (α =1) the two lines overlap.

The intersection of these two lines with each other and with the zero line creates three different scenarios for $\sigma_D^2 > \sigma_S^2$.[39] To the right of the two-line intersection but before either line intersects the *x*-axis ($\sigma_D^2 < (1+2\alpha)\sigma_S^2$; area I in the graph), σ_D^2 is only moderately larger than σ_S^2, so risk diversification leads to a decrease in earnings risk for both migrant and non-migrant. For intermediate values of σ_D^2, ($(1+2\alpha)\sigma_S^2 \leq \sigma_D^2 < \frac{2+\alpha}{\alpha}\,\sigma_S^2$; area II), earnings risk decreases for the non-migrant but increases for the migrant. Finally, for high values of σ_D^2, ($\sigma_D^2 \geq \frac{2+\alpha}{\alpha}\,\sigma_S^2$; area III), migration increases earnings risk for both household members.

The actual decision to migrate, however, also takes into account the relative gains in expected earnings. In the case of a zero earnings differential (net of migration cost) between source and destination region, migration will always be optimal in area I (in which both individuals reduce their exposure to risk by having one migrant in the household). There will be migration in area II as long as the utility gain in reducing uncertainty of the non-migrant member more than compensates for the loss experienced by the migrant. Finally, no migration will take place in area III. Positive earning differentials, however, may shift these decisions, meaning that migration may also take place in area III.

3.2.3. Who will migrate?

We now investigate the household's choice of whom of its members to send as a migrant. We first note that if the earnings variance is higher in the destination region than in the source region ($\sigma_D^2 \geq \sigma_S^2$), the migrant is always exposed to at least as high an income variance as the non-migrant (for any value of $0 \leq \alpha \leq 1$):

$$V[\tilde{y}^M] = \left(\frac{\alpha^2\sigma_S^2+\sigma_D^2}{(1+\alpha)^2}\right) \geq V[\tilde{y}^{NM}] = \left(\frac{\sigma_S^2+\alpha^2\sigma_D^2}{(1+\alpha)^2}\right) \qquad \text{if} \quad \sigma_D^2 \geq \sigma_S^2\,. \tag{8}$$

The decision of which of the two individuals will emigrate will be based on the comparison of household utility when one member, rather than the other, migrates. We have:

Proposition 1. As long as migration is riskier than non-migration, $V[\tilde{y}^M] \geq V[\tilde{y}^{NM}]$*, it is always optimal to choose the least risk averse individual in the household as the potential*

[39] A fourth case (area 0 in the graph) arises whenever $\sigma_D^2 < \sigma_S^2$. In this scenario, not only does the earnings risk decrease for both migrant and non-migrant, but the earnings risk of the migrant is lower than that of the non-migrant.

migrant (although it may be optimal to send nobody. If instead $V[\tilde{y}^M] \leq V[\tilde{y}^{NM}]$, *it is optimal to choose the most risk averse individual in the household.*

Proof. See Appendix A.I.A

If migration choices are made at the individual level, only the *absolute* risk aversion of individuals should matter for the migration decision. Proposition 1, however, implies that if the decision is taken at the household level, the elasticity of migration probabilities to individual risk aversion depends also on the way individuals with different risk attitudes mix within the household. Hence, the *relative* risk aversion of individuals with respect to the risk aversion of other household members should also matter. In other words, whereas two individuals with identical risk aversion would, all else being equal, have the same probability of migrating in an individual migration decision model, in a household decision model, that probability will differ depending on the composition of the risk aversion of the other household members.

Empirically, an individual decision model (which corresponds to the case where $\alpha = 0$) would predict a lower average risk aversion among the migrant population than among the non-migrant one when income variance at destination is higher than in the source region. This prediction is also compatible with the household migration decision model outlined above. However, whereas the individual model makes no predictions about how the migration probability relates to the risk aversion of other household members, the household decision model predicts that the relative position in the within household risk aversion ranking – and not just the absolute risk aversion – matters for the migration probability. This is one of the implications of the model that we will test below.

3.2.4. Which household will send a migrant?

Which households, then, are more likely to send migrants? The answer involves two counteracting factors within each household. On the one hand, migration can reduce the income uncertainty of the non-migrant household members, and their utility gain increases with their risk aversion. On the other hand, if migrating involves more exposure to uncertainty, the household needs members with sufficiently low risk aversion as suitable candidates for migration. Hence, in a household in which everyone is very risk averse, although there is a strong desire for risk diversification, no member will be a good candidate for migration. Conversely, in households in which all members have low risk aversion, there will be many candidates for migration but lower demand for risk diversification. Thus, the likelihood of a household sending a migrant will depend on the *distribution* of risk attitudes within the household. We formalize this intuition in the following proposition:

Proposition 2

(i) *Consider two households that differ only in the risk aversion of their members but have identical average risk aversion. If migration increases (reduces) the exposure to risk of the migrant member, the household with more (less) variation in its members' risk preferences will benefit the most from migration.*

(ii) *Consider two households that differ only in the degree of risk aversion of the least risk averse individual. If migration increases (reduces) the exposure to risk of the migrant member, the household whose least risk averse individual has lower (higher) risk aversion will benefit the most from migration. [Alternatively: Consider two households that differ only in the degree of risk aversion of the most risk averse individual. If migration reduces (increases) the exposure to risk of the non-migrant member, the household whose most risk averse individual has higher (lower) risk aversion will benefit the most from migration.]*

Proof. See Appendix A.I.B.

According to proposition 2, when migration is risky households are more likely to send migrants if they have some members with low risk aversion (who are good candidates for migration) and some with high risk aversion (who will gain most by sending another household member to reduce their exposure to income uncertainty). This observation implies that, beyond the risk aversion of individual members, the within household dispersion in risk aversion affects the likelihood that a household sends a migrant. Again, this is an implication tested below.

3.2.5. An illustration of individual and household decisions

Our model suggests that the risk attitudes of other household members, in addition to the risk preferences of individuals, should matter in shaping individuals' migration choices. Before exploring this question empirically, we examine the implications of an individual versus a household decision model for migration rates and for the selection of migrants and non-migrants according to their risk aversion. In the individual model, there is no income pooling ($\alpha = 0$) and each agent autonomously decides whether it is optimal to migrate or not. In the household decision model, instead, household members pool income ($0 < \alpha \leq 1$) and take joint decisions on the migration of their members.

In our simulation, we generate a population of 10,000 individuals with mean-variance utility functions that are randomly assigned a value of willingness to take risks (varying between zero and ten) whose distribution mimics the one we observe in our data. Further, we choose values for expected earnings $E(y_S)$ and earnings variance $V(y_S)$ in the source region S, assume that expected earnings $E(y_D)$ in destination region *D* are twice as large as in region *S*, and vary the earnings variance $V(y_S)$ to study how migration choices react to relative changes in the earnings variance in the two regions.[40]

We then simulate migration decisions under the two models discussed above: the individual model and the household model. In the first case, decisions are made individually, and individuals face the same expected income and income variance but differ in migration costs.[41] In the second model, we assign individuals to households so that the within household correlation in risk aversion roughly resembles that in our data (the within household standard deviation of willingness to take risks is 0.9). Each household has four members, the average household size in our data, which results in 2,500 households in the simulation. Once households are formed, we randomly reassign migration costs to the household using the same distribution as above. Finally, we assume that migrants pool about a third of their income with the origin family (i.e. we set the parameter $\alpha = 0.3$), and that at most one individual can migrate from each household. As in our model, a household chooses to send a member to destination region *D* if the utility is higher than the utility from keeping all members in region *S*.

[40] We set: $E(y_S) = 16$; $V(y_S) = 40$; $E(y_D) = 32$ and we let $V(y_S)$ vary in the interval: $[0.1 * V(y_D) \leq V(y_S) \leq 10 * V(y_D)]$.
[41] We assume migration costs are uncorrelated with risk attitudes. In our simulations, individuals are assigned a (pseudo) random value of migration cost drawn from a chi-squared distribution with 2 degrees of freedom so that the mean value of migration costs (7.9) is approximately equal to half of the expected earnings in the source region.

FIGURE 3.2 plots the predicted migration rates and the average willingness to take risks among migrants and non-migrants for the two models. The horizontal axis carries the earnings variance in the destination region D relative to the source region S (with expected earnings in region D assumed to be twice as high as in region S), while the vertical axis carries the migration rate on the left-hand side and the average willingness to take risks on the right-hand side. In both models the trend of the simulated migration rates are similar: when the variance ratio $V(y_D)/V(y_S) < 1$ the migration rates (solid line) are close to 100%, but they gradually decline as uncertainty in the destination region increases (relative to the source region). Similarly, both the individual and the household decision models imply that sorting leads to a higher average willingness to take risk for migrants (dash-dotted line) than for non-migrants (dashed line) when there is lower uncertainty in the source region than in the destination. Thus, migrants will always be less risk averse than non-migrants no matter whether the migration decision is taken at the individual or household level.

The two models diverge, however, in their quantitative predictions of the migration rate for any given level of relative earnings variance in the two regions. Whereas the individual model predicts a rapid decline in the share of migrants with increasing uncertainty in the destination region, such decline is less pronounced when migration decisions are taken at the household level. Thus, the household migration model predicts positive migration rates for levels of destination uncertainty for which an individual model would predict zero migration. It does so because first, the other household members benefit from risk diversification even if the earnings variance in the destination region is high and second, the migrant is partially insured against risks in the destination region by household members who stay at home.[42] Both these factors are absent in a model in which migration decisions are made at the individual level.[43] It is thus important to understand whether migration decisions are taken at the individual or the household levels and whether they depend on the level of risk aversion of other household members. We address both these issues empirically in the remainder of the paper.

[42]One can show that the lower is the share of income that the migrant pools with the rest of the family (parameter α in the model), the faster the migration rate drops as relative uncertainty in the destination region increases.
[43] When the risk aversion of the most risk averse household members increases, and the insurance parameter α increases, the solid line in panel B of **FIGURE 3.2** shifts further outwards.

3.3. Background and Data

3.3.1. Internal migration in China

In the late 1970s, rural communities in China moved from a "commune system" to a "household responsibility system" under which households, which were allocated land use rights, could choose their own crops, and were allowed to sell their produce freely on the market. While this shift significantly increased agricultural productivity, many basic social services provided by the communes were abolished, so households found themselves in the situation of having to finance their own health and education, as well as having to deal with other unforeseeable risks, such as adverse weather conditions. This change increased the need to diversify the sources of household income, but before the early 1990s, such diversification was limited by relatively strict rural-urban segregation enforced through a household registration system (or *hukou*) that gave people the right to live only in the jurisdiction of their birth (see Meng, 2012). It was not until the late 1990s, when the massive economic development of urban areas created a significant increase in demand for unskilled labour that the government began to loosen its enforcement of migration restrictions. According to data from the Chinese National Bureau of Statistics (NBS), the total number of rural-urban migrants increased from around 30 million in 1996 to 150 million in 2009, a rise from 2.5 to 11% of the total resident population.

However, the lack of an urban *hukou* prevents migrants in cities from accessing certain occupations and excludes them and their dependants from health care, pension insurance, unemployment insurance, and many other social services available to urban *hukou* holders (Meng & Zhang, 2001). The *hukou* system thus prevents rural migrants from settling in cities and causes them to leave their families behind (Meng & Manning, 2010). As a result, complete households seldom migrate to urban areas in China, choosing instead to send particular household members to migrate to urban centres (as represented by our model in the previous section). Migrants generally engage in circular migration and repeated short term migration spells are common (in our sample, migrants spend an average 9.6 months per year working in destination regions and the remaining 2.4 months at home).

Rural migrants face difficult conditions in urban areas, with average wages at the lower end of the urban wage distribution (Meng & Zhang, 2001; Frijters et al., forthcoming), receiving unequal pay even within the same occupation (Meng & Zhang, 2001), with about one in three falling below the poverty line (Du et al., 2005). Strenuous working hours, poor housing, and no access to health care are all factors that lead to serious health hazards (Du et al., 2005), contributing to the various risks associated with migration. In line with the theoretical model outlined in the previous section, if migrants are exposed to more uncertainty in the destination region than at home we should expect them to be relatively less risk averse than the non-migrant population.

3.3.2. Data and samples

Our primary data source is the Rural Household Survey (RHS) from the Rural-Urban Migration in China (RUMiC) project (henceforth RUMiC-RHS). RUMiC began in 2008 and it conducts yearly longitudinal surveys of rural, urban, and migrant households. The RUMiC-RHS was conducted for 4 years and administered by China's National Bureau of Statistics. It covers 82 counties (around 800 villages) in 9 provinces identified as either major migrant sending or receiving regions and is representative of the populations of these regions. The survey includes a rich set of individual and household level variables that contains not only the usual demographic, labour market, and educational data but also information on individual migration experience and subjective rating of willingness to take risks, both particularly relevant to this study. Unlike other surveys, it records information on all household members whose *hukou* are registered in the household. Thus, household members who were migrated to cities at the time of the survey were also included. Information on household members who were not present at the time of the survey was provided by the main respondent. However, questions related to subjective issues and opinions (e.g. risk attitudes) are only answered by individuals who were present at the time of the survey. In this paper, we use data from the 2009 RUMiC-RHS, conducted between March and June of that year, which was the first wave that reports information on risk aversion.

To identify migrants, the survey includes questions on the number of months each individual spent living away from home during the previous year (i.e. 2008) and the reason for their absence (e.g. education, military service, work/business, visiting friends and relatives.) We thus define a *labour migrant* as an individual who spent 3 or more months away from home in the previous year for work or business purposes.

In the 2009 wave of the RUMiC-RHS survey interviewees were asked to rate their *attitudes towards risk.* The question states "In general, some people like to take risks, while others wish to avoid risk. If we rank people's willingness to take risks from 0 to 10, where 0 indicates 'never take risk' and 10 equals 'like to take risk very much,' which level do you think you belong to?" According to a recent literature, responses to direct questions on self-reported risk aversion are reasonable proxies of more objective measures of risk attitudes obtained from having respondents playing lotteries (Ding, Hartog, & Sun, 2010; Dohmen et al., 2011). Moreover, Frijters, Kong, and Meng (2011) have specifically validated the risk attitude question used in the RUMiC survey.[44]

In our empirical analysis, we test the predictions of the theoretical model presented in section 3.2 by investigating individual as well as household migration probabilities (see section 3.4). For the *individual* level analysis we focus on individuals who are in the workforce and who, therefore, are potential migrants. The 2009 RUMiC-RHS survey includes 17,658 individuals in the labour force (i.e. aged between 16 and 60 and not currently at school or disabled) who provide information about age, gender, educational level and migration status.[45] To be able to carry out our analysis we restrict the sample to individuals living in households where at least two members in the work force have reported risk preference, which reduces the sample to 7,808 individuals. As Panel A in Appendix Table A **3.1** shows, the sample of individuals in households we focus on is almost identical in observables to that of individuals in households in the overall sample. Information on risk aversion is available for 81% of that sample, leading to a final estimating sample of 6,332 individuals. For the household-level analysis, we use all households where at least two members reported their willingness to take risks, but we also

[44] Frijters, Kong, and Meng (2011) ask a random sub-sample of 1,633 rural-urban migrants from the Urban Survey to play a risk game similar to that used by Dohmen et al. (2011). They find that self-assessed risk and the risk measures revealed by the game are highly correlated, with a correlation coefficient of 0.7.

[45] The 2009 RUMiC-RHS survey includes a total of 32,249 individuals. We focus on those aged 16–60 because the probability of being a migrant drops below 1% for individuals over 60. Nevertheless, shifting the upper bound of this age range by five years (in either direction) does not alter our empirical findings.

include individuals above age 60, as their risk aversion is likely to matter for decisions of the household whether or not to send a migrant, which results in a sample of 2961 households. [46] Panel B in Appendix **Table A 3.1** shows that these households are almost identical in observable characteristics to the overall sample.

The risk attitudes question can only be answered by respondents who are present at the time of the survey, which is a potential problem for migrants. In our data, the share of non-responses is higher among migrants (55%) than among non-migrants (10%).[47] This may be problematic if unobservables that affect the probability to be present at the time of the interview are correlated with individual risk aversion, conditional on observables. There is no reason to believe that migrants who happened to be present at home between March and June in 2009 differ systematically in risk attitudes from migrants who were absent. To nevertheless test this hypothesis, we make use of the fact that we observe individual characteristics also for those who are absent at the time of the survey as these are reported by other family members; as discussed above, attitudes towards risk is the only missing information in such cases. We estimate a simple selection model using family events such as death, marriage, or birth that occurred before or after the interview as instruments to identify the participation equation, i.e. whether the migrant was present at the interview. These events, while arguably uncorrelated with migrants' risk attitudes, may have induced the individual to return to the home village, or to remain longer at home, and hence increased the probability of participating in the survey. We then construct the generalised residuals and include them in an equation where willingness to take risk is the dependent variable, conditioning in both equations on other observables that are used in the main analysis. A test of correlation between the unobservables determining survey participation and individual risk attitudes corresponds then to a simple t-test of whether the coefficient of the generalised residual is significantly different from zero. Despite our instruments being strong predictors for interview participation, we cannot reject the null

[46] Excluding individuals over 60 from the household sample lead to very similar estimation results.
[47] In comparison with similar surveys in other developing countries, the RUMiC-RHS survey has a much higher response rate for migrants, due to the special institutional settings of internal migration in China. As discussed earlier, most migrants are still subject to a rural *hukou* in their home village and leave their immediate family behind to go and work in cities. To look after their left-behind relatives, repeated short term migration spells are common. In our sample migrants spend on average 9.6 months per year working in destination regions and 2.4 months at home. Moreover, the majority of migrants return home for the Chinese New Year (or Spring Festival), celebrated between late January and early February, and stay on for some weeks or months. All this increases the chances of finding migrants in their home village at the time of the survey.

hypothesis that the residual correlation in risk aversion and interview participation is zero for any of the specifications we estimate. We provide details of this test in appendix A.II, and report estimates in Appendix Table A 3.2.

3.3.3. Descriptive statistics

We provide descriptive statistics on individual characteristics in the upper panel of Table 3.1. The numbers show that males account for about half our sample, with an average age of 43.8 years and an average education of 7.15 years. About 92% of our respondents are married and have on average 3.1 siblings and 1.7 children. The average of our measure of willingness to take risks is 2.6 (with a standard deviation of 2.4). The lower panel of Table 3.1 shows the characteristics of the 2,961 households in our sample. The average household size is 4.1, with an average of 2.9 individuals of working age.[48] About 16% of the households in the sample have at least one member who migrated in the previous year, and 11% of the individuals in our sample can be classified as migrants, with the rate among males and females being 14.0% and 7.9%, respectively. Further, about 23% of the interviewees in our sample reported having migrated at least once in the past. In our empirical analysis, we will use this as a second measure for migration status to check the robustness of our findings.

The distribution by migrant status of our measure of willingness to take risk, which ranges between 0 (highest level or risk aversion) and 10 (lowest risk aversion), is plotted in Figure 3.3. For both groups of respondents, the distribution is skewed to the left: the mode value is zero for both migrants and non-migrants, and the share of respondents categorizing themselves as being at the highest level of risk aversion is 18% and 31%, respectively. The unconditional mean of the measure is 2.4 and 3.6 for non-migrant and migrants, respectively. Hence, the migrant distribution is clearly shifted more towards less risk aversion than the non-migrant distribution.

Our data also show a correlation between individual and household risk preferences that supports Dohmen et al.’s (2012) claim that intergenerational transmission of risk attitudes and assortative mating of parents may generate within household correlation in preferences

[48] The one-child policy introduced in 1979 was less restrictive in rural areas (allowing rural families to have a second child if the first one was a girl) and less strictly enforced. In our sample, individuals born before and after 1979 have an average of 3.3 and 2.1 siblings, respectively.

towards risk. Nevertheless, there is still substantial heterogeneity in the way individuals with the same degree of risk aversion are matched with other household members' risk preferences. To demonstrate these features, we compute the residuals from regressing individual willingness to take risks on basic demographic controls (gender, age, and age squared) and a full set of county of residence dummies.

Figure 3.4 plots the residuals for each individual in our sample (on the vertical axis) versus the average of other household members (on the horizontal axis); the fitted line shows a clearly positive relation between individual and household residual risk attitudes (with a correlation of about 0.58), which confirms Dohmen et al.'s (2012) findings. On the other hand, the scatter plot also shows considerable variation, a within household heterogeneity we exploit in our regression analysis (see section 3.4).[49]

3.4. Empirical Strategy

In our empirical analysis, we regress the probability of being a migrant, or the probability that a household sends a migrant, on different measures of willingness to take risk at both the individual and household level, as well as on a large set of background controls (individual characteristics, household characteristics, and area fixed effects). Our analysis addresses two issues: first, how risk aversion determines individual migration decisions, and second, the role of risk attitudes at the household level for migration decisions. In this second part, we first test whether and to what extent individuals are chosen to migrate according to their *relative* risk preferences within the family (*within household migration decision*) and then which households are more likely to send migrants (*across household migration decision)*.

Individual migration decision. To assess this first aspect, we estimate the following equation:

$$\Pr(M_{ihk} = 1) = \alpha_0 + \alpha_1\, wtRisk_{ihk} + \mathbf{X}'_{ihk}\beta + \mathbf{W}'_{hk}\theta + \eta_k + \epsilon_{ihk} \qquad (9)$$

where *i* indexes individuals, *h* households, and *k* administrative counties. The variable M_{ihk} is an indicator of whether individuals have spent at least 3 months working outside their origin

[49] This is in line with evidence provided by Mazzocco (2004) of imperfect assortative mating on risk aversion in US couples. Using data from the Health and Retirement Study (HRS), he shows that self-reported risk attitudes differ between husband and wife for about 50 percent of the couples in the sample.

area during the previous year. Our main variable of interest is the willingness to take risks, $wtRisk_{ihk}$, measured on a scale from 0 (most risk averse) to 10 (least risk averse). The vector $\mathbf{X}'_{ihk}$ collects a set of individual-level covariates that are important determinants of individual migration probability, including gender, age, age squared, marital status, number of children, years of education, number of siblings, and birth order. The vector $\mathbf{W}'_{hk}$ includes a set of family characteristics, such as household size and structure (number of family members under 16, in the work force, or older than 60); and per capita house value (in logs). We also include county fixed effects η_k to capture any time invariant observable and unobservable area characteristic that may be correlated with both attitude towards risk and propensity to migrate.[50] An individual or household migration decision model in which migration implies exposure to higher uncertainty would suggest that migrants are less risk averse than non-migrants. Therefore, if Chinese rural migrants are exposed to higher uncertainty in urban areas than their relatives who remained at home, we would expect the coefficient α_1 in equation (9) to be positive.

Within household migration decision. Proposition 1 of our theoretical model implies that the individual probability of being a migrant should depend on both the individual's own risk aversion and the risk aversion of other household members (section 3.2.3).

We test this proposition in two ways: First, we estimate individual-level regressions as in equation (9) but now including both the individual's absolute risk preferences ($wtRisk_{ihk}$) and the individual's position in the household ranking of willingness to take risk ($wtRisk\_rel_{ihk}$) among members in the workforce. This way, we can use the coefficient on the $wtRisk\_rel$ variable to identify individuals with higher relative risk preference within the family from individuals who have the same level of risk preference ($wtRisk$) but are in different positions on the risk aversion ranking within their respective households. According to proposition 1, when migration is risky, all else being equal, the least risk averse individuals in a household should have a higher probability of migrating. The ordinal measure of risk preferences should thus have an effect over and above the effect of the cardinal measure. If migration is purely an individual decision, then once individual risk attitudes are controlled for, the position in

[50] Dohmen et al. (2012) provide evidence of correlation in risk aversion among individuals residing in the same area, showing particularly that once parental attitudes are controlled for, regional risk attitudes are correlated with children's risk attitudes.

household ranking should not influence the migration probability (i.e. the coefficient on the $wtRisk\_rel$ variable should not be statistically different from zero).

Our second approach is to re-estimate equation (9) including both individual risk attitudes ($wtRisk_{ihk}$) *and* the average risk preferences of the other household members who are in the workforce ($wtRisk\_oth_{ihk}$). Conditional on their own risk attitudes, individuals who belong to a household in which the other members are relatively less willing to take risks (i.e. have lower values of the $wtRisk\_oth$ variable) should be more likely to migrate (because they are more likely to be the least risk averse in the household). If migration implies a higher exposure to uncertainty, we would thus expect to find a positive coefficient on the $wtRisk$ variable (as in all previous regressions) and a negative coefficient on the $wtRisk\_oth$ measure.

Across household migration decision. Finally, to assess which households have a higher probability of sending migrants, we estimate *household-level* regressions of the probability of sending a migrant, and then test statements (i) and (ii) of proposition 2 (see section 3.2.4).

The first statement suggests that, conditional on having the same mean risk aversion, households with a larger variation in risk preferences should be more likely to send migrants. We test this prediction by estimating the following equation:

$$\Pr(M_{hk} = 1) = \delta_0 + \delta_1\, HH\_avg\_wtRisk_{hk} + \delta_2\, HH\_range\_wtRisk_{hk} + \mathbf{W'}_{hk}\theta + \eta_k + u_{hk} \quad (10)$$

where the probability that a household sends a migrant depends on the average risk aversion in the household (HH_avg_wtRisk), the within-household range in risk attitudes (HH_range_wtRisk), other household controls and area fixed effects. Conditional on household average risk aversion, we expect households with a larger variance in risk attitudes to be more likely to send a migrant.

The second statement in proposition 2 implies that (if migration implies exposure to higher uncertainty) the probability of a household sending a migrant increases with the willingness to take risk of the least risk averse member but simultaneously decreases with the willingness to take risk of the other (non-migrant) members. To test this implication, we estimate the following household-level equation:

$$\Pr(M_{hk} = 1) = \gamma_0 + \gamma_1\, HH\_max\_wtRisk_{hk} + \gamma_2\, HH\_oth\_wtRisk_{hk} + \mathbf{W}'_{hk}\theta + \eta_k + u_{hk} \tag{11}$$

where we separately include in the regression the risk preferences of the least risk averse individual in the household (HH_max_$wtRisk$) and then the average risk attitudes among the other household members (HH_oth_$wtRisk$). Our theoretical framework would lead us to expect the coefficients on these two risk measures to have opposite signs if migration exposes the migrant to higher uncertainty but allows the household to diversify risk and thus reduce the other household members' risk exposure. In particular, we would expect a positive coefficient on the first variable and a negative one on the second.

3.5. Results

We first present our findings for individual and within household migration decisions and report the results of our robustness checks against alternative interpretations of our results. We then discuss our results for across household migration decisions.

3.5.1. Individual risk aversion

Table 3.2 summarizes the results from our estimation of a linear probability model of the individual probability of migrating based on equation (9).[51] Here, we use two alternative measures of migration status: whether the individual migrated for work during the year before the survey (columns 1–4) and whether the individual had ever migrated in the past (columns 5–8). In all regressions, we include a full set of 82 county dummies and cluster the standard errors at the household level to allow for within household correlation in the error terms.

In column 1, we report the results of regressing individual migration status on our measure of willingness to take risk, after which we successively add in further individual and household controls (columns 2–4). All estimates show a strong positive association between individual willingness to take risks and the probability of being a migrant, which suggests that individual risk attitudes play an important role in determining individual propensities to migrate. The estimated coefficient on the $wtRisk$ variable reduces in magnitude when basic individual

[51] The marginal effects based on probit or logit estimators, reported in Appendix **Table A 3.3**, are almost identical to those reported here.

controls are included (from 0.014 in column 1 to 0.005 in column 2), but remains stable when additional individual controls and household characteristics are added in (columns 3–4). This pattern is consistent with basic demographic characteristics such as gender and age being strong predictors of individual risk attitudes (see among others, Barsky et al. 1997 and Borghans et al. 2009). The effect estimated is economically relevant: in our most restrictive specification (column 4), a one standard deviation increase in the willingness to take risks is associated with a 1.2 percentage point increase in the migration probability, corresponding to an 11% increase with respect to the baseline migration probability of 11%. This positive relationship between willingness to take risks and probability of migration is consistent with internal migration in China exposing migrants to higher level of uncertainty than non-migrants.

In columns 5–8 of Table 3.2, we report estimates for the alternative migration status measure of whether individuals have ever migrated for work. About 23% of the interviewees in our sample reported having migrated at least once in the past. As before, willingness to take risk is a strong predictor of migration status: in the most general specification (column 8), a decrease of one standard deviation in the willingness to take risk is associated with a 3.3 percentage points increase in migration probability, corresponding to about 14% of the baseline sample probability, an estimate that is very close to the one obtained with migration in year 2008 as the main outcome.[52]

To investigate the linearity in the relation between migration propensity and risk attitudes, we estimate equation (9) with a set of five dummies for different levels of willingness to take risks (the excluded dummy corresponds to a zero willingness to take risks). Panels A and B of Figure 3.5 report the estimated coefficients and their 90% confidence intervals for the two measures of migration based on the specification in columns 4 and 8 of Table 3.2. The figure shows a clear and almost linear relation between migration probability and individual willingness to take risks above values of about 2.

Our findings on individual migration decisions are much in line with previous findings in the literature. For instance, while a one standard deviation decrease in individual risk-aversion

[52] In Appendix **Table A 3.4**, we report estimated coefficients on the other controls. As expected, male, non-married and younger individuals are more likely to migrate, while education does not seem to predict migration status (see column 4).

leads to an 11% or 14% increase, respectively, in the baseline probability of having migrated in the previous year or overall, Jaeger et al. (2010), using a specification almost identical to that reported in column 2 of Table 3.2, report that a one standard deviation decrease in individual risk aversion leads to a 12% increase in the baseline migration probability.

One concern with our results is that, because attitudes towards risk are measured after the migration decision, the migration experience itself may have affected the risk attitudes reported during the interviews. We can investigate this possibility by exploiting the longitudinal nature of the survey. Almost half of our estimation sample reported risk attitudes in both the 2009 and the 2011 waves of the RUMiC-RHS. These repeated measures, together with the information on 2010 migrations, allow us to investigate two empirical questions: Do individuals report consistent measures of risk aversion over time? Are migration experiences systematically associated with changes in self-reported risk aversion? The Appendix Figure A **3.2** reports the distribution of changes in self-reported risk attitude between 2009 and 2011. In our sample, the average change in self-reported risk attitudes over these two years is small, 0.39 for a measure ranging between 0 and 10. About one fourth of the respondents reported exactly the same value in both surveys, while almost half reported changes smaller than or equal to plus or minus one, and about 80% showing changes ranging between 0 and 3. These numbers suggest that interviewees consistently report their risk preferences over time.[53]

One concern may be that migration experiences are systematically related to changes in risk aversion. To investigate this, we follow Jaeger et. al. (2010) and regress the change in self-reported willingness to take risks between 2009 and 2011 (from the 2009 and 2011 waves of the RUMiC-RHS) on a dummy variable that equals one if the individual migrated in 2010. We report results in Panel A (columns 1-4) of Appendix Table A **3.5**. Alternatively, we regress the willingness to take risks reported in 2011 on a dummy for migration in 2010 and on the willingness to take risks reported in 2009 (Panel A, columns 5-8). We gradually include in the specification the individual and household controls used in our main analysis of individual

[53] On average, the change in self-reported risk aversion over two consecutive waves (2009 and 2010) is 0.2 and almost 40 percent of the sample reports identical risk preferences. A few recent papers suggest that individuals may be less willing to take risks after being affected by major negative events such as natural disasters (Cameron and Shah, forthcoming), war and extreme violence (Callen et al., 2014), or financial crises (Guiso, Sapienza, & Zingales, 2013). However, it is unclear whether this behavioural response is due to a change in the underlying degree of risk aversion, or to an increase in the degree of uncertainty individuals are exposed to.

selection, using the same specifications as in Table 3.2. According to the estimation results, having migrated in 2010 does not affect the observed change in risk preferences or the level of risk preferences in 2011 when controlling for risk attitudes in 2009. In all specifications, estimated coefficients are not significant and of small magnitude.

Panel B of Appendix Table A **3.5** reports the same regressions than Panel A, but we distinguish between individuals who migrated *only* in 2010 and individuals who migrated in both 2008 and 2010. Again, estimates are very small for both measures, and not significantly different from zero throughout.

To further investigate a possible relation between our measure of risk aversion and migration experience, we use data from various waves of the Urban Migrant Survey (UMS) of the RUMiC project and test whether risk preferences vary across migrations of different duration. In particular, we regress risk attitudes of migrants on the years since first migration, while controlling for individual characteristics as well as for city and year fixed effects. We report estimates in Appendix Table A **3.6**, where columns 1 and 2 report results unconditional and conditional on individual fixed effects, respectively. Estimated coefficients of migration duration are very small in magnitude and never significantly different from zero. We conclude from all these tests that risk attitudes are not systematically affected by previous migration experiences.

3.5.2. Within household migration decision

As pointed out earlier, finding that individual risk aversion determines migration choices is compatible not only with a model of individual choice but also with a model in which migration decisions are taken at the household level (as in the model developed in section 3.2). If such decisions are taken on a purely individual level, however, the risk attitudes of other household members should play no role in determining migration decisions. We now further examine the role of the household in migration decisions by exploring the testable implications of our propositions 1 and 2.

Proposition 1 (section 3.2.3) implies that the individual probability of being a migrant should depend on both the individual's own risk aversion and the risk aversion of other household members. As indicated before, we test this proposition in two ways.

In our first approach, we still run individual-level regressions but now explicitly include both the individual's absolute risk preferences ($wtRisk$) and the individual's position in the household ranking of willingness to take risk ($wtRisk\_rel$) among members in the work force. The coefficient on this latter variable is identified from individuals who have the same level of willingness to take risk ($wtRisk$) but who hold different positions in the risk aversion ranking within their respective households. According to proposition 1, the individual probability of migrating should increase with both the cardinal and ordinal measures of willingness to take risks. We also use two alternative measures for the variable $wtRisk\_rel$: the individual ranking in risk attitudes within the household and a dummy variable indicating the household member with the highest willingness to take risks. [54] To construct the individual rankings, we rank household members by their willingness to take risks, assigning a value of 1 to the most risk-averse person and a value of n (where "n" is the number of people with risk measure in the household) to the least risk averse individual, and we then normalize this measure by the number of members reporting risk preferences. Both these measures increase with the focal individual's willingness to take risks. If, as proposition 1 suggests, being relatively more willing to take risks with respect to the other household members makes individuals more likely to migrate, then we would expect positive coefficients for both the level and the relative risk variables.

We report estimation results in Table 3.3. For comparative purposes, column 1 of Table 3.3 exactly replicates column 4 of Table 3.2 (which includes county fixed effects as well as individual and household controls and clusters standard errors at the household level). In columns 2–5, we add our two alternative measures of relative risk attitudes, where we include

[54] In constructing these variables, we need to decide how to treat cases in which some household members reported identical values of risk attitudes. For the ranking measure, we assign an average ranking to individuals with the same willingness to take risks (e.g. if two individuals are ranked second in the household, we assign a ranking of 2.5 to each and a ranking of 4 to the next household member, if any). In our second procedure, we assign the value 1 if the individual has the lowest risk aversion in the household, irrespective of other household members possibly reporting the same level of willingness to take risks. We have experimented with alternative methods for dealing with ties in other unreported regressions, but our empirical results do not change. These estimates are available upon request.

only the relative measure for each variable in even columns and both the relative and absolute willingness to take risks in odd columns. Consistent with our theoretical predictions, the estimated coefficients are positive and significant for all relative measures of willingness to take risks. This finding also holds when we include both absolute and relative attitudes towards risk (columns 3 and 5): the estimated coefficients are positive and significant on both variables, implying that the relative measure of risk attitudes also affects the probability of migrating over and above the individual's absolute risk preference. As a result, not only are individuals with low risk aversion more likely to migrate, but this probability increases for those who are relatively less risk averse than their family members. Specifically, according to the estimates in column 5, being the least risk averse in the household implies a 1.4 percentage point higher likelihood of migrating (around 13% of baseline) than for an individual with the same individual risk attitude who is not the least risk averse in the household.

Our second approach to investigating within household selection is to add in the average risk preferences of the other household members who are in the workforce ($wtRisk\_oth$), in addition to the individual risk attitudes ($wtRisk$) variable. Following the structure of the previous columns in Table 3.3, column 6 reports the results for the $wtRisk\_oth$ variable alone, while column 7 lists the outcomes when both variables are included. Our expectations are that the average risk preferences of other household members will have no predictive power alone, but, conditional on individuals' own risk attitudes, an individual in a household where the other members are relatively less willing to take risks (i.e. have lower values of the $wtRisk\_oth$ variable) should have higher probability of migration. Both hypotheses are supported by the data: the estimated coefficient on $wtRisk\_oth$ is zero (column 6) but becomes significant and negative once we condition on individual willingness to take risks (column 7). As in all previous regressions, the coefficient on this latter variable is positive and significant.

A first important implication of our analysis is therefore that migration decisions in the context that we study are taken on the level of the household rather than the single individual. Our results further provide strong evidence of within-household migration decision being consistent with a model, where beyond individual willingness to take risks, risk preferences of other household members matter in determining migration decisions, with the direction of the effects being in line with our Proposition 1.

3.5.3. Across household migration decision

We now turn to the last part of our analysis, where we investigate which households have a higher probability of sending migrants. We first estimate household-level regressions of the probability of sending a migrant, and then test parts (i) and (ii) of proposition 2 (see section 3.2.4).

The first part of the proposition suggests that, conditional on having the same mean risk aversion, households with a larger variation in risk preferences should be more likely to send migrants. In Table 3.4, we report the results of regressing a dummy variable for whether a household sends at least one migrant on the average and the within household range of willingness to take risks, with other household controls and county fixed effects included.[55] When the regression includes only the household's average risk aversion (columns 1 and 3), the coefficient is positive and strongly significant: households that are on average less risk averse are more likely to engage in migration. As correlation in risk attitudes within households is sizeable in our sample (see section 3.3.3), this finding may simply reflect that less risk averse individuals are more likely to migrate and to belong to households whose members are also less risk averse. Hence, in columns 2 and 4 of Table 3.4, we also add in the within household range in risk attitudes. These estimates indicate that, in line with our theoretical model, households with a higher variation in risk preference across members are also more likely to send migrants *conditional* on the average household risk aversion. In both specifications, only the range, and not the mean, of household risk preferences is significantly (and positively) associated with having sent a migrant.

The second part of proposition 2 implies that the probability of a household sending a migrant decreases with the risk aversion level of the least risk averse member and increases with the degree of risk aversion of the other (non-migrant) members. To test this implication, we run

[55] We define the within household range as the difference between the highest and lowest values of willingness to take risks reported by each household. The household controls are number of family members under 16, in the work force, and older than 60; per capita house value; size of the family plot; and years of education and age of the head of the household.

household-level regressions of the probability of sending a migrant by separately adding the risk preferences of the individual with the highest willingness to take risks in the household ($HH\_\max\_wtRisk_{hk}$), and then the average risk attitudes of the other household members ($HH\_\text{oth}\_wtRisk_{hk}$). Based on our theoretical framework, we would expect the coefficients on these two risk measures to have opposite signs if migration exposes the migrant to higher uncertainty but allows the household to diversify risk and thus reduce the exposure to risk of other household members. All else being equal, the probability of sending a migrant should be higher for the household in which the least risk averse individual has a higher willingness to take risks (relative to most risk loving individual in other households), so the coefficient on $HH\_\max\_wtRisk$ should be positive. Conversely, the probability of sending a migrant should be higher for households in which the other individuals in the household on average have lower willingness to take risks relative to the average willingness to take risk of other households, implying that the coefficient on HH_oth_wtRisk should be negative.

Columns 1–4 of Table 3.5 report the estimates of regressing the probability that a household will send a migrant on $HH\_\max\_wtRisk_{hk}$ and $HH\_\text{oth}\_wtRisk_{hk}$. All regressions include county fixed effects, and household controls are added in columns 3–4. When only the willingness to take risks of the most risk loving individual in the household ($HH\_\max\_wtRisk_{hk}$) is included in the regression (columns 1 and 3), we find a positive and strongly significant coefficient. When the specification also includes the average risk aversion of the other household members ($HH\_\text{oth}\_wtRisk_{hk}$), the coefficients on both risk measures are significant but have opposite signs (column 2 and 4): the coefficient on $HH\_\max\_wtRisk$ remains positive (and increases slightly), whereas the coefficient on HH_oth_wtRisk is negative.[56] Hence, a household has a higher probability to send a migrant the lower the risk aversion level of the least risk averse member and the more risk averse the other household members are. This conclusion is in line with the predictions of our theoretical model for the case in which a migration that increases exposure to risk for the migrant members allows reduction of income uncertainty for the non-migrant members. The estimates in column 4, specifically, suggest that a one unit decrease in the measure of willingness to take risks of the

[56] The increase in the size of the coefficient on $HH\_\max\_wtRisk$ when conditioning on HH_oth_wtRisk is compatible with HH_oth_wtRisk having a negative effect on the migration probability and being positively correlated with $HH\_\max\_wtRisk$.

least risk averse household member implies a 1.5 percentage point increase in the household's probability of sending a migrant, corresponding to a 9% increase over the baseline household migration probability (see Table 3.1). At the same time, a one unit increase in the average risk aversion among all other household members, conditional on the most risk loving member's risk attitudes, is associated with a 0.8 percentage points increase in the household's probability of sending a migrant (or a 5% increase), although the coefficient is not precisely estimated.

In column 5 and 6 of Table 3.5, we check the robustness of our findings to changes in the age limit for individuals to be considered part of the workforce by reducing it from 60 to 50 years. Our estimates, remain unaffected, becoming if anything more significant in spite of a 25% reduction in sample size.

The findings in Table 3.5, combined with the other estimates in Table 3.4, suggest that the distribution of risk attitudes within the household plays an important role in the household's decision to send a migrant. Moreover, the direction of the effect is fully consistent with the predictions of our theoretical framework.

3.6. Concluding Remarks

This paper analyses empirically the relation between the distribution of risk attitudes - within and across households - and migration decisions. It provides strong evidence not only that, in the context of internal migration in China, migration decisions are taken at the household level, but that heterogeneity in risk aversion within the household plays an important part in determining whether a migration takes place, who emigrates, and which households send migrants.

The insight that migration decisions, in the context that we analyse, but also likely in other settings, are taken at household level, and are influenced by risk attitudes of other household members has important policy implications. For instance, the implementation of a policy that creates possibilities to insure against risk – such as the introduction of social safety net schemes - will possibly increase migrations if decisions are taken on an individual level. When the migration decision is taken at the household level, however, this may work in the opposite direction because it allows risk averse household members to diversify risk in other ways. Our model implies that household migration increases with the share of income pooled between migrant and non-migrant household members, as it allows other household members to diversify risk, and the migrant to insure against risk. Hence, the easier it is for households to transfer income back and forth between source and destination regions the higher will be the likelihood to engage in migration.

In demonstrating that the distribution of other household members' risk attitudes affects decisions to migrate, our analysis suggests that risk attitudes within the household may also affect other choices that are determined on a household level. Examples are the adoption of innovative farming practices, the selection of new crops, or the investment in a new family business, where decisions may be influenced by the distribution of risk attitudes within households and by the possible benefits of risk reduction to members other than the individuals directly concerned. Understanding direction and magnitude of the interactions between the effects of such decisions on different household members and their risk preferences should be an interesting avenue for future research, with the potential to contribute significantly to a better understanding of key economic decisions, particularly in developing countries.

Figures

FIGURE 3.1 - MODEL

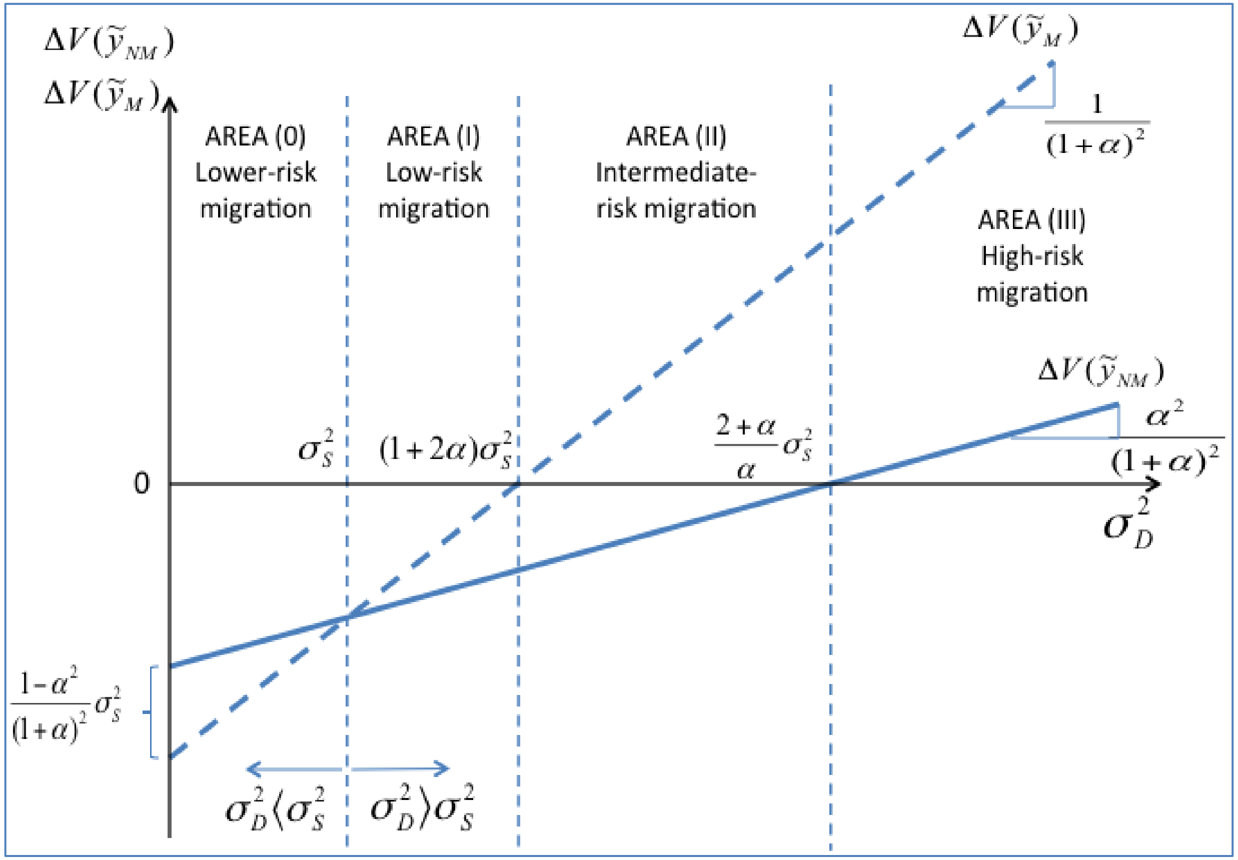
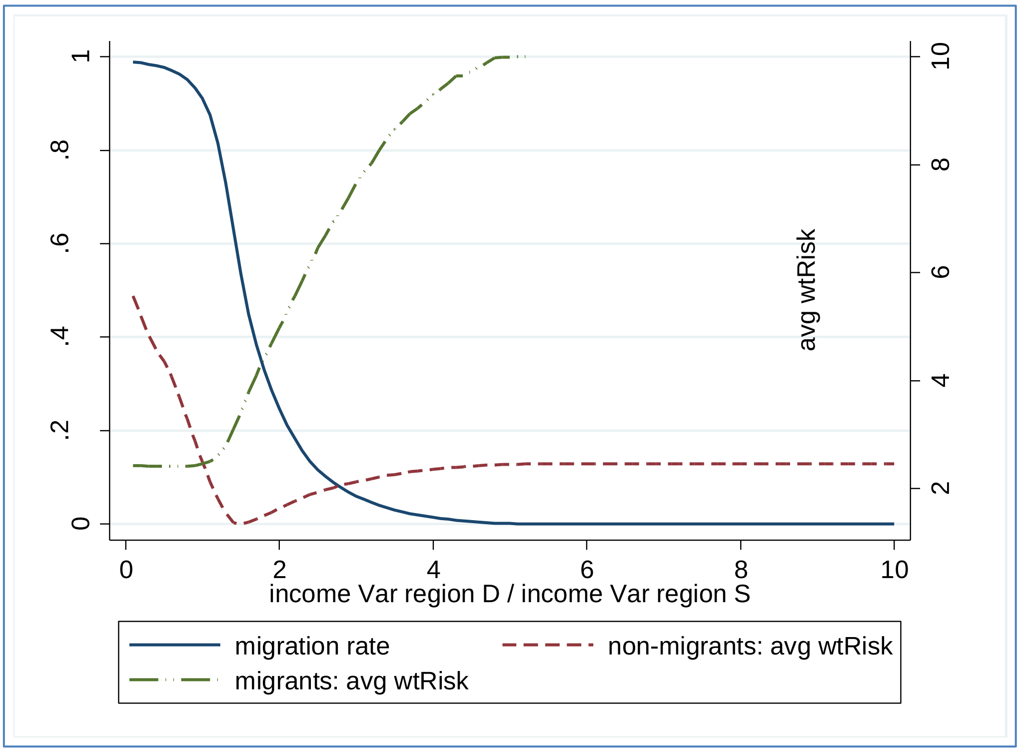


FIGURE 3.2 - INDIVIDUAL AND HOUSEHOLD MIGRATION DECISION MODELS

PANEL A: INDIVIDUAL MIGRATION DECISION MODEL



PANEL B: HOUSEHOLD MIGRATION DECISION MODEL

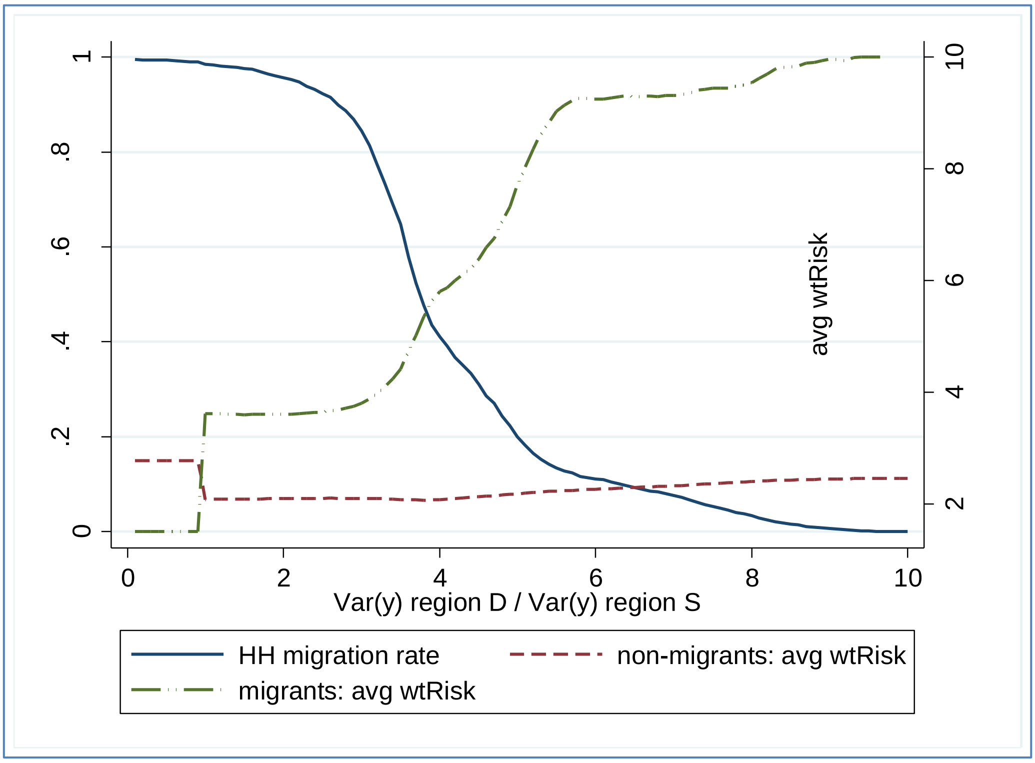
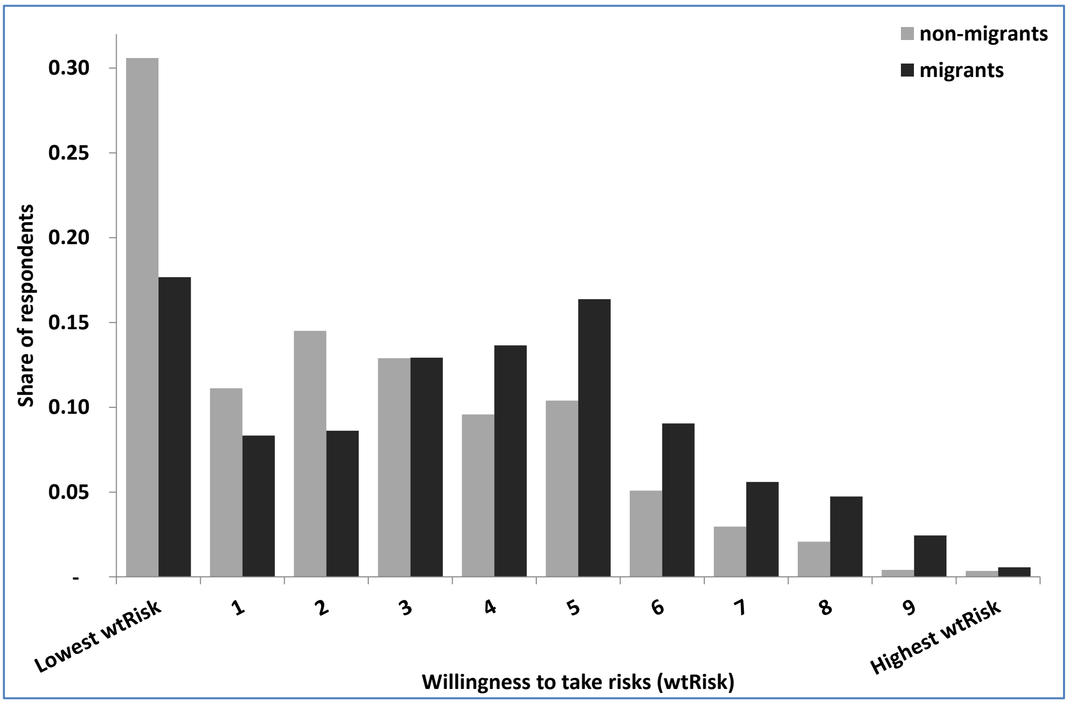
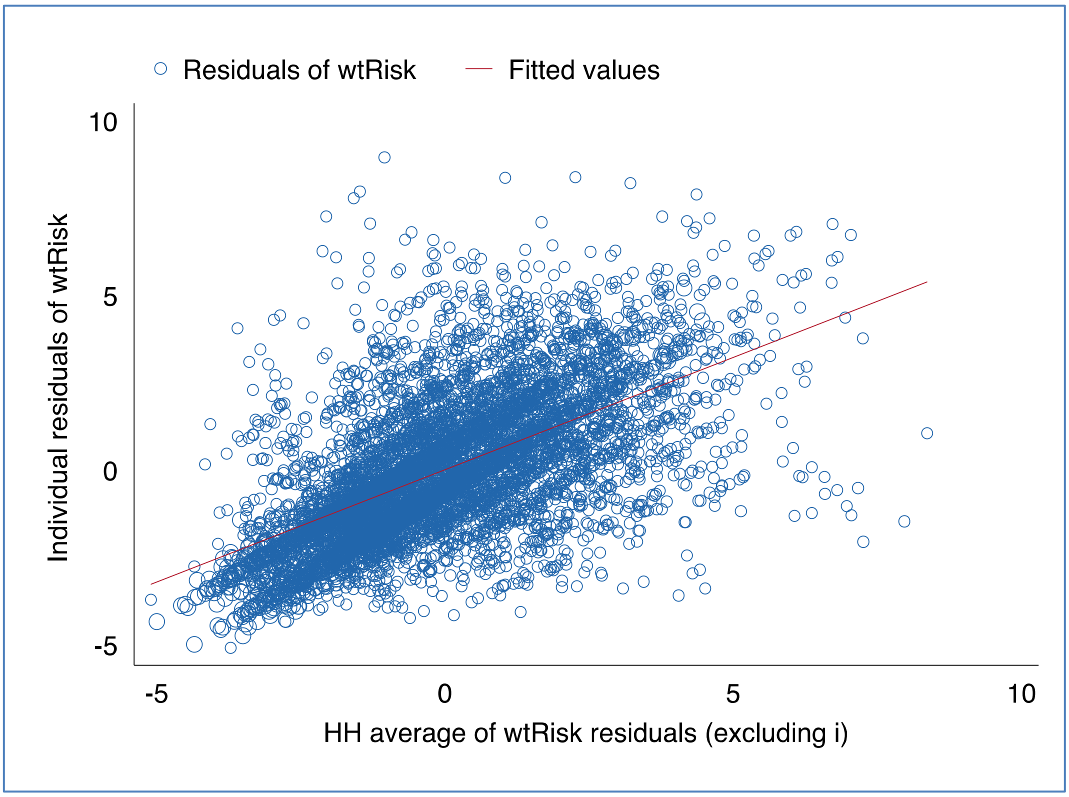


FIGURE 3.3 - DISTRIBUTION OF WILLINGNESS TO TAKE RISKS, BY MIGRANT STATUS



Note. The measure (*wtRisk*) varies between 0 (lowest level of willingness to take risk) and 10 (highest level of willingness to take risk). Source: RUMiC –RHS Survey.

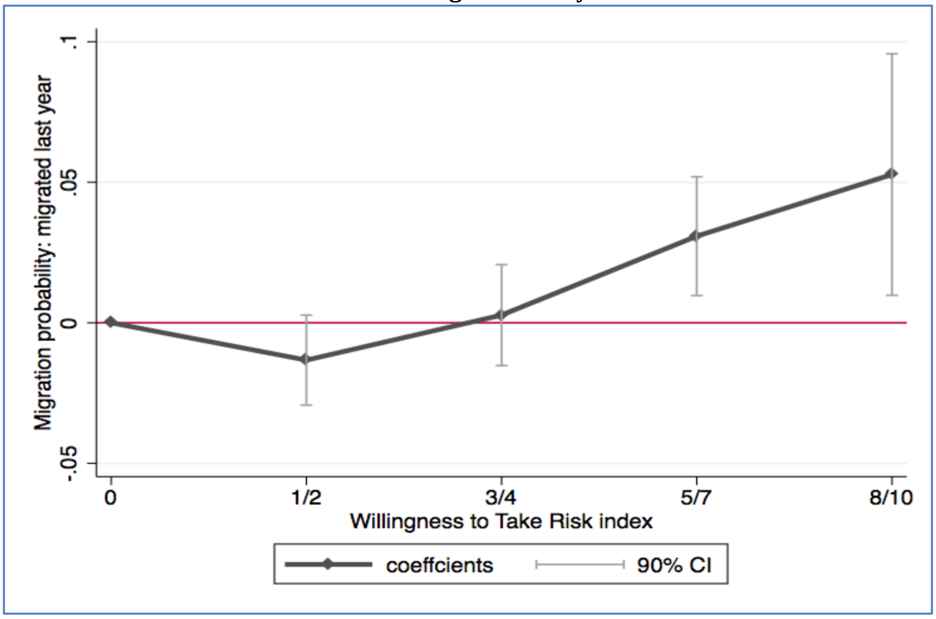
FIGURE 3.4 - INDIVIDUAL WILLINGNESS TO TAKE RISKS AND HOUSEHOLD AVERAGE



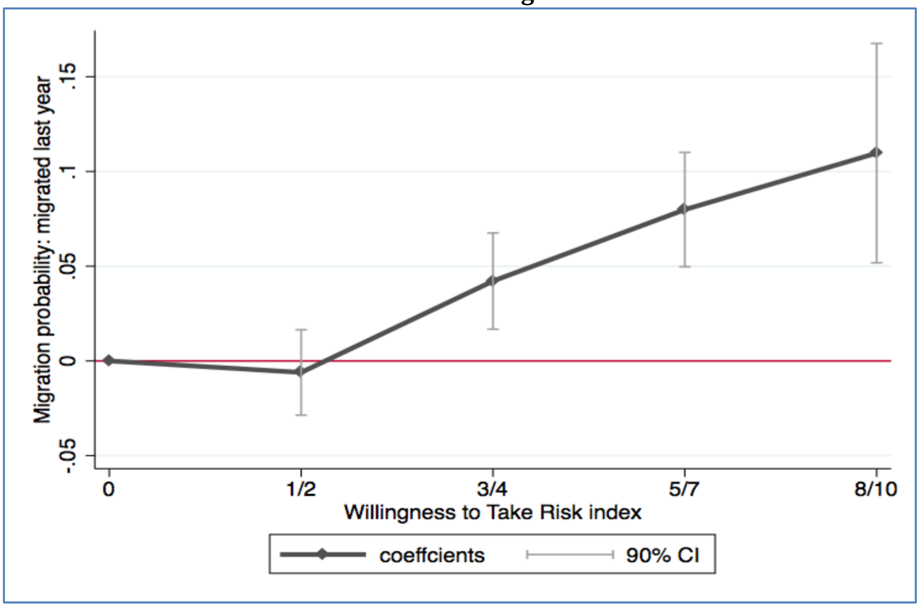
Note: The scatter plot shows residual willingness to take risks for each individual in our estimating sample (vertical axis) versus the average residual willingness to take risks of other members in the household (horizontal axis). Residuals are obtained by regressing individual willingness to take risks on basic demographic controls (gender, age, and age squared) and a full set of county of residence dummies. The figure shows the regression fitted line (correlation = 0.58).

FIGURE 3.5 - RISK ATTITUDES AND INDIVIDUAL PROBABILITY OF MIGRATING, BY LEVEL OF WILLINGNESS TO TAKE RISKS

Panel A: Migrated last year



Panel B: Ever migrated



Note. In panel A, individuals are defined as migrant if they migrated for work during the year before the survey; in Panel B, if they ever migrated for work in the past. Individual probabilities of being a migrant are regressed on five dummy variables identifying different levels of willingness to take risks in which the excluded category corresponds to a willingness to take risks equal to zero. The graph plots the estimated coefficients on these dummies together with their 90% confidence intervals. Included in the regressions are individual controls (age, age squared, a dummy for male, years of education, a dummy for married relation with HH head dummies, order of birth, number of siblings, and number of children) and household controls (number of family members under 16, in the work force, and older than 60; per capita house value (in logs)), and 82 county dummies.

Tables

Table 3.1 - DESCRIPTIVE STATISTICS

Variable	Mean	Std. Dev.	Min	Max	Obs
	Individuals				
Male	0.50	0.50	0	1	6,332
Age	43.82	10.65	16	60	6,332
Married	0.92	0.27	0	1	6,332
Years of education	7.15	2.83	0	13	6,332
Birth order	2.24	1.33	0	10	6,123
Number of siblings	3.15	1.64	0	11	6,250
Number of child	1.68	0.99	0	7	6,332
Willingness to take risks (wtRisk)	2.57	2.36	0	10	6,332
Migrated last year	0.11	0.31	0	1	6,332
Ever migrated	0.23	0.42	0	1	6,280
	Households				
Household size	4.08	1.32	2	11	2,961
HH members aged <16	0.57	0.73	0	5	2,961
HH members in the work force	2.89	1.09	1	8	2,961
HH members aged >60	0.34	0.61	0	4	2,961
HH head's education (years)	7.25	2.58	0	12	2,961
Plot size (Mu, 15Mu = 1 hectare)	4.12	4.08	0	75	2,961
House value per capita (Yuan, in logs)	9.16	1.33	1.20	14.04	2,961
HH avg willingness to take risks	2.46	2.03	0	10	2,961
At least one HH member migrated last year	0.16	0.36	0	1	2,961

Note. The sample includes all individuals in the labour force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the labour force has reported risk attitudes.
Source: 2009 RUMiC-RHS Survey.

Table 3.2 - INDIVIDUAL MIGRATION DECISION

	Migrated last year				Ever migrated			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
wtRisk	0.014***	0.005***	0.005***	0.005***	0.030***	0.014***	0.014***	0.014***
	(0.0018)	(0.0019)	(0.0019)	(0.0019)	(0.0025)	(0.0027)	(0.0028)	(0.0028)
Basic individual controls		X	X	X		X	X	X
Additional individual controls			X	X			X	X
Household controls				X				X
County fixed effects	X	X	X	X	X	X	X	X
Observations	6,332	6,332	6,103	5,992	6,280	6,280	6,052	5,946
R-squared	0.187	0.288	0.305	0.310	0.148	0.273	0.288	0.292

Note. The table reports estimates from LPM regressions of a dummy for individual migration status on individual willingness to take risk (*wtRisk*) and other controls. The migration status dummy equals one if the individual migrated for work in the year before the interview (columns 1–4) or had ever migrated for work (columns 5–8). The *wtRisk* variable measures individual willingness to take risks (decreasing with risk aversion) and has a mean of 2.57 and a standard deviation of 2.36. The basic individual controls are age, age squared, a dummy for male, years of education, and a dummy for married; the additional individual controls are a dummy for relation to head of household, order of birth, number of siblings, and number of children; and the household controls are household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs). All regressions include 82 county fixed effects. The sample includes all individuals in the labour force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the labour force has reported risk attitudes. Robust standard errors are clustered at the household level and reported in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.3 - WITHIN HOUSEHOLD MIGRATION DECISION: RELATIVE MEASURE AND RISK PREFERENCES OF OTHER HOUSEHOLD MEMBERS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
wtRisk	0.005***		0.003*		0.005***		0.009***
	(0.002)		(0.002)		(0.002)		(0.002)
wtRisk_rel: ranking in HH normalised		0.070***	0.055***				
		(0.018)	(0.020)				
wtRisk_rel: Dummy for highest wtRisk in HH				0.016**	0.014*		
				(0.008)	(0.008)		
wtRisk_oth: Average wtRisk of other HH members						-0.000	-0.006***
						(0.002)	(0.002)
Individual controls	X	X	X	X	X	X	X
Household controls	X	X	X	X	X	X	X
County fixed effects	X	X	X	X	X	X	X
Observations	5,992	5,992	5,992	5,992	5,992	5,992	5,992
R-squared	0.310	0.310	0.311	0.309	0.310	0.309	0.311

Note. The table reports the estimates from LPM regressions of a dummy for individual migration status (in the previous year) on different measures of willingness to take risks (at both the individual and household level) and other controls. The *wtRisk* variable measures individual willingness to take risk (which decreases with risk aversion) and has a mean of 2.57 and a standard deviation of 2.36. Columns 2–9 include two alternative measures of the individual's position in the household ranking of willingness to take risk among members in the work force (i.e. aged between 16 and 60 and not currently in school or disabled): (i) individual ranking in risk attitudes within the household, obtained by ranking household members by their willingness to take risks, assigning a value of one to the most risk-averse person and progressively higher values to the other members, and then normalizing this measure by the number of members reporting risk preferences (columns 2–3); (ii) an indicator for the individual having the highest willingness to take risks in the household (columns 4–5). In columns 6–7, we include the average risk preferences of the other household members who are in the workforce ($wtRisk\_oth$). The individual controls are age, age squared, a dummy for male, years of education, a dummy for married, relation with HH head dummies, order of birth, number of siblings, and number of children; and the household controls are household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs). All specifications include county fixed effects. The sample includes all individuals in the work force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the work force has reported risk attitudes. Robust standard errors are clustered at the household level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4 - ACROSS HOUSEHOLD MIGRATION DECISION (A)

	(1)	(2)	(3)	(4)
HH_avg_wtRisk	0.010***	0.004	0.009***	0.003
	(0.003)	(0.004)	(0.003)	(0.004)
HH_range_wtRisk		0.017***		0.016***
		(0.004)		(0.004)
Household controls			X	X
County fixed effects	X	X	X	X
Observations	2,961	2,961	2,961	2,961
R-squared	0.306	0.311	0.314	0.319

Note. The table reports estimates from LPM regressions of a dummy that equals one if the household has at least one migrant member in the labour force on different household-level measures of willingness to take risks and other controls. The variables HH_avg_wtRisk and HH_range_wtRisk measure the average and the range of willingness to take risks in the household, respectively. The household controls are household size and structure (number of family members under 16, in the work force, and older than 60); per capita house value (in logs); size of the family plot; and the years of education and age of the head of household. All specifications include 82 county fixed effects. The sample includes all households in which at least two individuals have reported risk attitudes, and at least one of these is in the labour force (i.e. aged between 16 and 60 and not currently in school or disabled). Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5 - ACROSS HOUSEHOLD MIGRATION DECISION (B)

		(1)	(2)	(3)	(4)	(5)	(6)
HH_max_wtRisk		0.012***	0.017***	0.011***	0.015***	0.016***	0.017***
		(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
HH_oth_wtRisk			-0.009*		-0.008	-0.012**	-0.012**
			(0.005)		(0.005)	(0.006)	(0.006)
Household controls				X	X		X
County fixed effects		X	X	X	X	X	X
WF age range:	**16-60**	X	X	X	X		
	16-50					X	X
Observations		2,961	2,961	2,961	2,961	2,189	2,189
R-squared		0.310	0.311	0.317	0.318	0.350	0.356

Note. The table reports estimates from LPM regressions of a dummy that equals one if the household has at least one migrant member in the labour force on the risk preferences of the individual with the highest willingness to take risks in the household ($HH\_\max\_wtRisk_{hk}$), the average risk attitudes among the other household members ($HH\_\text{oth}\_wtRisk_{hk}$) and other controls. In columns 1–4, the age bracket for workers to be considered part of the workforce is 16–60; in columns 5-6 it is 16–50. The household controls are household size and structure (number of family members under 16, in the work force, and older than 60); per capita house value (in logs); size of the family plot; and years of education and age of the head of household. All specifications include 82 county fixed effects. The sample includes all households in which at least two individuals have reported risk attitudes, and at least one of these is in the work force (i.e. within the defined age bracket and not currently in school or disabled).
Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A.I. Theoretical Framework

A. Proof of Proposition 1

Assume that individual 1 is more risk averse than individual 2 so that $k_1 > k_2$. Then the difference in household utility when individual 2 emigrates instead of individual 1 is

$$U_{SD}(1 = NM; 2 = M) - U_{SD}(1 = M; 2 = NM) =$$

$$= [E(\tilde{y}^{NM}) - k_1 V(\tilde{y}^{NM}) + E(\tilde{y}^{M}) - k_2 V(\tilde{y}^{M})] - [E(\tilde{y}^{M}) - k_1 V(\tilde{y}^{M}) +$$

$$+E(\tilde{y}^{NM}) - k_2 V(\tilde{y}^{NM})] = (k_1 - k_2)[V(\tilde{y}^{M}) - V(\tilde{y}^{NM})] \qquad \text{(A.1)}$$

The first term is positive because $k_1 > k_2$. The sign of the second term depends on the relative size of the earnings variance of being a migrant vs. not being a migrant, although it will always be positive as long as $\sigma_D{}^2 \geq \sigma_S{}^2$ (see proposition 1). Hence, as long as the earnings variance is higher for the migrant, which in our setting will always be the case if the earnings variance is larger in the destination (see Figure 3.1), it is optimal to choose the least risk averse individual in the household as the potential migrant. Nevertheless, it may still be that $\mathrm{U_{SD}} < \mathrm{U_{SS}}$, so that it is optimal for the household to send no migrant.

B. Proof of Proposition 2

Given two households, h_A and h_B, which differ only in the degree of their members' risk aversion, then it follows from proposition 1 that in both households, if a migrant is sent, it will be the member with the lowest risk aversion. Assuming that in both households individual 2 is less risk averse than individual 1, each household will evaluate whether the household utility increases when individual 2 migrates compared to the non-migration option. For both households, the utility gain from migration is

$$\Delta U^{j} = \Delta\, E(\tilde{y}^{NM}) - k_1^{j}\Delta\, V(\tilde{y}^{NM}) + ME(\tilde{y}^{M}) - k_2^{j}\Delta\, V(\tilde{y}^{M}) \qquad j = h_A, h_B \qquad \text{(A.2)}$$

Which household gains the most from migration depends on the difference in utility gains:

$$\Delta U^{h_B} - \Delta U^{h_A} = \Delta\, V(\tilde{y}^{NM})\left(k_1^{h_A} - k_1^{h_B}\right) + \Delta\, V(\tilde{y}^{M})\left(k_2^{h_A} - k_2^{h_B}\right) \qquad \text{(A.3)}$$

We can now prove statements (i) and (ii) of proposition 2:

(i) Supposing that the two households have the same average risk aversion ($\bar{k}^{h_A} = \bar{k}^{h_B}$) but differ in the within household variance in risk attitudes, $k_1^{h_A} - k_2^{h_A} \neq k_1^{h_B} - k_2^{h_B}$, we can substitute $k_1^{h_A} = 2\bar{k}^{h_A} - k_2^{h_A}$ and $k_1^{h_B} = 2\bar{k}^{h_B} - k_2^{h_B}$ into A.3:

$$\Delta U^{h_B} - \Delta U^{h_A} = \Delta\, V(\tilde{y}^{NM})\left(2\bar{k}^{h_A} - k_2^{h_A} - 2\bar{k}^{h_B} + k_2^{h_B}\right) + \Delta\, V(\tilde{y}^{M})\left(k_2^{h_A} - k_2^{h_B}\right) =$$

$$= \left(k_2^{h_B} - k_2^{h_A}\right)(\Delta\, V(\tilde{y}^{NM}) - \Delta\, V(\tilde{y}^{M})) \qquad \text{(A.4)}$$

Given that $\Delta\, V(\tilde{y}^{NM}) < \Delta\, V(\tilde{y}^{M})$ (for $\sigma_D^2 \geq \sigma_S^2$; see section 3.2.2), household B will benefit more from migration ($\Delta U^{h_B} > \Delta U^{h_A}$) if its least risk averse member is less risk averse than the least risk averse member of household A ($k_2^{h_B} < k_2^{h_A}$). Having assumed that the average risk aversion in the two households is the same, this last condition implies also that the most risk averse individual in household B must be more risk averse than the most risk averse individual in household A ($k_1^{h_B} > k_1^{h_A}$). Hence, for household B to benefit more from migration than household A, the risk attitudes of household members must be more heterogeneous.

(ii) Assuming that member 1 has the same level of risk aversion in both households ($\mathrm{k}_1^{h_A} = \mathrm{k}_1^{h_B}$), while member 2 is less risk averse in household 2 ($\mathrm{k}_2^{h_A} > \mathrm{k}_2^{h_B}$), then the difference in utility gain reduces to

$$\Delta U^{h_B} - \Delta U^{h_A} = \quad \Delta V(\tilde{y}^{M})\left(k_2^{h_A} - k_2^{h_B}\right) \qquad \text{(A.5)}$$

so that $\Delta \mathrm{U}^{h_B} > \Delta \mathrm{U}^{h_A}$ as long as $\Delta\, V(\tilde{y}^M) > 0$ (areas II and III in Figure 3.1) and $\Delta \mathrm{U}^{h_B} < \Delta \mathrm{U}^{h_A}$ if $\Delta\, V(\tilde{y}^M)<0$ (area I in Figure 3.1). That is, if migrating increases (reduces) the exposure to risk of the migrant member, the household that gains most from migration is the household in which individual 2 (i.e. the least risk averse in her own household) is less (more) risk averse.

Supposing instead that member 2 (with the lowest risk aversion in each household) has the same level of risk aversion ($\mathrm{k}_2^{h_A} = \mathrm{k}_2^{h_B}$) in both households while member 1 is less risk averse in household 2 ($\mathrm{k}_1^{h_A} > \mathrm{k}_1^{h_B}$), then the difference in utility gains from migration between the two households is

$$\Delta U^{h_B} - \Delta U^{h_A} = \Delta\, V(\tilde{y}^{NM})\left(k_1^{h_A} - k_1^{h_B}\right) \tag{A.6}$$

Now, $\Delta \mathrm{U}^{h_B} > \Delta \mathrm{U}^{h_A}$ as long as $\Delta\, V(\tilde{y}^{NM}) > 0$ (area III in Figure 3.1) and $\Delta \mathrm{U}^{h_B} < \Delta \mathrm{U}^{h_A}$ if $\Delta\, V(\tilde{y}^M)<0$ (area I and II in Figure 3.1). In other words, if migration exposes the non-migrant individual to lower (higher) uncertainty, the household gaining the most from migration is the household where individual 1 is less (more) risk averse.

C. Extension: Non-zero correlation ($\sigma_{SD} \neq 0$)

Assuming now that $Cov(\varepsilon_S \varepsilon_D) = \sigma_{SD} \neq 0$, the household utility from sending one migrant to region D is

$$U_{SD} = [E(\tilde{y}^{NM}) - k_1 V(\tilde{y}^{NM})] + [E(\tilde{y}^M) - k_2 V(\tilde{y}^M)] =$$

$$= \underbrace{\left[\left(\frac{\bar{y}_{\mathrm{S}}+\alpha(\bar{y}_{\mathrm{D}}-c)}{1+\alpha}\right) - k_1\left(\frac{\sigma_S^2+\alpha^2\sigma_D^2+2\alpha\sigma_{SD}}{(1+\alpha)^2}\right)\right]}_{NM} + \underbrace{\left[\left(\frac{\alpha\bar{y}_{\mathrm{S}}+(\bar{y}_{\mathrm{D}}-c)}{1+\alpha}\right) - k_2\left(\frac{\alpha^2\sigma_S^2+\sigma_D^2+2\alpha\sigma_{SD}}{(1+\alpha)^2}\right)\right]}_{M} \tag{A.7}$$

The household will now send a migrant whenever $\mathrm{U_{SD}} - \mathrm{U_{SS}} > 0$:

$$\mathrm{U_{SD}} - \mathrm{U_{SS}} = \underbrace{\left(\frac{\bar{y}_{\mathrm{S}} + \alpha(\bar{y}_{\mathrm{D}} - c)}{1+\alpha} - \bar{y}_{\mathrm{S}}\right)}_{\Delta\, E(\tilde{y}^{NM})} - k_1 \underbrace{\left(\frac{\sigma_S^2 + \alpha^2\sigma_D^2 + 2\alpha\sigma_{SD}}{(1+\alpha)^2} - \sigma_S^2\right)}_{\Delta\, V(\tilde{y}^{NM})} +$$

$$+ \underbrace{\left(\frac{\alpha\bar{y}_{\mathrm{S}} + (\bar{y}_{\mathrm{D}} - c)}{1+\alpha} - \bar{y}_{\mathrm{S}}\right)}_{\Delta\, E(\tilde{y}^{M})} - k_2 \underbrace{\left(\frac{\alpha^2\sigma_S^2 + \sigma_D^2 + 2\alpha\sigma_{SD}}{(1+\alpha)^2} - \sigma_S^2\right)}_{\Delta\, V(\tilde{y}^{M})} > 0 \qquad (\mathrm{A.8})$$

Here, as explained in section 3.2.2, the terms characterize the change in expected earnings and in earnings variance from migration (with respect to non-migration) for both migrant and non-migrant members of the household. The presence of a non-zero correlation between shocks in source and destination regions ($\sigma_{SD} \neq 0$) does not substantially change the conditions under which the household gains from the migration of one of its members (see section 3.2.2). It should be noted that the change in earnings variance for both the migrant ($\Delta\, V(\tilde{y}^{M})$) and the non-migrant ($\Delta\, V(\tilde{y}^{NM})$) now increases with the correlation σ_{SD}, with the first derivative being identical for both terms:

$$\frac{\partial \Delta\, V(\tilde{y}^{M})}{\partial \sigma_{SD}} = \frac{\partial \Delta\, V(\tilde{y}^{NM})}{\partial \sigma_{SD}} = \frac{2\alpha}{(1+\alpha)^2} > 0 \qquad (\mathrm{A.9})$$

In Figure 3.1, a positive (negative) correlation σ_{SD} implies an upward (downward) shift in the intercepts of the functions $\Delta\, V(\tilde{y}^{M})$ and $\Delta\, V(\tilde{y}^{NM})$ and reduces (increases) the threshold values of σ_S^2 for which migration implies a reduction in earnings variance. In other words, if the shocks in source and destination regions are positively (negatively) correlated, migration will allow the household to reduce exposure to risk for lower (higher) values of σ_S^2, as compared to the case where the correlation is zero.

A.II. Sample selection

The fact that risk aversion is only observed for individuals who were present at home at the interview may bias our estimates if unobservables in the interview participation equation are correlated with risk aversion, conditional on observables.[57] To address this concern we estimate the following sample selection model:

$$wtRisk^{*}_{ihk} = \mathbf{X}'_{ihk}A + \mathbf{W}'_{hk}B + \eta_k + e_{ihk} \tag{A.10}$$

$$int_{ihk} = 1[y^{*}_{ihk} = \mathbf{X}'_{ihk}C + \mathbf{W}'_{hk}D + \boldsymbol{Z}'_{\boldsymbol{ihk}}E + \mu_k + u_{ihk} \geq 0] \tag{A.11}$$

where $wtRisk^{*}_{ihk}$ is the latent willingness to take risk and int_{ihk} is a dummy equal one if the individual i was at home at the interview (i.e. $int_{ihk} = 1$ if the latent variable $y^{*}_{ihk} \geq 0$), so that:

$$wtRisk_{ihk} = \begin{cases} wtRisk^{*}_{ihk} & if \quad int_{ihk} = 1 \\ not\ observed & if \quad int_{ihk} = 0 \end{cases}$$

The vectors $\mathbf{X'}_{ihk}$ and $\mathbf{W'}_{hk}$ collect the same observable individual-level covariates and family characteristics as in our main outcome equation (9), and $\eta_k$and μ_k are county fixed effects. The selection equation is non-parametrically identified by the variable vector $\boldsymbol{Z}_{ihk}$ that includes major events in the families of interviewees such as pregnancies, births, illnesses, deaths, and that occurred in the months before or after the interview.[58] These events, while arguably uncorrelated with risk attitudes, may have induced the individual to return to the home village, or to remain longer at home, and have hence affected the probability of being at home at the time of the interview. To test for selection, we estimate equation (A.11) using a probit model (thus assuming that u_{ihk} is normally distributed) and construct the generalised residuals which we include in equation (A.10) (see Heckman 1978). A test of correlation between the unobservables determining participation and individual risk aversion corresponds

[57] Within the migrant population, individuals absent at the survey are more likely to be males, younger and less likely to be married.

[58] We gather information about events from the 2009 and the 2010 surveys. The events recorded in the 2009 survey refer to year 2008 and, therefore, took place *before* the 2009 interview. The 2010 survey collected information on events taking place in the twelve months previous to the survey and on their month of occurrence. We combined this information to identify events that took place *after* the 2009 survey but by the end of year 2009.

to a simple t-test of whether the coefficient of the generalised residual is significantly different from zero.

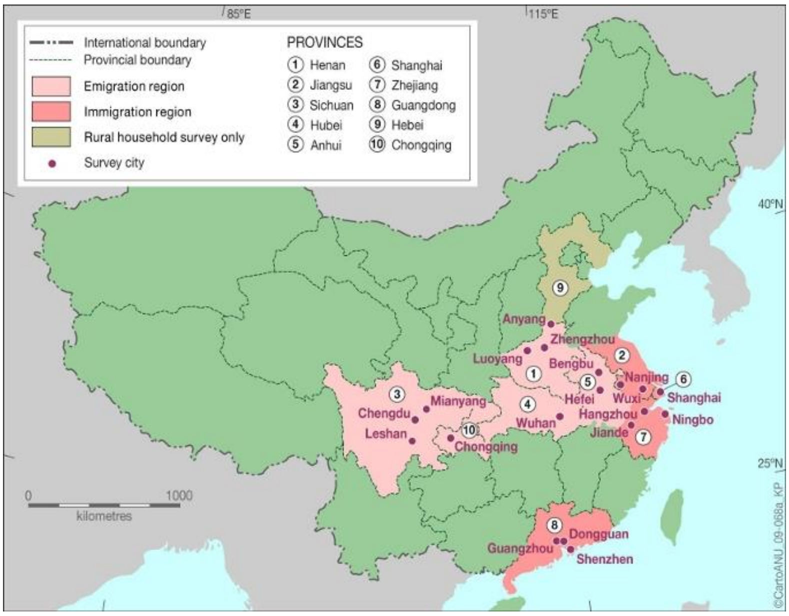
We report probit estimates of the first stage in the lower panel of Table A 3.2 where the dependent variable is the probability of being at home for the interview (which occurred between March and June 2009). The first four columns report estimates where we use events that occurred before the interview (during year 2008) as instruments, while the last four columns use events that occurred after the interview, but close enough to the interview date so that their occurrence could have been anticipated by families. The instruments are a dummy for a “pregnancy/birth” in the wider family (column 1 and 5), a dummy for “illness or death” (column 2 and 6), dummies for “pregnancy/birth” and “illness/death” (column 3 and 7) and a dummy for any of the events “pregnancy/birth/illness/death” (column 4 and 8).[59] In all specifications, we condition on individual and household controls and on county fixed effects. As Table A 3.2 shows, the occurrence of major life events in the months before the interview (columns 1-4) is a strong predictor for the probability of being at home at the time of interview. Events that happen after the interview (columns 5-8) are also significant in all regressions, although estimates are slightly less precise.

In the upper panel of Table A 3.2, we report the estimated coefficient on the generalised residuals (or inverse Mills ratios) that we have included in equation A.10. This coefficient is small (ranging from 1.2 and 2.6 percent of the average value of wtRisk in our sample) and not statistically different from zero in any of the specifications, with a coefficient/standard error ratio that is never larger than 0.35. Thus, conditional on observables, individual risk attitudes are not correlated with unobservables that determine participation in the survey.

[59] The share of respondents reporting at least one event among pregnancy/birth, illness and death is 9.6% for year 2008 and 3.6% for year 2009.

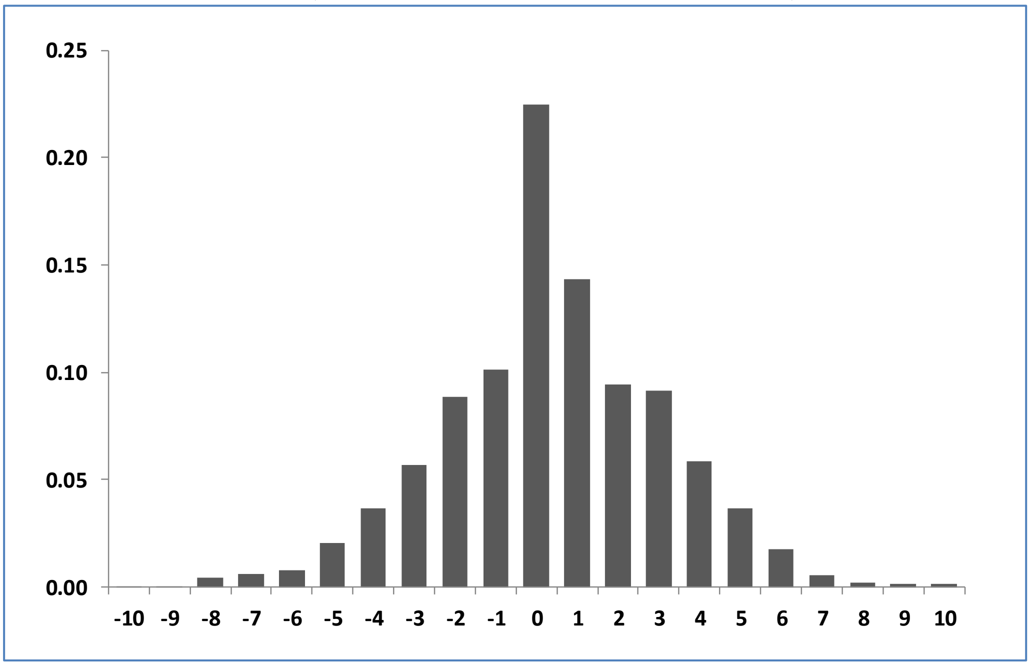
Appendix Figures

FIGURE A 3.1 - MAP OF RUMIC SURVEY



Note. The figure shows the provinces in which the RUMiC survey is conducted.

FIGURE A 3.2.– DISTRIBUTION OF CHANGES IN SELF-REPORTED WILLINGNESS TO TAKE RISKS (2009 AND 2011 RUMIC-RHS WAVES)



Note: The sample is composed of 2,906 individuals from our estimating sample who reported *wtRisk* in both waves.

Appendix Tables

Table A 3.1 - SAMPLE OF INDIVIDUALS IN RELEVANT HOUSEHOLDS VS ENTIRE SAMPLE

	Entire sample		At least 2 individuals reporting wtRisk in the HH	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev**
		Panel A - Individuals		
Male	0.51	0.50	0.51	0.50
Age	40.4	12.16	40.6	12.15
Married	0.82	0.38	0.83	0.37
Years of schooling	7.4	2.76	7.4	2.78
Birth order	2.2	1.31	2.2	1.28
Number of siblings	3.0	1.64	3.0	1.61
Number of child	1.5	1.08	1.5	1.06
Migrated last year	0.22	0.41	0.20	0.40
Ever migrated	0.35	0.48	0.32	0.47
Number of individuals	17,658		7,808	
		Panel B - Households		
Household size	4.1	1.30	4.1	1.32
HH members aged < 16	0.58	0.74	0.57	0.73
Hh members in the work force	2.9	1.10	2.9	1.09
HH members aged > 60	0.24	0.52	0.34	0.61
HH head's education (years)	7.5	2.38	7.3	2.58
Plot size (Mu, 15 Mu = 1 hectare)	4.5	4.64	4.1	4.08
House value per capita (Yuan, in logs)	9.1	1.32	9.2	1.33
Number of households	6,425		2,961	

Note. The table compares characteristics of individuals in households in which more than one member in the labour force has reported risk attitudes with those of individuals in other households.
Source: 2009 RUMiC –RHS Survey.

Table A 3.2 - SAMPLE SELECTION

	Events occurred in 2008				Events occurred in 2009			
Panel a) outcome = wtRisk	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Inverse Mill's	0.054	0.043	0.032	0.032	0.053	0.065	0.063	0.067
	-0.187	-0.185	-0.186	-0.186	-0.193	-0.194	-0.194	-0.194
Observations	5893	5893	5893	5893	5627	5627	5627	5627
R-squared	0.253	0.253	0.253	0.253	0.247	0.247	0.247	0.247
F-stat (Inverse Mills)	0.08	0.06	0.03	0.03	0.07	0.11	0.1	0.12
Prob > F (Inverse Mills)	0.7723	0.8145	0.8651	0.8634	0.7859	0.7377	0.746	0.73
Panel b) outcome = reporting wtRisk	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Pregnancy/Birth	0.013**		0.013**		0.022**		0.021*	
	-0.006		-0.006		-0.011		-0.011	
Illness/death		0.017***	0.017***			0.015*	0.015*	
		-0.007	-0.007			-0.009	-0.009	
Pregnancy/Birth/Illness/Death				0.015***				0.018**
				-0.005				-0.007
Observations	6609	6609	6609	6609	6347	6347	6347	6347
Pseudo R-squared	0.636	0.636	0.636	0.636	0.632	0.632	0.632	0.632
Chi2 (x,N)	3.4	4.77	7.74	6.21	1.88	1.91	3.53	3.83
Prob > chi2	0.0653	0.029	0.0208	0.0127	0.1709	0.1665	0.1713	0.0503

Note. Panel B of the table reports marginal effects from probit regressions of a dummy that equals one if individuals reported risk attitude during the 2009 survey on indicators for a number of major life events having occurred to them and/or their relatives during 2008 or 2009. We define indicators for the following events or combinations of them: pregnancy/birth in 2008 (column 1 and 3), at least one illness or one death in 2008 (column 2 and 3), at least one pregnancy/birth, illness or death in 2008 (column 4), one pregnancy/birth in 2009 (column 5), at least one illness or death in 2009 (column 6), at least one pregnancy/birth, illness or death in 2009 (column 8). The sample includes all individuals (regardless of having reported risk attitudes or not) in the work force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the labour force has reported risk attitudes. Panel A reports estimates from OLS regressions of wtRisk on individual, household controls and the estimated Inverse Mill's Ratio. For each column, the inverse Mills ratio is computed using the instrument(s) reported in the lower panel of the table. All regressions include individual controls (age, age squared, a dummy for male, years of education, a dummy for being married, relation with the HH head dummies, number of siblings, order of birth, and number of children) household controls (household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs)) and county fixed effects. Robust standard errors are clustered at the household level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.3 - INDIVIDUAL MIGRATION DECISION: PROBIT AND LOGIT ESTIMATES (MARGINAL EFFECTS)

	Probit				Logit			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
wtRisk	0.013***	0.004**	0.004**	0.004**	0.014**	0.004*	0.003**	0.004**
	(0.004)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)
Basic individual controls		X	X	X		X	X	X
Additional individual controls			X	X			X	X
Household controls				X				X
County fixed effects	X	X	X	X	X	X	X	X
Observations	6,332	6,332	6,103	5,992	6,332	6,332	6,103	5,992
R-squared	0.232	0.386	0.400	0.409	0.234	0.391	0.404	0.414

Note. The table shows the marginal effects derived using the probit (columns 1-4) and logit (columns 5-8) estimators of an individual indicator for migrants (in the previous year) on individual willingness to take risk (*wtRisk*) and other controls. The *wtRisk* variable measures individual willingness to take risks (decreasing with risk aversion) and has a mean of 2.57 and a standard deviation of 2.36. The basic individual controls are age, age squared, a dummy for male, years of education, and a dummy for married; the additional individual controls are: relation with HH head dummies, order of birth, number of siblings, and number of children; and the household controls are household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs). All regressions include 82 county fixed effects. The sample includes all individuals in the labour force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the labour force has reported risk attitudes. Robust standard errors are clustered at the household level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.4 - Individual Migration Decision: Full Specification

	Migrated last year				Ever migrated			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
wtRisk	0.014***	0.005***	0.005***	0.005***	0.030***	0.014***	0.014***	0.014***
	(0.0018)	(0.0019)	(0.0019)	(0.0019)	(0.0025)	(0.0027)	(0.0028)	(0.0028)
Male dummy		0.060***	0.081***	0.086***		0.135***	0.132***	0.132***
		(0.0064)	(0.0145)	(0.0147)		(0.0087)	(0.0178)	(0.0179)
Age		-0.021***	-0.005	-0.004		-0.020***	0.005	0.003
		(0.0040)	(0.0051)	(0.0053)		(0.0046)	(0.0059)	(0.0060)
Age squared*100		0.015***	0.001	-0.000		0.009*	-0.015**	-0.013**
		(0.0044)	(0.0055)	(0.0056)		(0.0052)	(0.0063)	(0.0063)
Years of education		0.001	0.001	0.001		0.002	0.002	0.002
		(0.0014)	(0.0014)	(0.0014)		(0.0020)	(0.0020)	(0.0020)
Married		-0.032	-0.044	-0.055*		-0.013	-0.032	-0.035
		(0.0274)	(0.0289)	(0.0286)		(0.0291)	(0.0305)	(0.0310)
Order of birth			-0.002	-0.003			-0.002	-0.002
			(0.0028)	(0.0027)			(0.0043)	(0.0043)
# of siblings			0.002	0.001			0.003	0.003
			(0.0027)	(0.0027)			(0.0040)	(0.0040)
# of children			-0.002	0.001			-0.008	-0.005
			(0.0059)	(0.0057)			(0.0079)	(0.0080)
# HH members below age 16				0.009				0.008
				(0.0059)				(0.0083)
# HH members in work force				-0.005				-0.011*
				(0.0040)				(0.0059)
# HH members above age 60				-0.004				0.009
				(0.0094)				(0.0130)
Ln (p.c. house value)				-0.002				0.002
				(0.0034)				(0.0049)
Relationship with HH head dummies			X	X			X	X
County fixed effects	X	X	X	X	X	X	X	X
Observations	6,332	6,332	6,103	5,992	6,280	6,280	6,052	5,946
R-squared	0.187	0.288	0.305	0.310	0.148	0.273	0.288	0.292

Note. The table reports estimates from LPM regressions of a dummy for individual migration status on individual willingness to take risk (*wtRisk*) and other controls. The migration status dummy equals one if the individual migrated for working reasons in the year before the interview (columns 1–4) or has ever migrated for working reasons (columns 5–8). The *wtRisk* variable measures individual willingness to take risks (decreasing with risk aversion) and has mean of 2.57 and a standard deviation of 2.36. The basic individual controls are age, age squared, a dummy for male, years of education, and a dummy for married; the additional individual controls are: relation with HH head dummies, order of birth, number of siblings, and number of children; and the household controls are household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs). All regressions include 82 county fixed effects. The sample includes all individuals in the labour force (i.e. aged between 16 and 60 and not currently in school or disabled) who live in households in which more than one member in the labour force has reported risk attitudes. Robust standard errors are clustered at the household level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.5 - CHANGES IN SELF-REPORTED WILLINGNESS TO TAKE RISKS (2009-2011 RUMIC-RHS WAVES)

	Change in wtRisk 2009-2011				wtRisk 2011			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Panel A			
Migration in 2010	0.037	0.120	0.106	0.108	0.151	-0.059	-0.088	-0.093
	(0.232)	(0.239)	(0.245)	(0.244)	(0.192)	(0.196)	(0.201)	(0.201)
Observations	2,906	2,906	2,813	2,791	2,906	2,906	2,813	2,791
					Panel B			
Migration *only* in 2010	-0.121	-0.027	-0.032	-0.013	0.056	-0.164	-0.192	-0.199
	(0.303)	(0.307)	(0.316)	(0.315)	(0.261)	(0.263)	(0.270)	(0.269)
Migration in 2008 and 2010	0.195	0.267	0.242	0.227	0.246	0.045	0.015	0.011
	(0.319)	(0.325)	(0.333)	(0.331)	(0.257)	(0.255)	(0.261)	(0.261)
Observations	2,906	2,906	2,813	2,791	2,906	2,906	2,813	2,791
wtRisk 2009					X	X	X	X
Basic individual controls		X	X	X		X	X	X
Additional individual controls			X	X			X	X
Household controls				X				X
County fixed effects	X	X	X	X	X	X	X	X

Note. This table tests the relationship between changes in self-reported risk attitudes between 2009 and 2011 and migration experience in 2010. In columns 1-4, the dependent variable is the change in self-reported willingness to take risks between the 2009 and the 2011 waves, while in columns 5-8 the dependent variable is self-reported willingness to take risks in 2011. In Panel A, the main regressor of interest is an indicator for the individual being recorded as migrant in year 2010. In Panel B, the main regressors of interest are an indicator for the individual having migrated only in 2010 and an indicator for having migrated in both 2008 and 2010. In Panel B, willingness to take risks reported in 2009 is always included in the controls. The basic individual controls are age, age squared, a dummy for male, years of education, and a dummy for married; the additional individual controls are: relation with HH head dummies, order of birth, number of siblings, and number of children; and the household controls are household size and structure (number of family members under 16, in the work force, and older than 60); and per capita house value (in logs). All regressions include 82 county fixed effects. The sample includes all individuals in our estimating sample who also reported risk attitudes in the 2011 wave. Robust standard errors are clustered at the household level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.6 - MIGRATION DURATION AND RISK ATTITUDES (RUMIC URBAN SURVEYS)

	OLS (1)	Fixed Effects (2)
Years since first migration	0.006	-0.002
	(0.004)	(0.007)
Individual controls	X	X
Year and city dummies	X	X
Individual fixed effects		X
Observations	22,208	22,208
R-squared	0.132	0.013

Note. This table tests the relationship between attitude toward risks and the length of migration experience. It reports estimates of wtRisk on years since first migration for a sample of migrants living in urban areas. Individual controls are age, age squared, a dummy for male, years of education, a dummy for married and the number of cities the individual has migrated to. OLS estimates are presented in column 1 while estimates including individual fixed effects are presented in column 2. The sample is an unbalanced panel of rural-urban migrants living in urban areas coming from six waves (from 2008 to 2013) of the urban module of the RUMiC Survey. Robust standard errors are clustered at the household level and reported in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 4

4. Weather Shocks and Labour Supply Reallocation in Rural China

4.1 Introduction

Rural households in developing countries, by relying mainly on agricultural activity, face substantial idiosyncratic and common risk, which can result in high income variability. Furthermore, due to imperfect insurance and credit markets, their ability to smooth consumption and insure against adverse events is typically limited; and since many households live close to, or below, the poverty line, failure to cope with shocks can have negative impacts on nutrition, health, mortality rate, and translate into persistent poverty. Maccini and Yang (2009) show, indeed, that income shocks, even temporary ones, can have sizable negative long-term consequences on education, health, and labour market outcomes. In order to cope with negative economic shocks, in the absence of adequate markets, households have developed a number of strategies as risk sharing (Rosenzweig and Stark, 1989; Townsend, 1994); self insurance and precautionary savings (Rosenzweig and Wolpin, 1993); asset depletion and disinvestment in education (Udry, 1995; Thomas et al., 2004). All these mechanisms have received quite extensive attention. Yet, another way through which households can smooth consumption is by smoothing income. In other words individuals can respond to negative productivity shocks in agriculture by temporary shifting the labour supply across sectors and locations. To the extend that non-agricultural labour market and own-farm productivity are not perfectly correlated, indeed, supply of labour to the local non-agricultural sector, as well as to the urban one, are two means that households can use in order to cope with negative agricultural productivity shocks. The use of labour markets to smooth income has been, relatively to the other potential coping mechanism, under-researched. It is however, of great importance for economists and policy makers to understand how labour market opportunities and institutions help poor households to smooth income and consumption when their primary source of income is under threat.

The research question this paper wants to answer is if, and in what measure, individuals and households in rural China reallocate labour across sectors – away from farming and toward local off-farm and urban sectors - as an ex-post response to negative productivity shocks in agricultural sector. The paper focuses on both the participation and the intensive margin of adjustment of the allocation of labour, as well as on the heterogeneous responses to shocks. Furthermore, it studies the role that institutional features, such as land tenure insecurity, play in influencing and constraining labour reallocation away from agriculture.

There are a number of reasons why it is relevant to study how households use the labour market to respond to negative agricultural productivity shocks in China. First, despite the outstanding growth record China has enjoyed during the last two decades, many are still those left behind, especially in rural areas where half of the population, and about 90%-95% of all the poor live (World Bank). Agriculture is the most important source of income in most rural areas, and weather is responsible for about 25-30% of the annual variation in agricultural production (Zhang & Carter, 1997). Second, China is characterised by high rates of internal mobility, with estimates of about 150 million of rural migrants working in Chinese cities in year 2009 (NBS). Furthermore, migration is mostly temporary, also because of restrictions to permanent change of residence such as the *houku* system. According to RUMiC, a longitudinal household survey that is the main source of data this paper is based on, almost one out of three individuals aged 16-65 spent some time working in the city between year 2008 and 2010. Interestingly enough, there is large variability in the share of time over the year spent in the city both in the cross sectional than in the time dimension. In an average year, 42% of rural-urban migrants (i.e. individuals who have spent a positive number of days working in the city) [60] spend less than 300 days working in the city, and 18%

[60] In this paper I use a broad definition of rural-urban migrants, considering as such all individuals who have spent at least 1 day working in a city outside the home village. The usual definition considers as migrants those who have spent at least 3 months away from home. Furthermore the definition used

spend less than 200 days. A 33% of them also reported to have been working in the home village as well as in the city of destination during the same year. As far as the variation over time is concerned, if one takes two consecutive years, in 70% of the cases the length of time spent working in the city differs between them. According to these data rural-urban migrants are a very mobile population, so called floating population, which goes back and forth from the native village to the city for different length of time across years. I will show that some of this variability can be explained as an optimal response to shocks in the productivity of the main agricultural sector.

The paper proposes a stylised framework of household labour allocation across sectors in the presence of temporary productivity shocks. Then, in the empirical section, I use data from a longitudinal household survey conducted in rural China between 2008 and 2011 to relate changes in days of work supplied to each of three different sectors - farm, local off-farm in the home village, and urban sector) with weather shocks affecting agricultural productivity at the county level. Rainfall shocks have been shown to the relevant determinants of agricultural productivity in China, especially for rice cultivation (Shili, 2005). Jiles (2006) also underlines the relevance of rainfall shocks for rural Chinese households and the importance of the opening up of rural labour markets to provide new margins of income smoothing. For identification I will thus exploit the yearly variation in labour supplied by individuals (and households) to each of the sectors along both the intensive and the extensive margin together with year-by-county variation in rainfalls, which is generated by the Chinese peculiar size and climatic heterogeneity.

I find that yearly working days devoted to farming drop by 4% while those spent working in the urban sector increase by almost 6% in correspondence to mild negative rainfall shocks, i.e. rainfall realisation 1 standard deviation below the long term average. The increase in number of days individuals spend working in the city derives from both longer spells in the city for those already engaging in urban work (intensive margin) and from increase in the likelihood to participate at all in the urban sector (extensive margin). Indeed the probability to engage in rural-urban migration increases by 3.7% on the baseline value. I find interesting

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here does not constraint individuals to have left the home while working in the city (they might be commuting). Nevertheless, I will often refer to those who participate in some form of urban labour market as rural-urban migrants throughout the paper.

heterogeneous response across generations driven by age specific productivities in the urban sector and costs of leaving (even temporarily) the home village. While younger individuals tend to shift labour supply from farming toward working in the city, older individuals generally shift labour from farming toward local off-farm work, without leaving the home village. At a higher level, I calculate that in correspondence with rainfall 1 standard deviation lower than the average households reduce by 2.6% the total labour supply to the farming sector and reallocate it almost completely to the urban one. Finally, I look at the interplay between land reallocation risk and propensity to move labour from farming toward rural-urban migration in bad years. Results suggest that the elasticity of rural-urban migration to agricultural productivity in villages with high risk of land reallocation is about half the size of that in other villages.

This paper aims to contribute to various areas of the literature. The first one is the literature on labour supply as ex-post response to shocks. The two papers that are closest to this are Kochar (1999) and Rose (2001). The first one makes use of self-reported information on crop losses, included in the ICRISAT dataset from India, to analyse how households respond to shocks by increasing off-farm labour. The second one uses district level rainfall as measure of aggregate shocks and looks at how households change their labour force participation. Neither of these papers has looked at internal migration as a further margin of adjustment, and this paper is trying to fill that gap. Internal, temporary migration can indeed be a relevant option for households to respond to shocks, especially when these shocks are aggregate and affect the entire community (as rainfall shocks do). The second type of literature this paper wishes to contribute to, is the one employing rainfalls as an IV for migration. Starting from the seminal paper from Munshi (2003) rainfalls have been used to instrument migration flows, especially in the Mexico-U.S. case. However, aggregate data being usually employed, the relationship between rainfall shocks and migration is still a black box. This paper hopes to shed some light on the mechanisms in play and on the heterogeneity driving responses to rainfall shocks. Furthermore I focus on a different type of migration, temporary rural-urban migration as opposed to international.

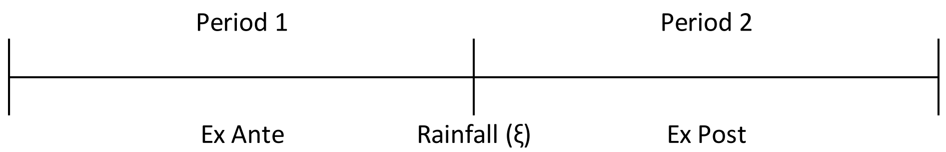
The rest of the chapter is organised as follows: section 4.2 presents the theoretical framework; section 4.3 introduces the data and some descriptive statistics; section 4.4 describes the empirical strategy; section 4.5 discusses the results and section 4.6 concludes.

4.2 Agricultural Productivity Shocks and Labour Reallocation

In this section I present a very simple labour allocation framework. I will start by assuming that each household has an endowment of labour and has to decide how to allocate it across different sectors in order to maximise utility. The three options are farm sector (farm work in or outside the family plot), local off-farm sector within the home village, and work in the urban sector (rural-urban migration). Farm production function depends on rainfalls ξ, a stochastic productivity factor which distribution (μ, σ) is known by the household:

$$Y = \xi F^{\alpha} K^{1-\alpha}$$

Because local off-farm activities are likely to be linked (directly or indirectly) to the agricultural sector, off-farm wage is also considered a function of rainfalls, $w_r(\xi)$, as well as of other factors. Finally, if one decides to work in the city she will earn a fixed wage that does not depend on rainfalls: w_u. The year is divided into two periods as shown in the figure below.



The first period is before rainfall realisation and could be seen as the cultivation and preparation stage of agriculture. In this period the household chooses the allocation of labour according to wages and the known distribution of rainfalls. At the beginning of period 2 actual rainfalls are realised and the household can observe their deviation from the average: $\epsilon_t = \mu + \xi_t$. With the new information in hand the household can eventually respond to the shock by optimally adjusting the labour allocation for the second part of the year. This conceptualisation is compatible with the structure of the agricultural year in China, where rainfalls during the first months of the calendar year are crucial for agricultural productivity through the whole year and highly correlated with the total amount of yearly rainfall.

In this simplified framework the responsiveness of productivity to rainfalls varies across sectors. More precisely, it is highest in the farm sector, from the moment that small plots are usually not, or only partially, irrigated. Consequently productivity strictly depends on rainfall annual fluctuations. Differently, because productivity in the off-farm sector does not directly depend on rainfalls, elasticity to rainfalls is lower. Finally, the productivity in the urban sector is the one that plausibly least depends on rainfalls since they should not directly affect economic activity in the city. As an extreme, exemplifying case, elasticity of productivity to rainfalls is set to zero in the urban sector. Utility of working in each one of the sectors, as a function of an adverse rainfall shock (which can be though as a negative deviation of rainfalls from the long term average) is presented in panel A of Figure 4.1.

In presence of adverse weather shocks households can find optimal to shift some labour from the most affected sector, farming, toward off-farm and urban work. It is important to underline that individual heterogeneity in, for instance, migration costs or productivity in the different sectors will cause the intercept of the curves in Figure 4.1 panel A, as well as their slopes, to varies. Panel B of Figure 4.1 shows the case where for certain individuals working off-farm delivers higher utility to start with, i.e. even for zero levels of adverse rainfall shocks. What is crucial for the qualitative implications of this simplified framework to hold is that the ranking of elasticity of productivity with respect to rainfalls is preserved. If that is the case, we should always expect to observe, if anything, labour reallocation that goes from activities more affected by rain to activities less affected and not the other way around. This unless general equilibrium effects drive wages in the city down to a level that more than counter balance the decline in agricultural productivity due to rainfall shocks.

4.3. Data and Descriptive Statistics

4.3.1. Data

Labour supply. This paper uses data from the Rural Household Survey (RHS) from the Rural-Urban Migration in China (RUMiC) project (henceforth RUMiC-RHS). RUMiC began in 2008 and it conducts yearly longitudinal surveys of rural, urban, and migrant households. The RUMiC-RHS covers 82 counties (around 800 villages) in 9 provinces identified as either major migrant sending or receiving regions and is representative of the populations of these regions. A map of RUMiC-RHS surveyed provinces is proposed in Figure 4.2. The survey was conducted for 4 years and administered by China's National Bureau of Statistics and includes a very rich set of individual and household level variables. I use information from the 2009, 2010 and 2011 rounds of the survey as they contain detailed information about the number of working days individuals have devoted to each specific sector during the past calendar year. In particular, the survey asks the number of days the individual has dedicated, during the previous calendar year, to each of the following alternative occupations: 1) *farm work*; 2) *local* (within local countryside) *off-farm work*; and 3) *work in urban area*, i.e. outside local countryside. RUMiC-RHS survey includes 18,910 individuals in the labour force (aged between 16 and 65 and not currently at school or disabled) who provide information about age, gender, educational level and days devoted to each of the above alternative sectors in at least two of the three survey rounds between 2009 and 2011 (referring to years 2008, 2009 and 2010). Out of the 18,910 individuals above, complete labour supply information in each and every year are reported by 10,394 individuals, and in two of the three years by the rest of them of them (8,516), producing an estimating sample of 48,214 individual*year observations. For the part of the analysis at the household level, in order to keep the composition of household members reporting labour supply data fixed over time, I focus on those individuals who have reported labour supply information for all three years, from 2008 to 2010. That leaves me with a balanced panel of 3,713 households, corresponding to 11,139 household*year observations[61].

Weather shocks. I use detailed, county specific, information about daily rainfall to proxy agricultural productivity shocks. Daily precipitation data come from the Chinese National Ground Surface Dataset (GNGSD) provided by the Chinese National Meteorological Information Centre. Precipitation data are matched to counties in the RUMiC-RHS survey using the distance between the closest weather stations and the centroid of each county. I construct a county-specific measure of rainfall shock, that is the deviation of rainfalls in year t from the long term average, normalised by its county-specific standard deviation as follows:

[61] I also drop 830 individuals who are the only member in their households reporting complete labour supply information for the three years.

$$Zscore\_Rain_{tk} = \frac{y_{tk} - \overline{y_k}^{78-10}}{SD_k^{78-10}(y)}.$$

The long term average is computed over a period of 33 years, from 1978 to 2010. Figure 4.3 shows the distribution of the *Zscore_Rain* for all county-year observations from year 2000 to 2010. Standardising the yearly rainfall deviation by the long term county–specific standard deviation allow to control for the fact that some counties might have very high raimfall standard deviations and thus are more likely in each period to experience large deviations from the average. Standardisation also provides a straightforward interpretation of the variable as Zscore_Rain=1 (-1) corresponds to rainfalls 1 standard deviation above (below) the mean. Because I do not want to focus my analysis on extreme events, such as flooding, I exclude observations in counties that experienced values of *Zscore_Rain* above 2 between 2008 and 2010[62].

4.3.2. Labour allocation across the farm, local off-farm and urban sector

Before moving to the empirical strategy I think it is worth to describe some interesting patterns in the way individuals and households allocate labour across different sectors in rural China. From them it arises a picture of a pretty fluid labour market where households (as well as individuals) tend to diversify their supply of labour across different sectors.

Individual level. Descriptive statistics about individual labour supplies to different sectors are presented in Table 4.1. Statistics are calculated on the pooled estimating sample of 48,214 observations from year 2008, 2009 and 2010. Males represent about half of the sample, average age is 43, 84% of respondents are married and average education is 7.2 years. About 2 individuals out of 3 devote a positive amount of working days to the farm sector, confirming the importance of agriculture as the primary source of occupation. On the other hand, 28% of the sample supplies positive amount of working days to the local off-farm sector and 24% to the urban one (rural-urban migration). Participation shares sum up to more than 1 because, as I will show in more detail below, many individuals tend to work in more than one sector during the same year. The unconditional average number of days per year

[62] Only 3 counties have experienced values of Zscore_Rain above 2 in the period of interest.

supplied to the farm, local off-farm and urban sector are, respectively, 93, 60 and 65. While conditional on participation, the average number of days supplied to the three sectors is about 139, 214 and 270. In an average year, 42% of rural-urban migrants (i.e. individuals who have spent a positive number of days working in the urban sector) spend less than 300 days working in the city, and 18% spend less than 200 days.

Further, these numbers mask relevant heterogeneity along the age distribution in the amount of days of work spent in different sectors. Indeed, as Figure 4.4 shows, labour supply to the urban sector is highest for individuals aged 25-35 and declines with age, while supply to the farming sector increases with age and picks around age 55-65. Finally labour supply to the local off-farm sector is highest for individuals aged between 30 and 50 and is lower for both younger and older ones. Although young individuals are more likely to engage in urban sector work while elderly ones are more likely to farm, there is a non-negligible positive probability of participating to each of the three sectors at any age between 16 and 65. Furthermore, it is not uncommon for individuals in our sample to engage in more than one sector during the same year. The first column in the bottom panel of Table 4.1 reports the share of individuals in each of the following 8 categories of labour allocation: 1) no work at all; 2) farm only; 3) local off-farm only; 4) urban sector only; 5) farm + off-farm sector; 6) farm + urban sector; 7) off-farm + urban sector; and 8) all three sectors. 95% of individuals work and almost half of them are dedicated only to farming, while 11% and 17% of individuals work in the local off-farm and in the urban sector only respectively. Yet, almost 1 person out of 4 diversifies his supply of labour across more than one sector during the same year. When people do so they tend to pair farming with either working in the local off-farm sector or in the urban one. It is indeed interesting to notice that almost 1 individual out of 3 of those who have been working in the urban sector have also supplied some positive amount of labour to one of the other two, in most of the cases the farming one.

The likelihood of individuals to spread their supply of labour across different sectors, and the extent to which they do so, varies across both the gender and the age dimension. Panel A of Figure 4.5 shows that although "farming only" is by far the most common choice for both females and males, males are double as likely than females to diversify their supply of labour across different sectors during the same year. Indeed 32% of males report to have been working in at least 2 sectors during the last year, while only 15% of females do so. As far as young (aged below 41) versus elderly (aged above 40) individuals, Panel B of the same Figure 4.5 shows that those aged above 40 are much more likely to engage in farming only while the shares of young and elderly individuals who participate to more than one sector are similar, respectively 22% and 25%.

Household level. I show descriptive statistics about household characteristics and their labour supply choices in Table 4.2. Household descriptive statistics are calculated on the pooled estimating sample of 11,139 observations from year 2008, 2009 and 2010. Average household size is 4 and the average number of members in the work force is 2.9. 86% of households in the sample engage in farm work, 48% in the local off-farm sector and 39% in the urban one. When we look at how households allocate their supply of labour across different sectors we observe that, despite the diffusion of off-farm and urban work, 1 out of 4 of rural households still engages in farming only. On the other hand 61% of them allocate labour supply across more than one sector, 40% have someone who has spent some days working in the urban sector, and 12% are fully diversified, i.e. engage in all 3 sectors.

Labour supply variation over time. The descriptive statistics above show relevant cross sectional variation in the likelihood of individuals and households to participate to different sectors and in the amount of working days supplied conditional on participation. This reveals how households tend to diversify the supply of labour across different sectors and away from farming to reduce, ex-ante, their exposure to income risk related to each one of the sectors. Yet, what is of particular interest for this paper is how they change their labour supply allocation over time, in response to variations in the relative productivity of sectors. Figure 4.6 shows the great amount of variation in the number of days dedicated to each one of the sectors within individuals over time. The figure plots the distribution of changes, within individuals and between consecutive years, in the number of days worked in each sector and in the total number of days worked. In each of the panels, the sample is restricted to individuals who reported positive days of work in the specific sector in at least one year. As far as days of work in the urban sector are concerned, for only 30% of the observations there is no change (i.e. a change ranging between -/+10 days) between two consecutive years. Similar patterns are observable in the farm and in the off-farm sectors as well as in the total amount of days worked in a year. These statistics combine changes in the amount of days devoted to each sector deriving from variations along both the extensive and the intensive margin. In the empirical analysis I will show how such changes are in part an optimal response to weather shocks affecting agricultural productivity.

4.4. Empirical Strategy

The main threat to identification in this study is the endogeneity of agricultural productivity shock. Household level farm productivity may indeed be correlated with unobservables that contribute to determine the supply of labour to off-farm and urban sectors as well. A household could, for instance, opt to invest less in pesticides and fertilizer because has decided to send a migrant away working in the city. In this case the estimates of the (negative) relationship between farm productivity and the probability to observe a rural-urban migrant in the household would be biased. To solve the endogeneity problem I employ rainfalls as an instrumental variable for agricultural productivity. As outlined above rainfalls have significant impact on farm productivity and income. At the same time they cannot be affected by farmers' behaviour providing thus a fairly exogenous source of variation in agricultural productivity, which has been indeed widely used in the literature (see Rosenzwaig and Wolpin, 2000, for an extensive literature review on the use of rainfalls as natural experiment). Furthermore, crucially for identification, China's size and climatic heterogeneity generates variation in rainfalls both across counties within years and between years within counties. Not having available data on household farm productivity I will identify a reduced form effect of rainfall shocks on labour reallocation rather than any structural parameter relating the latter to agricultural productivity. The empirical analysis looks at both individual level and household level labour allocation responses to rainfall shocks.

Individual level analysis. For the individual level analysis I estimate various versions of the following equation:

$$L_{ihkt} = \alpha_0 + \alpha_1 (Zscore\ Rain)_{kt} + Z'_{ihk}\xi + \gamma_i + \lambda_t + \varepsilon_{ihkt} \qquad \text{Eq. (1)}$$

where i indexes individuals, h households, k administrative counties, and t years. L_{ihkt} is either a binary variable indicating whether the individual participates in different sectors or the number of days of work spent in those sectors during the previous year. On the one hand, when estimating the binary outcome equation (using a linear probability model) I study the participation decision to different sectors, i.e. the response to shocks through the extensive margin. On the other hand, when I estimate the days of work equation (unconditional on participation and using OLS) I am capturing a mixture of intensive and extensive margin response. There are three sectors: farm; local off-farm; and urban sector (to which I will often refer to as rural-urban migration). Zscore_Rain is the county-specific rainfall shock defined above as the deviation of rainfall at time t from the long-term average, normalised by its standard deviation. The estimates of the impact of rainfall shocks on labour supply allocation have to interpreted as reduced form parameters of a two step model where rainfalls affect agricultural productivity and individuals respond to the latter. Zscore_Rain is measured at the county level (there are 82 counties in the RUMiC sample), thus in order to allow the error terms of individuals (and households) who live in the same county to be correlated, I cluster robust standard errors at the county level throughout the analysis. The vector Z includes individual and household time varying characteristics such as marital status, number of family members respectively aged less than 16, in the work force and older than 65, and sex ratio of family members in working age. Finally, $\gamma_i$and λ_t are respectively individual and time fixed effects. I employ an individual fixed effects specification to condition on every time-invariant individual observable and unobservable characteristic - such as ability, preferences, productivity, migration costs etc. - that might affect labour supply decisions in the farm, off-farm and urban sector. This allows me to focus on ex-post responses to shocks - i.e. on changes in the labour supply across years within individuals which are determined by unexpected weather shocks – rather than on ex-ante labour supply strategies driven by, for instance, diversification purposes.

Household level analysis. In the household level analysis I study how the allocation of household total labour supply is shifted across sectors in response to weather shocks affecting agricultural productivity, both on the participation and on the intensive margin. To do so I estimate various versions of the following equation:

$$L_{hkt} = \beta_0 + \beta_1(Zscore\ Rain)_{kt} + Z'_{hk}\xi + \delta_k + \mu_t + u_{hkt} \qquad \text{Eq. (2)}$$

where h indexes households, k administrative counties, and t years. L_{hkt} is either: a binary variable indicating whether the household participates in different sectors; the number of days of work, per household member in the work force, allocated to those sectors; and the share of total household working days devoted to those sectors. Similarly to the individual case I use the binary outcome (estimating a linear probability model) to identify responses along the participation margin. Similarly to above I rely on the panel structure of the data and include household fixed effects (δ_h) to identify ex-post responses to shocks.

4.5. Results

4.5.1. Individual level analysis

Days of work. I start by exploring the average response to weather shocks. Table 4.3 reports OLS estimates of equation (1) above where the output is the number of days worked by the individual in different sectors (columns 1-3) and in total (column 4). Individuals respond to negative (positive) deviations of rainfalls from the long term average by decreasing (increasing) the time devoted to farming. Females do so to a higher extend than males (Panel B). As expected, people farm more when agricultural productivity (which is increasing in rainfalls until a value of *Zscore Rain* of +2) is higher and vice versa. On the other hand individuals respond to negative (positive) agricultural productivity shocks by working more (less) days in the urban sector, where wages and job opportunities are not (or at least less) affected by agricultural productivity. Males tend to increase more than females their work in the urban sector during bad times, even when considering the difference between the two genders at baseline. This is probably due to females facing a higher fixed cost for rural-urban migration than males. Days spent working in the city seem to replace almost completely the decrease in days of farming.

The estimates are both statistically significant and economically relevant. Days of farming decrease by 4% and days of work in the urban sector increase by 5.7% (6.9% and 3.6% respectively for males and females) on the baseline value when rainfall realization is one standard deviation below the average. The coefficient in the local off-farm equation is positive but much smaller in size with respect to that in the farming equation, indicating that agricultural productivity seems to affect the productivity in the local off-farm sector in the local countryside. Yet the coefficient is not statistically significant, and I will show later how that masks interesting heterogeneity.

Males shift their labour allocation across sectors leaving unchanged their total labour supply. On the other hand females, who are less engaged in the labour force to start with, do work more in years when agricultural productivity is high. The estimates presented in this section capture a mix between the response along the participation margin (those shifting from zero days of work in a sector to some positive number and vice versa) and the intensive margin. We can imagine that, especially for sectors where entry costs are higher, such as local off-farm and rural-urban migration, differentiating between the response along the extensive and intensive margin might be relevant.

Participation. Table 4.4 presents estimates of a LPM of equation (2) where the output is an indicator as whether the individual supplied positive amount of days to different sectors (columns 1-3) and to any of them (column 4). As far as farming is concerned, no significant response along the participation margin is detected when looking at males and females together (Panel A) suggesting that individuals are attached to the farming sector and tend to engage in it even when agricultural productivity is low. Only the coefficient for females (Panel B) is significantly different from zero although its magnitude is small. On the other hand the probability to engage in rural-urban migration increases by 3.7% on the baseline value in response of a 1 standard deviation negative rainfall shock. This percentage effect is smaller than the one detected in the days of work equation (5.7%) suggesting that the increase in aggregate days of work in the urban sector steams from both the participation and the intensive margin, unless one assumes that the "new" rural-urban migrants spend on average many more days working in the city than the "old" ones. The response along the participation margin as far as rural-urban migration is concerned is striking different across genders. While the estimated effect of a 1 standard deviation negative rainfall shocks is equal to 4.9% on the baseline value for males, the coefficient for females is close to zero. These results confirm the possibility that fixed costs to participate to the urban sector (i.e. migration costs) are higher for females than for males and that the change in productivity in the farm sector vis-a-vis the urban one is not large enough to overcome fixed costs of moving. For this reason females mainly respond through the intensive margin. Coefficients for the local off-farm equation are positive and statistically significant for both females and males. Finally, variations in agricultural productivity do not trigger individuals to move in and out of the labour force (column 4).

Intensive margin. To attempt to assess the relevance of the change in aggregate days of work to various sectors coming from individuals who move in and out of the sector compared to that derived from individuals always participating to it, I, for each sector, compare estimates obtained on the full "unconditional" sample (the same presented in Table 4.3) with those obtained on a sample of observations conditional on days of work >0 (for each specific sector). Results are presented respectively in Panel (A) and (B) of Table 4.5**.** Estimates for both the farm and the urban sector equation are of the same sign in the two samples. Yet, those in the sample when I condition on participation are about 80% of those in the unconditional sample. These results represent suggestive evidence that the majority of the effect comes from changes in the amount of days devoted to sectors conditional on participation rather than from individuals moving in and out of them. Local off-farm sector presents somehow more puzzling results with the coefficient on the conditional sample turning negative and statistically significant.

4.5.2. Response heterogeneity

I now turn to study the heterogeneity of the response to shocks along the distribution of age. Figure 4.7 shows predicted coefficients (and 90% confidence intervals) in correspondence of a negative rainfall shock equal to a 2 standard deviations for six different age groups. Coefficients where the outcome is days of work are presented in Panel (A) while those for the participation equations in Panel (B). Days of work in the farm sector decrease homogenously (estimates are all statistically significant at the 10% level) along the distribution of age until age 55. Because individuals aged <45 do much less farming to start with (refer to Figure 4.4 for descriptive statistics about sectorial participation by age) for many of them a decrease in days of farming is translated into moving out of the sector (Panel B). Individuals >55 are the group that reduces farming the most, yet they tend not to bring their farming days to zero.

Working days in the urban sector increase in response to negative rainfall shocks for almost all age groups, and so does the likelihood to work in the city. Estimates for younger individuals are larger (Panel A) but once the mean group-specific values of days of work in the urban sector are taken into account (engagement in rural-urban migration declines with age) individuals between 46 and 55 appear to be the most responsive group. As far as total working days are concerned, there is no clear pattern in the increase of total labour supply. Indeed, most of the adjustment seems to be coming from individuals reallocating time across sectors as opposed to increasing (decreasing) the total amount of labour supplied.

It is interesting to notice how estimates for the local off-farm sector differ between young (< 45/50) and elderly individuals (>55), for both the days of work and the participation specifications. Indeed, younger individuals tend to respond to negative shocks by leaving the farming and the local off-farm sector and move to work in the urban area. On the other hand older individuals tend to farm less, although without leaving the farm sector completely. In fact they tend to remain in the home village and increase participation into the local off-farm sector, while only marginally increasing rural-urban migration. Both young and elderly individuals respond to negative rainfall shocks by shifting labour supply away from farming, yet their next best alternative appears to be different. On the one hand, younger individuals, who face low migration costs and have relatively high productivity in urban sectors, tend to leave the home village and engage in rural-urban migration. They indeed seem to also exit the local off-farm sector - whose productivity is likely to be partially affected by rainfalls, although to a lower extent - in bad times. On the other hand, older individuals, who face high migration costs and low productivity in the urban sector, have their best alternative in taking a non-farming job within the rural home village which might potentially include substituting in some family run business a younger family member who moved to the city. Finally there is no clear pattern in the increase of total labour supply. Indeed, most of the adjustment seems to be coming from individuals reallocating time across sectors as opposed to increasing (decreasing) the total labour supply.

4.5.3. Household level analysis

We might be interested to know how the individual level responses showed so far are translated at the household level. Thus, I now turn to the analysis of labour allocation responses to weather shocks at the household level. I aggregate individual labour supply data within families and in doing so I focus on those individuals who have reported complete labour supply information for all three years, from 2008 to 2010. That leaves me with a balanced panel of 3,713 households, whose composition of individuals from whom I aggregate labour supply data is fixed over time. First, to make sure that the sample used to construct the household level data is indeed similar to the full estimating sample employed for the individual level analysis I replicate baseline individual level results for the sample used to construct the household level data. Reassuringly, estimates for both the days of work and participation equations, presented in Appendix Table A 4.1**,** are very similar in size and significance level to those in Panels (A) of Table 4.3 and Table 4.4.

Results for the days of work and participation analysis at the household level are presented in Table 4.6. Responses in terms of days of work per household members by sectors (columns 1-4) are similar to those estimated at the individual level, as expected. Further, no increase in the total household supply of labour is detected. When I look at the share of total household days of work dedicated to different sectors as outcome (columns 5-7) I find that about 1.2-1.3% of total labour supply is shifted from farming toward rural-urban migration. That corresponds to a reduction of 2.6% with respect to the baseline share of labour time devoted to farming and an increase of 5.4% with respect to the baseline one devoted to the urban sector. Interestingly, the share of household labour supply to the local off-farm sector remains unaffected. This result might suggest that some within household re-allocation occurs as far as engagement in the off-farm sector is concerned and might be compatible with a story where young household members previously working in the local off-farm sector leave to work in the city in coincidence with a negative weather shock, while older members from the same households substitute them in the (perhaps family owned) off-farm activity. Finally when I look at the likelihood of households to participate at all in different sectors, I find that the participation to the farm sector (and to the local off-farm) does not respond to weather shocks: some amount of farming is always performed even when agricultural productivity is low. On the other hand the likelihood of households to send a member to work to the city increases by 1.2 percentage points, corresponding to an economically relevant 3.1% increase with respect to the baseline share of households who have a member working in the city.

4.5.4. Land tenure insecurity

The analysis in his paper shows that Chinese households do reallocate labour across sectors and away from farming when hit by a negative agricultural productivity shocks. Yet institutional features might have a role in easing or making more difficult the use of labour markets as an ex-post coping mechanism. One relevant institution is land property rights. Under China's constitution, rural land is the property of administrative villages, or collectives, but exclusive use rights are contracted out to individual households. Land can be reallocated within a village if necessary. Because the presence in the village and the active work of it limits the likelihood that an household will face loss of land in a reallocation, heterogeneity in the use of administrative land reallocation across counties might influence the extend to which households are willing to shift away from agricultural work when hit by bad shocks. In the 2009 survey households are asked to report whether in the village there has been a land reallocation in the last 5 years. I use the answer to this question as a proxy for the inclination of administrative authorities to reallocate land in a specific village, and therefore for the likelihood that land reallocation will occur in the future. This assumption is based on the fact that reallocations depends on may factors, but Giles and Mu (2014) identify some village characteristics, such as lineage group composition or demographic change, that in the cross section make some villages more incline to reallocate land. In other words, reallocation seems to be just much more common in some villages than in others, thus it is reasonable to consider a past reallocation event as a proxy for the likelihood that reallocation will take place again in the future.

Formally I interact the rainfall shock variable with my proxy for the risk that a reallocation will occur in the future in the specific village:

$$LABOUR_{ivkt} = \alpha_0 + \alpha_1(ZSCORE\ RAIN)_{kt} + \alpha_2(LOW\ RISK)_k + \alpha_3(ZSCORE\ RAIN * LOW\ RISK)_{vkt} + Z'_{ivk}\beta_1 + \gamma_i + \lambda_t + \varepsilon_{ivkt} \qquad \text{Eq. (3)}$$

Where LOWRISK is an indicator variable for the low risk that a reallocation will take place in the future in the village. The parameter α_1 tells the response to weather shocks in villages characterised by high risk of reallocation and $\alpha_3 + \alpha_1$ provides the response for individuals in villages characterised by low risk of land reallocation[63]. Table 4.7 reports estimates from individual level specifications employing individual fixed effects. I find that for individuals living in villages where the risk of land reallocation is high the elasticity of rural-urban migration to rainfall shocks is about half the size than the elasticity in low-reallocation risk villages, and it is not statistically different from zero. These results, although the potential endogeneity of the risk of reallocation does not allow to attach any causal interpretation to them, are consistent with a story where households living in villages where reallocations are more frequent are less incline to respond to shocks by shifting labour from the agricultural to other sectors and locations because doing so would increase the likelihood of loosing some land when a reallocation occurs. These findings also confirm results from a current study from Giles and Mu (2014) who find that the probability that a rural resident migrates out of the county declines by 2.8 percentage points in response to an expected land reallocation in the following year. In this environment land tenure insecurity seems to work as a constraint for households to freely reallocate labour across sectors to accommodate variations in sector productivities.

4.6. Concluding Remarks

The research question this paper wants to answer is if, and in what measure, individuals and households in rural China reallocate labour across sectors – away from farming and toward local off-farm and the urban sector - as an ex-post response to negative shocks in agricultural productivity. The paper focuses on both the participation and the intensive margin of adjustment of the labour supply, as well as on the heterogeneous responses to shocks. Furthermore, it studies the role that institutional features, such as land tenure insecurity, play in influencing and constraining labour reallocation away from agriculture in bad years.

I find that yearly working days devoted to farming drop by 4% while those spent working in the urban sector increase by almost 6% in correspondence to mild negative rainfall shocks,

[63] LOWRISK does not vary with time so α_2 cannot be identified.

i.e. rainfall realisations 1 standard deviation below the long term average. The increase in number of days individuals spend working in the city derives from both longer spells in the city for those already engaging in urban work (intensive margin) and from increase in the likelihood to participate at all in the urban sector (extensive margin). Indeed, the probability for individuals to engage in rural-urban migration increases by 3.7% on the baseline value. I find interesting heterogeneous responses across generations driven by age specific productivity in the urban sector and cost of leaving (even temporarily) the home village. While younger individuals tend to shift labour supply from farming toward working in the city, older individuals generally shift labour from farming toward local off-farm work, without leaving the home village. At a higher level, I calculate that in correspondence with rainfall 1 standard deviation lower than the average households reduce by 2.6% the total labour supply to the farming sector and reallocate it almost completely to the urban one. Finally, some preliminary evidence of the relationship between land tenure insecurity and the decision of households to reallocate labour toward rural-urban migration is provided. Findings would suggest that easing more secure land property rights could increase efficiency of rural labour markets and allow households to better cope with negative income shocks.

Figures

Figure 4.1 - Productivity shocks and labour reallocation

Panel A

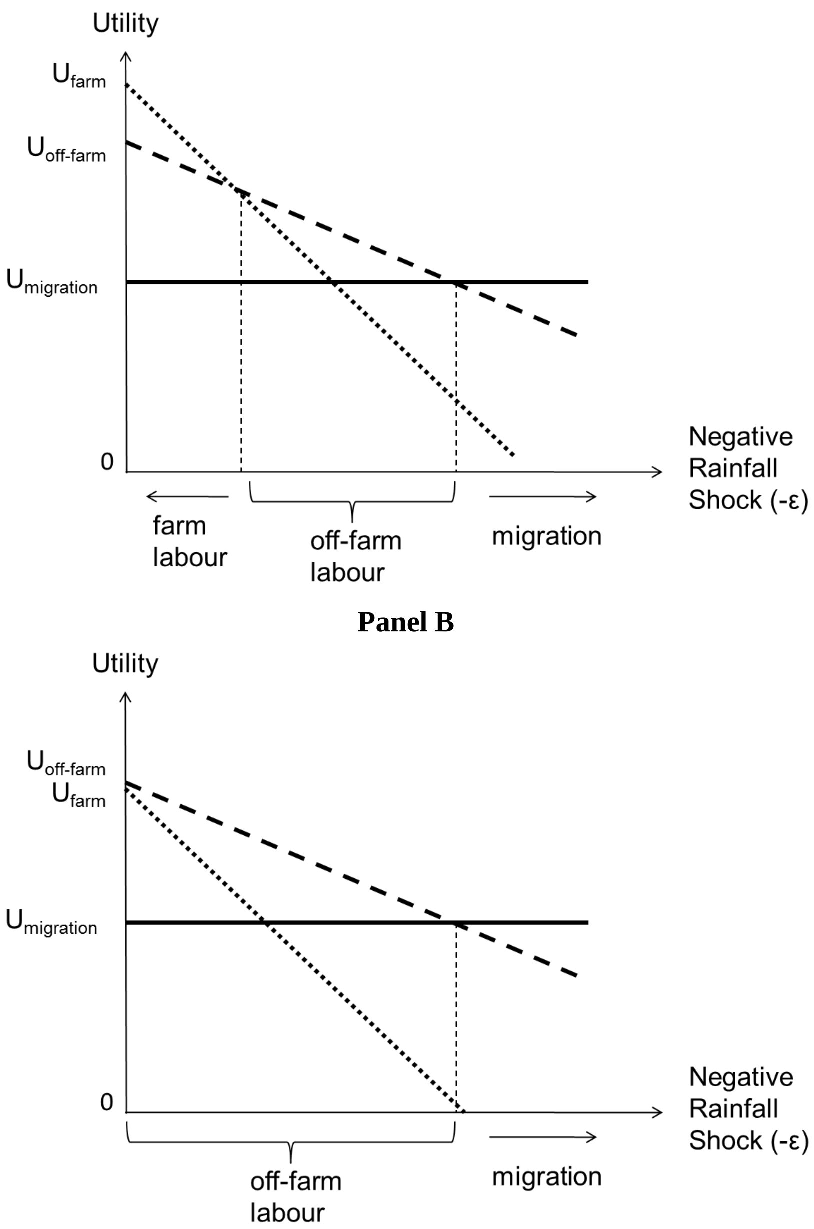
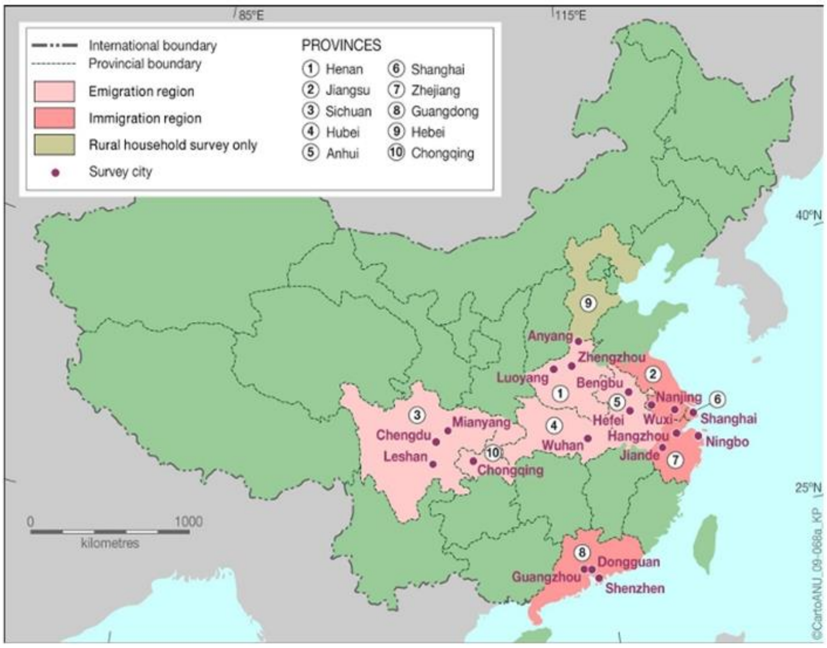
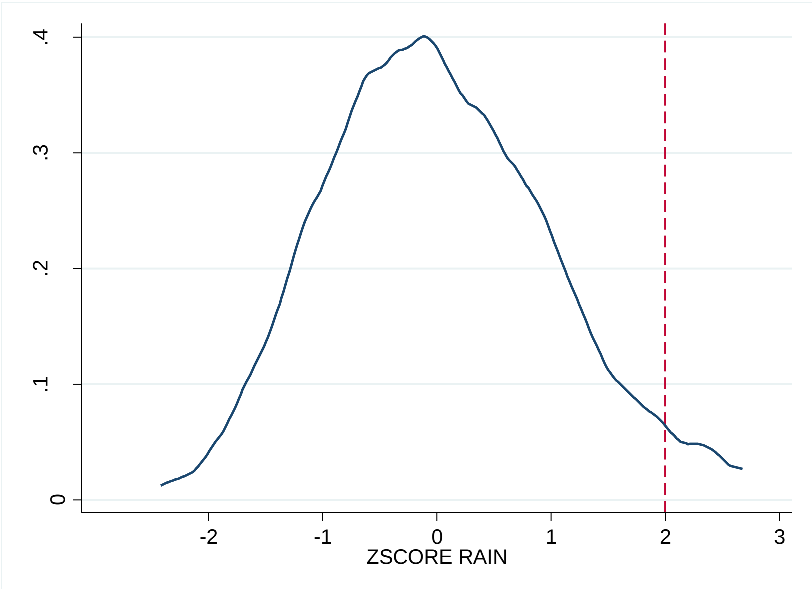


Figure 4.2 - Map of RUMiC Survey



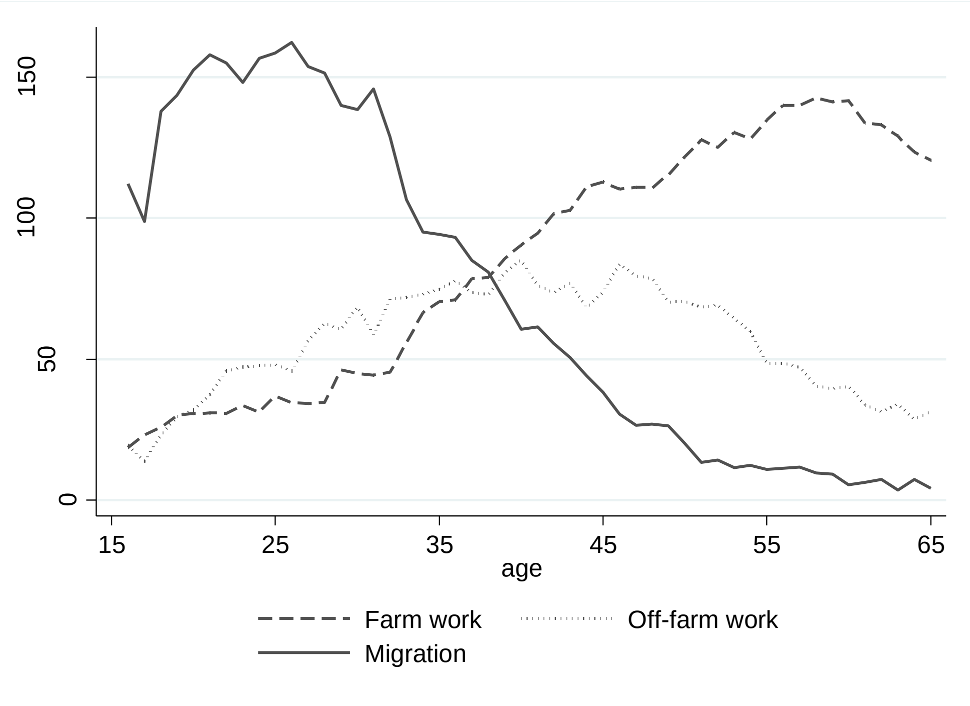
Note. The figure shows the provinces in which the RUMiC survey is conducted.

Figure 4.3 - Rainfall shocks distribution



Note. The figure shows the distribution of the main measure of rainfall shock (Zscore_Rain) for all county-year observations from 2000 to 2010. Zscore_Rain is a county-specific measure, given by the deviation of rainfall in year t from the long term average, normalised by its standard deviation: $Zscore\_Rain_{tk} = \frac{y_{tk} - \overline{y_k}^{78-10}}{SD_k^{78-10}(y)}$

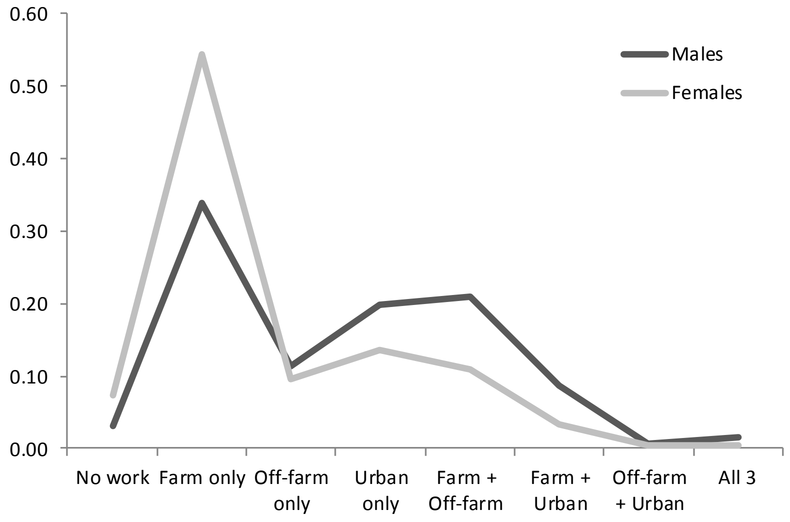
Figure 4.4 - Yearly days of work by sector and age



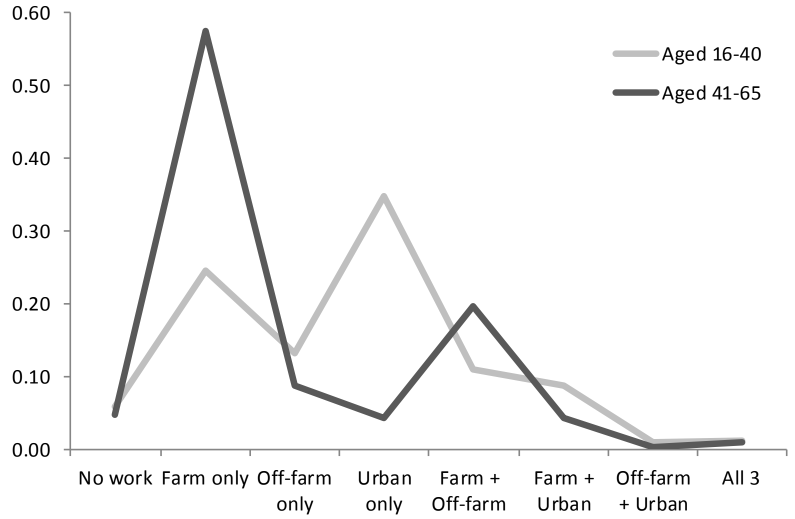
Note. The figure shows distributions of yearly days of work for each of the three sectors along the distribution of age. Pooled estimating sample: 48,214 individual*year observations from year 2008, 2009 and 2010.

Figure 4.5 - Share of individuals by sectoral participation

Panel (A): by gender

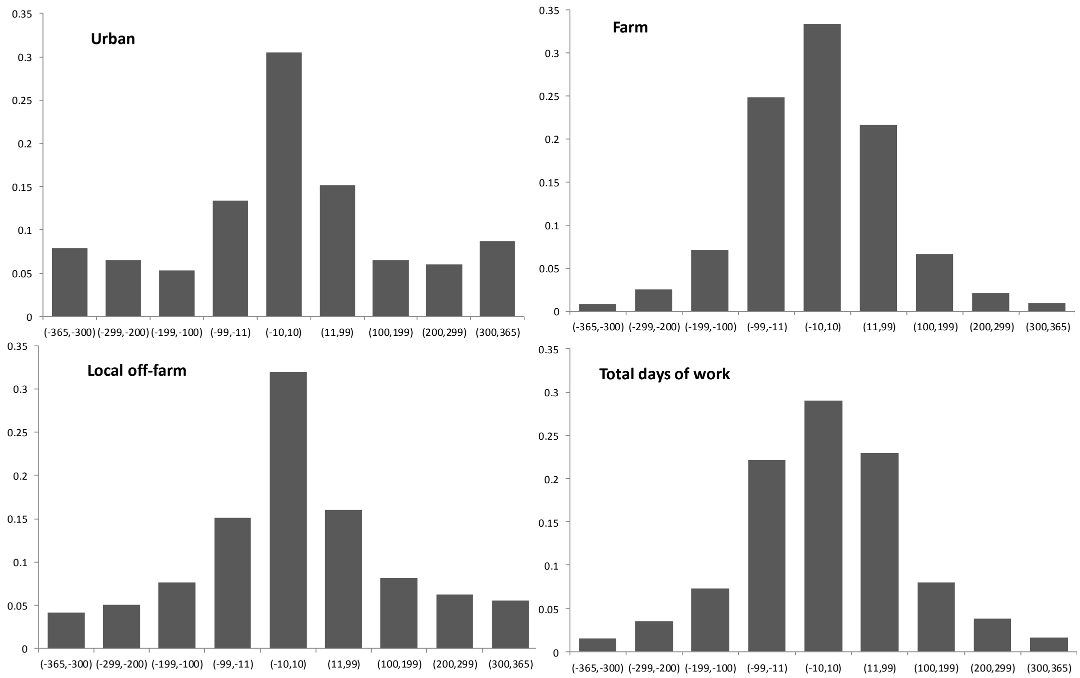


Panel (B): by age



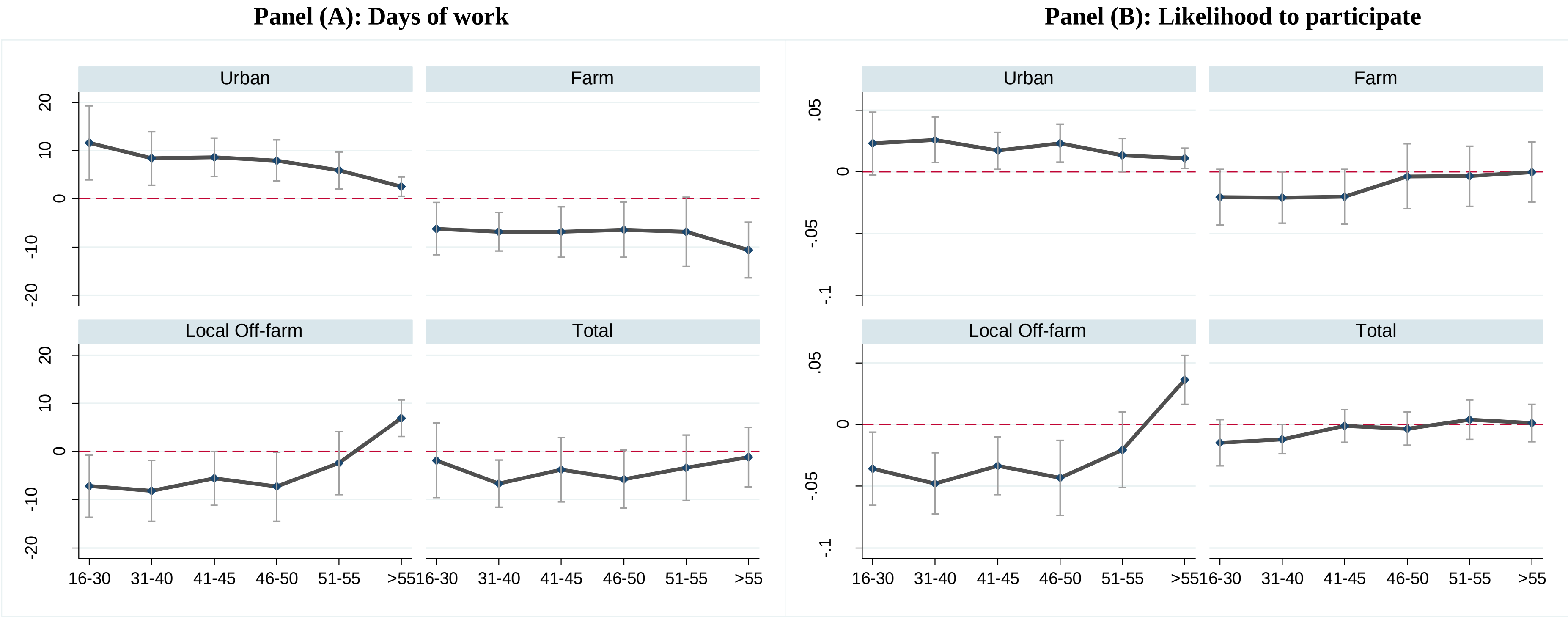
Note. The figure shows the shares of individuals participating to different sectors and combination of them. Pooled estimating sample: 48,214 individual*year observations from year 2008, 2009 and 2010.

Figure 4.6 - Yearly changes in days of work supplied: by sector



Note. The figure shows distributions of within-individuals changes in the number of days of work supplied to each sector (and the sum of them) between two consecutive years. The sample includes, for each sector, individuals who supplied a positive number of days in that specific sector in at least one of the three years between 2008 and 2010. More precisely the number of individuals for each panel is as follow - Urban: N=5930; Farm: N=13733; Local Off-farm: N=7269; Total days: N=1781

Figure 4.7 - Heterogeneous response to shock by age group



Note. The figure reports predicted coefficients on Zscore_Rain (and 90% confidence intervals based on robust standard errors clustered at the county level) in correspondence of a negative rainfall shock equal to a 2 standard deviations, from regressions of outcomes on Zscore_Rain and controls in an individual fixed effect specification, by age group. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel (A) predicted coefficients derive from OLS regressions with days of work as outcome; y-axis: days of work. In Panel (B) predicted coefficients derive from LPM regressions with an indicator for days of work >0 (participation); y-axis: probability of participation to the sector.

Tables

Table 4.1 - Descriptive statistics: individuals

Panel (A)	Mean	Std. Dev.	Min	Max
Male	0.51	0.50	0	1
Age	43	13	16	65
Married	0.84	0.37	0	1
Years of education	7.2	2.8	0	14
Participation by sector:				
Farm	0.67	0.47	0	1
Local Off-farm	0.28	0.45	0	1
Urban	0.24	0.43	0	1
Any	0.95	0.22	0	1
Days of work by sector:				
Farm	93	106	0	365
Local Off-farm	60	112	0	365
Urban	65	120	0	365
Any	218	110	0	365

Panel (B)	Mean	Number of days by sector:		
Participation by sector:		Farm	Off-farm	Urban
No work	0.05			
Farm only	0.44	174		
Local Off-farm only	0.11		287	
Urban only	0.17			291
Farm + Local Off-farm	0.16	81	181	
Farm + Urban	0.06	50		225
Local Off-farm + Urban	0.00		95	176
All 3	0.01	66	78	116

Note. The sample includes all individuals aged between 16 and 65 and not currently in school or disabled who reported complete labour supply information in at least two of three years. Individual descriptives are based on an unbalanced panel of 18,910 individuals resulting in 48,214 observations. Source: 2009, 2010 and 2011 RUMiC-RHS Survey.

Table 4.2 - Descriptive statistics: households

Panel (A)	Mean	Std. Dev.	Min	Max
Household size	4.0	1.2	2	10
HH members in the work force	2.9	1.0	1	7
Participation by sector:				
Farm	0.86	0.35	0	1
Local Off-farm	0.48	0.50	0	1
Urban	0.39	0.49	0	1
Any	0.99	0.10	0	1
Days of work by sector (as share of household's total):				
Farm	0.47	0.38	0	1
Local Off-farm	0.29	0.38	0	1
Urban	0.24	0.33	0	1

Panel (B)	Mean	Fraction of total days of work:		
Participation by sector:		Farm	Off-farm	Urban
No work	0.01			
Farm only	0.25	1.00		
Local Off-farm only	0.09		1.00	
Urban only	0.04			1.00
Farm + Local Off-farm	0.26	0.38	0.62	
Farm + Urban	0.22	0.37		0.63
Local Off-farm + Urban	0.01		0.52	0.48
All 3	0.12	0.27	0.29	0.45

Note. The sample includes all households with more than one individual in working age who reported full labour supply information in each of the three survey years, resulting in a balanced panel of 3,713 households (i.e. 11,139 observations).
Source: 2009, 2010 and 2011 RUMiC-RHS Survey.

Table 4.3 - Labour supply responses: days of work

Outcome - Yearly days of work:	Farm		Local Off-Farm		Urban		Any	
	Panel (A)							
	(1)		(2)		(3)		(4)	
Zscore Rain	3.767***		1.697		-3.649***		1.815	
	(1.163)		(1.095)		(0.805)		(1.234)	
In % of mean outcome	4.0%		2.8%		5.7%		0.8%	
Observations	48,214		48,214		48,214		48,214	
	Panel (B): by gender							
	Males	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Zscore Rain	3.053**	4.497***	1.898	1.504	-5.564***	-1.678**	-0.613	4.324***
	(1.213)	(1.240)	(1.292)	(1.087)	(1.081)	(0.766)	(1.267)	(1.420)
Mean of outcome	89	98	73	47	81	47	243	192
Observations	24,748	23,466	24,748	23,466	24,748	23,466	24,748	23,466
Individual and HH contr.	X	X	X	X	X	X	X	X
Individual fixed effects	X	X	X	X	X	X	X	X

Note. The table reports OLS estimates from individual level regressions of the number of days devoted to working in different sectors on Zscore_Rain and controls, as well as individual fixed effects. Zscore_Rain is the annual rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B the same analysis is replicated separately for males and females. Robust standard errors are clustered at the county level (82 counties) and reported in brackets.
*** p<0.01, ** p<0.05, * p<0.01

Table 4.4 - Labour supply responses: participation

Outcome - Participation:	Farm		Local Off-Farm		Urban		Any	
	Panel (A)							
	(1)		(2)		(3)		(4)	
Zscore Rain	0.006		0.010**		-0.009***		0.002	
	(0.004)		(0.005)		(0.003)		(0.003)	
In % of mean outcome	0.9%		3.6%		3.7%		0.2%	
Observations	48,214		48,214		48,214		48,214	
	Panel (B): by gender							
	Males	Females	Males	Females	Males	Females	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Zscore Rain	0.002	0.010**	0.011*	0.010*	-0.015***	-0.004	0.000	0.005
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)	(0.004)
Mean of outcome	0.65	0.69	0.34	0.21	0.31	0.18	0.97	0.93
Observations	24,748	23,466	24,748	23,466	24,748	23,466	24,748	23,466
Individual and HH contr.	X	X	X	X	X	X	X	X
Individual fixed effects	X	X	X	X	X	X	X	X

The table reports estimates from a linear probability model of an indicator for the individual working positive number of days in different sectors (participation) on Zscore_Rain and controls, as well as individual fixed effects. Zscore_Rain is the annual rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B the same analysis is replicated separately for males and females. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 4.5 - Labour supply responses: days of work conditional on participation

Outcome - Yearly days of work:	Farm (1)	Off-Farm (2)	Urban (3)	Any (4)
	Panel (A): Unconditional (baseline)			
Zscore Rain	3.767***	1.697	-3.649***	1.815
	(1.163)	(1.095)	(0.805)	(1.234)
Observations	48,214	48,214	48,214	48,214
	Panel (B): Conditional on days>0			
Zscore Rain	3.068**	-3.427**	-2.938**	1.249
	(1.438)	(1.460)	(1.402)	(1.013)
Observations	32,380	13,523	11,742	45,735
Individual and HH controls	X	X	X	X
Individual fixed effects	X	X	X	X

Note. The table reports OLS estimates from regressions of the number of days devoted to working in different sectors on Zscore_Rain and controls, as well as individual fixed effects. Zscore_Rain is the annual rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B, for each column, the sample is restricted to those observations with positive days of work in the specific sector. In order to allow the estimation of individual fixed effect, only individuals who have contributed to the sector a positive number of days for at least 2 years are included. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 4.6 - Household level labour supply responses

	Days of work by HH member				Share of total HH days of work			Participation		
	Farm	Off-Farm	Urban	Any	Farm	Off-Farm	Urban	Farm	Off-Farm	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Zscore Rain	3.737**	1.373	-3.408***	1.702	0.012**	0.001	-0.013***	-0.002	0.006	-0.012**
	(1.462)	(1.382)	(0.820)	(1.501)	(0.005)	(0.005)	(0.003)	(0.006)	(0.007)	(0.005)
In % of mean outcome	4.0%	2.0%	6.2%	0.8%	2.6%	0.3%	5.4%	0.2%	1.3%	3.1%
Observations	11,139	11,139	11,139	11,139	11,034	11,034	11,034	11,139	11,139	11,139
HH controls	X	X	X	X	X	X	X	X	X	X
HH fixed effects	X	X	X	X	X	X	X	X	X	X

Note. The table explores the effect of weather shocks on household labour supply. In columns 1-4 the outcome are days of work divided by the number of household members in the estimating sample; in columns 5-6 the outcome are the shares of total household days of work in different sectors; in columns 8-9 estimate derive from a LPM where the outcome are indicators of the household participating in different sectors. Zscore_Rain is the annual rainfall deviation from the county long-term average normalised by its standard deviation. Household time-varying controls include number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. Household fixed effects are included in all regressions. The sample includes all households with more than one individual in working age who reported full labour supply information in each of the three survey years, resulting in a balanced panel of 3,713 households (i.e. 11,139 observations). Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 4.7 - Land tenure insecurity

Outcome: days of work	Farming	Migration
	(1)	(2)
Rain shock * high reallocation risk	8.859***	-1.788
	(1.350)	(1.599)
Rain shock * low reallocation risk	3.316***	-3.602***
	(0.437)	(0.517)
Individual controls	X	X
Household controls	X	X
Individual fixed effects	X	X
Observations	43,655	43,655

Note. The table reports estimates from individual level regressions of the number of days devoted to farming (column 1) and rural-urban migration (column 2) on ZSCORE, LOWRISK, an interaction between the two (ZSCORE*LOWRISK) and controls, as well as individual fixed effects. LOWRISK is an indicator variable for the low risk that a reallocation will take place in a particular village. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. The table reports coefficients for individuals living, respectively, in high and low risk of reallocation villages. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.

Appendix

Appendix Tables

Table A 4.1 - Robustness of individual level estimates

	Farm	Off-Farm	Urban	Any
	(1)	(2)	(3)	(4)
	Panel (A) - Outcome: days per year			
Zscore Rain	3.600**	1.572	-3.633***	1.540
	(1.488)	(1.351)	(0.876)	(1.505)
	Panel (B) - Outcome: participation			
Zscore Rain	0.005	0.011*	-0.009***	0.002
	(0.005)	(0.006)	(0.003)	(0.003)
Observations	28,692	28,692	28,692	28,692
Individual and HH controls	X	X	X	X
Individual fixed effects	X	X	X	X

Note. The table tests the robustness of baseline estimates to the sample of individuals used to construct the household level outcomes data, i.e individuals who have reported labour supply data for all 3 years and who are not the only ones in their households. Panel (A) should be compared to the same panel in Table 4.3; Panel (B) should be compared to the same panel in Table 4.4. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Chapter 5

5. Concluding Remarks

This thesis addresses questions in applied microeconomics within two topic areas: the first is the role of news media in shaping perceptions and political outcomes (chapter 2); the second is household and individual decision making about internal migration and labour allocation in developing country settings (chapters 3 and 4).

The **second chapter** (based on joint work with Nicola Mastrorocco) investigates the influence of news media, and in particular partisan ones, on crime perceptions and voting behaviour. To do so, we exploit a natural experiment in the Italian television market where the staggered introduction of the digital TV signal across regions led to a drastic and sudden drop in the viewing shares of partisan channels and, as a consequence, to a lower exposure to potentially biased news about crime. We find that the lower exposure to partisan news channels led individuals to revise their perceptions about crime as one of the priority problem in Italy downward. The effect is mainly driven by individuals from older cohorts who are likely to be more exposed to the potential bias before the digital introduction and to place a higher weight on information coming from television. Findings suggest that the digital reform induced a reduction in exposure to crime news of about 12 percent of the average value and that a 1 standard deviation decrease in exposure to crime news is associated with a 9.2 percent decrease in crime concern, among those aged above 65. Finally, using data from an electoral survey collected just before the introduction of digital TV, we predict that the reduction in crime concern caused by the digital reform might induce about 3% of those aged above 65 who voted for the centre-right coalition to change their vote. Our findings contribute to shed light on one of the possible mechanisms through which media manage to influence voting decision and policies: the manipulation of individuals' perceptions with respect to politically salient topics. On the one hand we observe that manipulating people's perceptions is more difficult when individuals acquire information from a variety of sources. On the other hand individuals for whom we find a significant effect, those aged above age 52, make up about 30 percent of Italian voting population. Hence, for an office-seeking politician, being able to influence their beliefs about politically salient issues might have relevant implications in terms of voting outcomes. Media are nowadays a pervasive presence in people's lives and the increasing availability of data about them provides unique opportunity to further explore the mechanisms through which they impact on economic decisions and outcomes. Interesting future areas of research include: studying the effect of the digital TV introduction on voting, political participation and other outcomes; exploring the supply of persuasive communication, i.e. the incentives driving the selective provision of information by partisan media.

The **third chapter** (based on joint work with Christian Dustmann, Francesco Fasani and Xin Meng) studies the relation between household migration decisions and the distribution of risk attitudes within a household. To do so we build and test a theoretical framework of household migration decisions where household members differ in their preference toward risk. Our findings suggest: (i) that conditional on migration gains, less risk averse individuals are more likely to migrate; (ii) that within households, the least risk averse individual is more likely to emigrate; and (iii) that across households, the most risk averse households are more likely to send migrants as long as they have at least one family member with sufficiently low risk aversion. The paper provides strong evidence not only that, in the context of internal migration in China, migration decisions are taken at the household level, but that heterogeneity in risk aversion within the household plays an important part in determining whether a migration takes place, who emigrates, and which households send migrants. The insight that migration decisions, in the context that we analyse, but also likely in other settings, are taken at household level, and are influenced by risk attitudes of other household members has important policy implications. For instance, the implementation of a policy that creates possibilities to insure against risk – such as the introduction of social safety net schemes - will possibly increase migrations if decisions are taken on an individual level. When the migration decision is taken at the household level, however, this may work in the opposite direction because it allows risk averse household members to diversify risk in other ways. Finally, it would be possible and interesting to apply our model with heterogeneous preferences to other household decisions that embody uncertainty, such as investment in risky assets, or even human capital investments.

The **fourth chapter** analyses if and in what measure individuals and households in rural China reallocate labour across sectors as an ex-post response to agricultural productivity shocks. I employ various waves of a longitudinal survey of rural households to construct a panel of individual and household labour supply histories, and match them to detailed weather information, which I use to proxy agricultural productivity. Results suggest that farming is reduced by 4% while urban sector employment is increased by almost 6% in correspondence to mild negative rainfall shocks, i.e. rainfall realisation 1 standard deviation below the long term average. Individuals increase the number of days spent working in the city along both the participation and the intensive margin. While younger individuals tend to shift labour supply from farming toward working in the city, older ones generally shift labour from farming toward local off-farm work, without leaving the home village. Finally, I find that the elasticity of rural-urban migration to agricultural productivity in villages with high risk of land reallocation is about half the size of that in other villages. Findings confirm previous studies in suggesting that providing more secure land property rights could increase efficiency of rural labour markets and allow households to better cope with negative income shocks. China is a fascinating country for the study of migration processes. The many institutional changes that are taking place could allow to answer many other questions such as: how the relaxation of different constraint to internal migration – such as more secure land property right or less stringent *houku* residence system – affect internal movement. Finally, the multiple impacts that parental migration has on the wellbeing of left-behind children in another topic of great policy relevance and that certainly needs to be more deeply researched.

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