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Essays on Wage Determinants in the Long and the Short Run

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Abstract

This thesis consists of three independent chapters, each of which studies the processes behind the determination of workers' wages. The first chapter takes a long run perspective; it investigates the labour market consequences of advances in automation technology in the late 20th century, with an emphasis on how this technology affected earnings of workers in different occupations, as well as the career choices and opportunities for social mobility of their children. The remaining chapters have a shorter run perspective: the second chapter studies how individual and parental wealth affect job search behaviour and earnings; and the third chapter studies wages over the career-cycle in a particular setting where both earnings and performance can be directly measured: the market for professional footballers.

Intergenerational Occupational Mobility and Routine-biased Technological Change

This chapter analyses intergenerational occupational mobility in the presence of routine-biased technological change (RBTC). During the recent era of job polarization, fathers in cognitive jobs became relatively more likely to have sons with cognitive jobs, while the rise in low-skilled manual jobs was mainly accounted for by children of routine workers. These facts, among others, are rationalized in a general equilibrium, overlapping generations model where both financial resources and learning ability are transferred from parents to their children. Education choices are endogenous, and the cost of education depends on the cognitive wage rate – hence both parents' income *and* the economy-wide cognitive wage premium affect the education decision. The model is calibrated to the US economy and successfully captures key empirical patterns. Despite depressing routine wages, altruistic preferences meant that routine workers born 1950-1965 saw welfare gains due to RBTC, although they would have preferred a slower adoption.

Intergenerational Transfers, Wealth, and Job Search Behaviour

This chapter, which is co-authored with Ludo Visschers, analyzes the effects of individual wealth and parental wealth on job search behaviour. Making use of the quasi-random timing of the 2008 economic stimulus payments in the US, we confirm a finding from the previous literature: an increase in liquid wealth tends to lower job finding rates and increase reemployment wages, especially for lower wage and younger individuals. We also investigate how this finding may generalize to *parental* wealth. Using data from the 1979 National Longitudinal Survey of Youth, as well as its follow-up child and young adult survey, we find that parental inter-vivos transfers depend on both the (adult) child's employment status and the income of the parents. This finding suggests that individuals from wealthier background may be better insured against negative labour market shocks such as a job loss. Motivated by this, we estimate the effect of parental income on job search behaviour. In the cross-section, we find that the correlation between parental income and job search behaviour is different from the exogenous wealth shock: richer parents tend to be associated with higher job finding rates as well as higher reemployment wages, even after controlling for a rich set of characteristics. However, when estimating the effect of a job loss of a mother on the job search behaviour of her (adult) children we do find a positive effect on the job finding hazard and a negative effect on the occupational rank of the new job. This effect is stronger for individuals with deceased or absent fathers. We argue that these results motivate further investigation into intergenerational insurance and job search.

The Age-wage-productivity puzzle: A Contribution from Professional Football

This chapter, which is co-authored with Rachel Scarfe, Carl Singleton and Adesola Sunmoni, concerns the evolution of wages and productivity over a worker's career. There is a positive relationship between age and wages in most labour markets and occupations. However, the effects of age on productivity are often unclear. We use panel data on the productivity and salaries of all the elite professional footballers in North America to estimate age-productivity and age-wage profiles. We find stark differences between these profiles; while the productivity of professional footballers peaks at the age of 26, wages continue to increase throughout most of their careers.

This discrepancy has been observed in other labour markets, and poses the question: why are older workers seemingly overpaid relative to their contemporaneous productivity? The richness of our dataset allows us to consider a number of possible mechanisms that could be responsible. However, we fail to solve the age-wage-productivity puzzle that we have identified in this market.

Lay Summary

This thesis studies the economic forces that determine the wages earned by workers in the labour market. These forces are important to understand as they will further understanding of how earnings respond to policy and to economic conditions. The analyses presented here may have consequences for how a policy maker think of issues such as unemployment insurance, taxation, education funding and trade barriers. Since each chapter of the thesis forms a self-contained article, I will below summarize these chapters in turn.

Chapter 1

In the first chapter I study the role of automation technology, education costs and social mobility in determining wages and well-being of workers in different broad occupational groups. Many economists have argued that the increase in automation technology in the 1980s and 1990s – mainly through rapid advancements in information and communication technologies – had negative effects on large groups of workers. In particular, the technological advances are thought to have caused a fall in demand for workers in occupation with a large share of ‘routine’ tasks, which can easily be replaced by the new technology. This has lead to stagnant wages in this group as well as a fall of their aggregate share of the labour force. Furthermore, it turns out that many routine occupations are associated with wages that lie in the middle of the wage distribution. Hence, it is believed that the technological change drove a phenomenon known as *job polarization*: a decline in the share of occupations in the middle of the wage distribution coupled with an increase in the share of occupations in the low- and high ends of the distribution, which has been observed in labour market statistics and has been a large contributor to the increasing wage inequality in recent decades.

Economists disagree on how to evaluate the impact of this rapid displacement of routine jobs on the well-being, or welfare, of workers. A counter-argument that has been raised against the idea of detrimental effects on routine workers is that the replacement of workers due to technology is part of a natural process of ‘creative destruction’, and should be viewed positively even by the workers who are replaced as it means that their children will grow up in a more prosperous society. Hence, if these workers are altruistic, or empathic, toward their children they may have benefited from the technological change despite the negative impact on their labour market outcomes. One of the main goals of this chapter is to evaluate the validity of this argument by estimating the welfare consequences of technology on different classes of workers after taking altruism towards their children into account. This is in part an empirical question; the extent to which replaced workers can take comfort in the fact that their children grow up in a richer society will depend crucially on the intergenerational mobility rates between occupational classes. For example, if many children of routine workers were able to adapt to the new technological advances by investing in the new skills required in the labour market, it may be the case that technology was welfare enhancing even for replaced workers, after accounting for altruism towards future generations. To measure the extent of such ‘intergenerational occupational mobility’ I use data from the longitudinal survey ‘Panel Study of Income Dynamics’, which has surveyed multiple generations of a representative sample of families in the US going back to 1968. Using this data I find that occupational choice is persistent over generations in the US, and in fact that this persistence was increasing over the period of rapid advances in automation technology in the 1980s and 1990s. This finding suggests that the negative shocks to the group of routine workers may have persisted over generations, and hence it is not clear that the the new technology benefited the children of the replaced workers. However, to fully evaluate the welfare consequences of the technological change an empirical analysis is not sufficient: in the data there is not a clear correspondence between wages and well-being, and it is impossible to evaluate ‘counterfactual’ scenarios to answer crucial questions such as: what would wages and opportunities to social mobility have been if the revolution in information and communication technologies never occurred? To be able to answer such questions I construct a model of the labour market that incorporates the empirical findings, and adds an underlying structure that allows for such counterfactual analyses. In the model children inherit financial resources and imperfectly

inherit cognitive ability from their parents, before choosing an education which determines their occupation over their working life. A firm hires workers of different types (corresponding to low-middle- and high-paying jobs), and a technological shift occurs that increases demand for jobs with high wages at the expense of ‘routine’ jobs in the middle of the wage distribution. I show that the model is able to replicate a number of empirical facts regarding intergenerational mobility, education levels, and cognitive ability across occupations and conditional on family background. Using the model I then study counterfactual realities, where the pace of technological change differs, and labour market policies are adjusted. The main finding is that routine workers born between 1950-1965 (who at this point made up the largest occupational group in the economy) were negatively affected by the technological shift in the 1980s and 1990s. This is manifested in two ways: their wages were lower than they would have been in the absence of technological change, and the technological shift reduced the opportunities to upwards social mobility for their children (mainly due to an increase in the cost of education that was caused by the technological shift). However, I also find that it is not the technological change *per se* that generates this result, but rather the pace at which technology was adopted. If technology was instead introduced at half the pace (this can perhaps be thought of as a ‘protectionist’ policy), workers of all types, and in all generations, achieve higher welfare in a world with the new technology compared to one without. I also find that other policy tools of the government can enhance the welfare of routine workers in the presence of technological change: in particular, funding for higher education appears to be important, which may explain part of the differences in the experience of technological change in the US and Europe; in many European countries, which typically have larger welfare states and more public funding for higher education, the increase in low-wage occupations was less pronounced than in the US.

Chapter 2

The second chapter investigates how job search behaviour depends on individual wealth, and on the wealth of ones parents. A large strand of economic literature has suggested that an increase in wealth could lead to individuals searching for better jobs, but with a lower chance of finding a match. The reason for this is that wealthier individuals can fall back on their savings in case

they cannot find a job quickly, and hence can afford to trade off a job application with higher chance of success for one with higher quality. In this chapter I add new empirical findings in support of this hypothesis, by analysing the impact of the stimulus payments made in the US in 2008 on the job search behaviour of unemployed individuals. I find that the increase in wealth that came with the stimulus checks was associated with individuals taking longer to find a job on average, but that those who did find a job in close proximity to their stimulus check tended to do so in a higher paying occupation. Having established this result of the effect of individual wealth on job search behaviour I next apply this finding to a new setting: by analysing the effect of *parental* wealth on the job search behaviour of the child. I find that richer parents are more likely to pay for their (adult) children's living expenses, in particular when the child is unemployed, which suggests that the same insurance effect that helps higher wealth individuals find better jobs may also apply to individuals with wealthy parents. Such an effect would exacerbate earnings persistence across generations, as individuals with wealthier parents will themselves find work in better paid occupations, and may lead to inefficient matches in the labour market. To explore this further I investigate the correlation between parental income and children's job search behaviour. I find that having wealthier parents tends to be associated with both higher rates of job finding out of unemployment, and higher wages upon reemployment, which goes against findings of the effect of individual wealth, where job finding rates fell after an increase in individual wealth. This is perhaps not so surprising: having richer parents is associated with a number of advantages in the labour market, for example through access to better contact networks. Although efforts are made to disentangle these forces in the data, the positive correlation between parental wealth and the probability of successful job search appears to be robust. To get closer to a 'random' variation in parental wealth, more akin to the stimulus payments studied in the first part of this chapter, I also investigate the changes in the job search behaviour of a child upon a job loss of their mother. Here the findings support the theoretical prediction: in the months close to a job loss of the mother individuals tend to find jobs faster, and generally in lower paying occupations. Motivated by these findings this chapter concludes by pointing out how the effect of parental wealth on job search behaviour warrants more research, as it can have important consequences for how to design labour market policies such as public unemployment insurance.

Chapter 3

The third chapter investigates the link between wages and productivity. A prediction of neoclassical economic theory is that a worker's productivity should be reflected in their wages. Were this not the case, competing firms would be able to recruit the worker by offering a higher wage and make a positive profit. This theory implicitly informs many empirical studies of the returns to education, tenure, and experience over the life-cycle. Since the productivity of workers typically cannot be measured directly in the data, these studies use wages as a proxy for a worker's productivity, with the underlying assumption that wages reflect the added value of the worker. In this chapter we challenge this assumption by making use of a particular labour market in which many components of productivity are directly observed: the labour market for professional footballers. We estimate separately the wage profiles and performance profiles of footballers as they age, carefully controlling for issues of selection, which turn out to be important. A surprising finding emerges: in terms of performance footballers peak at a relatively early age – between age 22-25 depending on how we measure their performance – yet, wages continue to increase after this point for several years until reaching a peak around age 31. Thus, in this market, there appears to be a discrepancy between the productivity and wages of the workers. We investigate a number of potential explanations for this puzzle such as labour market institutions, unobserved productivity (i.e. superstardom or leadership qualities), and wage premia for 'known talents' but do not find any of these explanations to be strong enough to account for the puzzle.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Paul Telemo

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Intergenerational Occupational Mobility and Routine-biased Technological Change

1.1 Introduction

The decline of middle-wage jobs and increase in low- and high-wage jobs in the US and Europe over the past 40 years is a well-established fact.¹ This ‘job polarization’ in the labour market is often attributed to a technological process known as ‘routinization’ or ‘routine-biased technical change’ (RBTC). The RBTC hypothesis claims that the driver of job polarization is the ability of automation technology to substitute for so-called ‘routine’ tasks, which tend to be associated with occupations in the middle of the wage distribution.² At the same time technology is thought to complement high-wage ‘cognitive’ workers, which explains the relative increase in wages earned by workers in occupations predominantly using cognitive skills.

Many papers have investigated the effect of advances in automation technology on workers in routine occupations during this period, but little attention has been given to the impact on their children. The outcomes of children matter greatly for welfare considerations in the case where utility is dynastic: perhaps hardship due to technology borne by routine workers today is something many would accept if it means that their children grow up in a more prosperous society – or, alternatively, perhaps the negative shock that these workers face today have ripple effects that also damages the opportunities of their children. Intergenerational considerations may also affect

1. See, for example, Autor, Katz, and Kearney 2006, Acemoglu and Autor 2011, Autor and Dorn 2013 for US, Goos and Manning 2007, Goos, Manning, and Salomons 2014, Adermon and Gustavsson 2015 for Europe.

2. It has also been suggested that globalization may have played a key part in job polarization through offshoring of routine tasks (Robert-Nicoud 2008, Jung and Mercenier 2014), although estimates in the literature suggest that this accounts for a smaller share (Goos et al. 2014, Autor, Dorn, and Hanson 2015).

aggregate labour market dynamics following a technological change. In particular, since most of the rise in cognitive labour is accounted for by an increase in college enrolment (Cortes, Jaimovich, and Siu 2017) adverse shocks to routine workers may affect their children's ability to obtain a university education, which in turn affects the relative supply of different occupational classes. The aim of this paper is to shed more light on these issues.

To do so I first document a number of novel facts about routinization and intergenerational mobility. Using data from the Panel Study of Income Dynamics (PSID) I show that there is significant persistence in occupational choice over generations, with fathers in cognitive occupations being more likely to have sons in cognitive occupations and so on. Second, I document a time trend where not only the job market has become more polarized, but there has also been a divergence in intergenerational occupational mobility. I find that the probability of upwards social mobility for a son with a routine father declined for cohorts born after 1960, whereas the opportunities of those with fathers in cognitive occupations improved during the same time, with a son to a father in a cognitive occupation being more likely to work in a cognitive occupation. I also show that the propensity to work in a low-wage manual occupation increased more for sons with routine fathers than for sons with cognitive fathers, which means that the increase in the manual share of labour is mainly accounted for by individuals with routine fathers. These findings are puzzling, as the rapidly increasing cognitive wage premium when these individuals chose their education level should have increased incentives for investment in the skills required for cognitive jobs for individuals of all backgrounds.

Having documented these facts I rationalize the observed trends through the lens of an overlapping generations model set in general equilibrium. Three forces in the model affect intergenerational persistence in labour market outcomes. The first channel is a financial friction in the form of a borrowing constraint, where young agents who are investing in skills for the future are unable to fully borrow against their future incomes, and therefore rely on their parents to pay for part of their education. This means that, *ceteris paribus*, those with richer parents are more likely to invest in skills than those from a poorer background. The second channel is a persistence in learning ability. Learning ability affects a person's skill choice as investments in the skills necessary for each occupational class comes with a *psychic* cost, as well as a monetary investment, and this psychic

cost is decreasing in learning ability. The third channel is an idiosyncratic occupational preference shocks, which adds noise to the sorting from parental background and ability to occupation. A novel feature of the model is that I allow for an causal response of the monetary cost of education to wage inequality, by allowing the cost of college to vary with the cognitive wage. This endogenously generates a stronger link between income inequality and opportunities to (upwards) intergenerational mobility, a correlation which has been documented across countries (Corak 2013) and is known as the Great Gatsby curve (A. Krueger 2012).

The model is calibrated to the US economy between 1980 to 2010. Some model parameters are estimated directly from the data, including the cost of college, its relation to the cognitive wage, and the share of costs paid by parents. Other parameters are estimated while solving the model, using a GMM procedure to fit observed data moments. Apart from the intergenerational occupational mobility rates I also target distributions of cognitive ability across occupations and *conditional on parental occupation*, which are observed in the National Longitudinal Surveys of Youth (NLSY79 & NLSY97). These moments turn out to be key for identifying the relative importance of financial frictions, ability inheritance, and idiosyncratic preferences, as the model gives distinct predictions of the sorting by ability – conditional on parental background – depending on the size of each of these forces.

After establishing that the model does a good job at matching the data, I use the calibrated model to analyse counterfactual outcomes. In a first counterfactual experiment I investigate the overall welfare consequences of RBTC across occupational classes and generations. Despite finding that RBTC depressed wages of routine workers by 2%–3%, I find that routine workers born between 1950–1965 experienced welfare gains due to RBTC equivalent to 0.24%–3.43% of their age 30–45 consumption. The welfare gains are due to altruistic preferences and their children being significantly better off due to RBTC (by a magnitude of 5.79%–6.57% of their age 15–30 consumption). For manual and cognitive workers there was no tradeoff between own income and altruistic preferences, with both wages and welfare increasing due to technological change for these groups. I also consider counterfactuals where the pace of technological growth is varied, which can

be thought of as a possible policy tool for the government (e.g. a more protectionist policy that stops the offshoring of routine tasks may slow down the pace of RBTC). Here the main finding is that, although the observed technological change had positive welfare effects on routine workers, they would be even better off if the pace of technological growth occurred at half the rate.

In a second counterfactual experiment I investigate the relative importance of financial frictions and non-financial ability inheritance in determining intergenerational occupational persistence. To do so I re-evaluate the model while (in turn) shutting down the borrowing constraint and the ability persistence. This analysis reveals that the importance of parental wealth for career choices has been increasing over time: in 1980, ability persistence played a larger role than financial frictions in generating intergenerational occupational persistence; accounting for roughly two thirds of the difference in the propensity of working in cognitive jobs for those with cognitive relative to routine parents. However, following the technological change, and in particular due to the increased cost of education, financial frictions played the dominant role in intergenerational occupational persistence in 2010.

In a final counterfactual experiment I investigate how the interaction between RBTC and financial frictions affect the dynamic labour supply response into the three occupational classes. This exercise reveals that the observed rise in low-skilled manual occupations is linked to the financial friction; relaxing the borrowing constraint facing young agents reduces the rise in the manual share of labour following a technological shift. The model predicts that 28% of the rise in the manual worker share is due to the borrowing constraint, which is suggested as a potential explanation to observed differences in job polarization across countries, where European economies have tended to have job polarization less skewed towards low-wage manual jobs than the US.

This paper builds on a large literature on the distributional effects of technological change. The RBTC hypothesis was first formulated in Autor, Levy, and Murnane (2003) and has since been the subject of numerous empirical and theoretical research papers. On the empirical side, many papers have investigated the flows of workers between manual, routine and cognitive occupations. Related to this paper are Cortes (2016), who also uses PSID data to show that, among routine workers, it is those with relatively higher wages that tend to leave for cognitive jobs, while those with relatively lower wages tend to leave for manual jobs. Cortes et al. (2017) use CPS

data and find that most of the observed job polarization can be explained by (i) a decline in the share of men with low education levels, and (ii) a decreasing propensity of low-educated men to work in routine occupations. Martinez (2019) also uses CPS data and finds that most observed job market polarization is driven by younger cohorts and is, on the high end, mostly accounted for by an increasing share of educated workers in high-wage occupations together with an increase in the education level. All-in-all these empirical findings point towards sorting by ability and education as important drivers of the observed aggregate trends, which means that the analysis of *intergenerational* considerations may be important, given that parents have a large influence on their children in these dimensions. This motivates the focus of this paper which documents intergenerational trends in occupational sorting along the manual, routine, cognitive dimensions. The link between job polarization and intergenerational mobility has been studied in other contemporaneous work. A negative link between job polarization and intergenerational mobility, as found in this paper, has also been noted for the the case of UK in Garcia-Penalosa, Petit, and van Ypersele (2022) and the US in Hennig (2022), although these papers use different data and methodology to the paper presented here.

On the theoretical side this paper builds on a tradition of models such as Galor and Zeira (1993), Maoz and Moav (1999), and Hassler, Rodríguez Mora, and Zeira (2007), but it is more quantitative in nature, as has become more common in the literature (e.g. Abbott, Gallipoli, Meghir, and Violante 2019, Lee and Seshadri 2019, and Colas, Findeisen, and Sachs 2021). Common to these papers is that they use models set in an overlapping generations framework with financial transfers from parents to children, which through a borrowing constraint affect the education decisions – and hence the skill sets – of future generations. The benefit of this approach is that it allows for an endogenous supply of cognitive workers; other papers in the theoretical RBTC literature have typically had a short-run perspective, where the quantity of high-skilled workers is assumed fixed (e.g. Autor and Dorn 2013), or assumed that the increase in cognitive workers follows an exogenously increasing trend, typically estimated by the increase in education level (e.g. Albertini, Hairault, Langot, and Sopraseuth 2017, Hartmann and Föll 2020). Since the model presented here instead features an endogenous education decision, counterfactual analyses do not only investigate the distributional impact of RBTC for a given increase in education levels, but

also allow the technological change itself to affect the amount of highly-educated, cognitive workers in the labour market. The model also shares features with recent work by Lo Bello and Morchio (2022), who also use a model to decompose intergenerational occupational mobility into three similar forces: parental networks, comparative advantage and preferences. However, this paper uses this decomposition to study long-run dynamics in general equilibrium over a technological shift, whereas Lo Bello and Morchio (2022) take a shorter-run perspective. Most similar to this paper is likely the contemporaneous work by Brinca, Duarte, Holter, and de Oliveira (2022), who also devise an overlapping generations model with discrete occupational choice along the manual, routine and cognitive dimensions, which they calibrate to the US economy to analyse the role of RBTC in the increased wage dispersion over recent decades. However, in Brinca et al. (2022) there are no direct links from parent to child: bequests from the dying cohorts are shared equally among the young, and all agents draw their ability from an identical and independent distribution, hence this model does not capture the intergenerational considerations which lie at the heart of the model presented here.

The remainder of the paper is organized as follows: section 1.2 lists a number of stylized facts that will be explained through the model along with some model intuition, section 1.3 presents the full model, section 1.4 reports the calibration strategy, section 1.5 presents the results from the counterfactual analyses, and section 3.7 concludes.

1.2 Empirical Findings

This section presents the stylized facts that will be endogenous outcomes of the model. In order, these facts are: (A) job polarization among prime-aged men is pervasive, and the wage premium of cognitive jobs has been increasing with time; (B) there is significant intergenerational persistence in occupational choice along the routine and cognitive dimensions; (C) the likelihood of working in a cognitive occupation for individuals with cognitive relative to routine fathers has been diverging over time; (D) the increase in the aggregate share of manual workers is mainly accounted for by individuals with fathers in routine occupations; (E) worker types are selected according to cognitive ability; cognitive workers have the highest average cognitive ability, and routine workers tend to

have higher ability than manual workers; (F) *conditional on ability*, individuals with cognitive fathers are more likely to work in a cognitive occupation compared to those with routine fathers; (G) *conditional on occupational class*, individuals with cognitive fathers have higher ability on average; and finally (F) the amount and cost of education of cognitive workers has been increasing over time.

All the empirical findings are based on prime-aged men. The reason for focusing on men is that the supply-side of the men's labour market has been more constant over the last 50 years than that of women – where the increasing labour force participation means that direct comparisons between mothers' and daughters' occupations are difficult. The reason for the focus on prime-aged men is to capture the 'main' occupation of an individual. This brings the empirical findings closer to the model, where each individual is allowed only one occupation over their lifetime. Two empirical facts motivates the choice of age 40 as capturing the main occupation of a worker. First, the probability of changing occupations is declining in age, but flattens around age 40. This can be seen in figure 1.1d, which plots the probability of switching occupation across the manual, routine and cognitive dimensions between two consecutive PSID waves. The estimates suggest that around 20 percent of workers change occupation at age 19, whereas by the time workers reach 40 the probability of job switching has stabilized at around 10%. Second, the propensity to work in a certain occupation changes over the life cycle, with, for example, the likelihood of working in a cognitive occupation increasing with age. The suitability of using age 40 as capturing an individuals 'main' occupation can be seen in figure 1.1, which plots the fraction of individuals in each occupation by age for three different generations. It is clear that, whereas the propensity to work in a given occupation is quite variable at young age, it stabilizes from age 40.

Data

The empirical findings draw on data from a multitude of sources. Data on occupations and wages of linked father-son pairs are taken from the Panel Study of Income Dynamics (PSID), a longitudinal survey that started interviewing 4,800 U.S. families in 1968, and has since then annually or biennially continued to interview these families and their descendants. I only include individuals from the original sample, which was designed to be representative at the time. This

means that estimates for intergenerational mobility should be reasonably representative for the US population in 1968, but does not take into account the intergenerational mobility of more recent immigrants. To get more precise estimates information on the evolution of shares, wages and education level of the different occupational groups I use the larger Current Population Study (CPS), which is a quarterly, cross-sectional survey of $\sim 60,000$ U.S. households. Information on the ability is taken from two of the National Longitudinal Surveys, which annually or biennially interview a sample of 12,686 people born between 1957-1964 (NLSY79) and 8,984 people born between 1980-1984 (NLSY97). The benefit of the NLS surveys is that respondents undertake the Armed Services Vocational Aptitude Battery (ASVAB) tests, which consist of a multitude of tests designed to measure the applicants cognitive and non-cognitive abilities. These tests have been shown to perform better at measuring respondents' cognitive ability than the limited information in the PSID (Cunha, Karahan, and Soares 2011). Finally, data on the cost of college is taken from the College Board, a non-profit organization aimed at expanding access to higher education that annually publishes a report called *Trends in College Pricing*, which contains detailed information on tuition fees of private and publicly funded universities in the US (The College Board 2021).

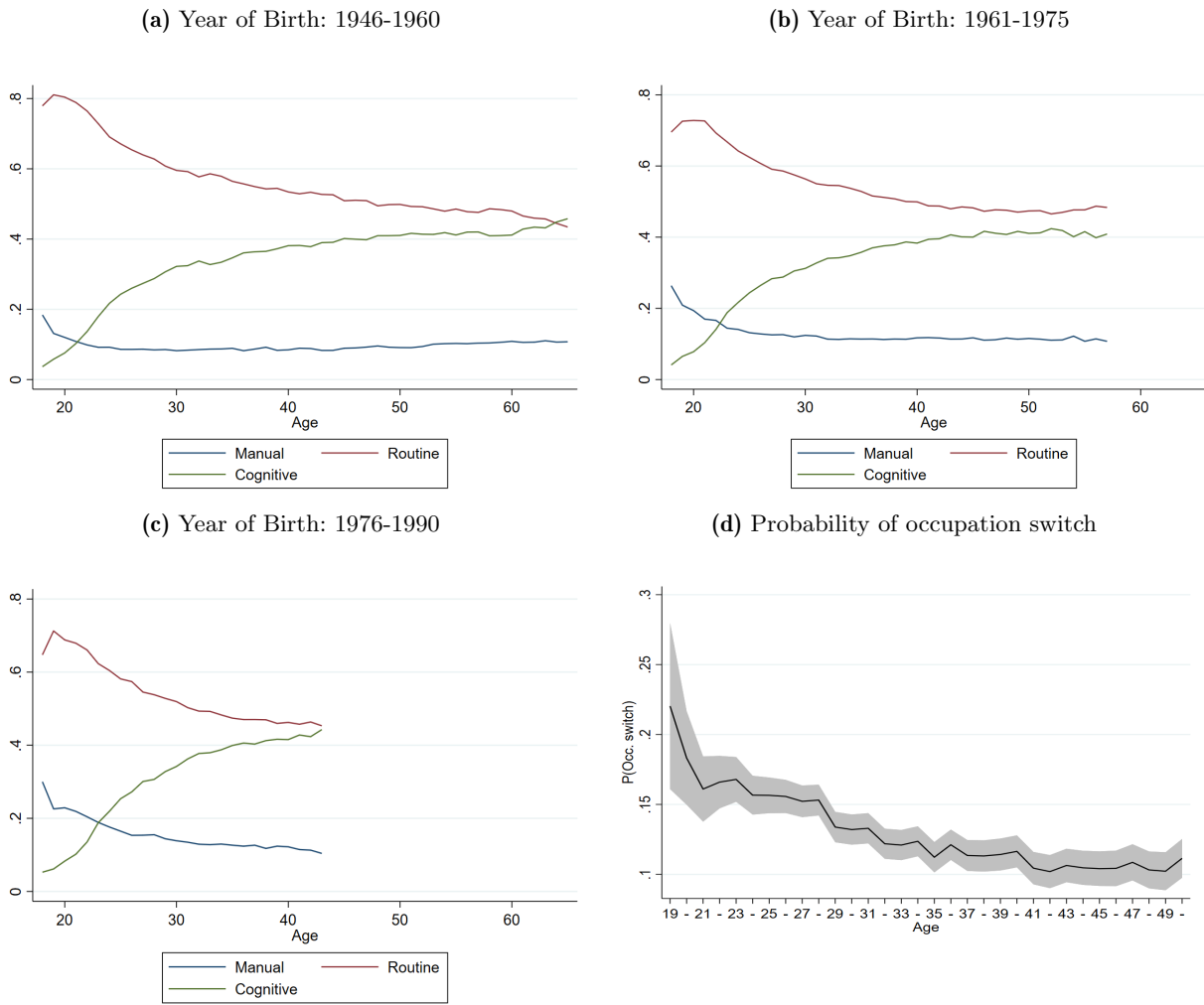
In each of the datasets occupations are sorted into three broad occupational classes: manual, routine and cognitive, based on their census occupational codes following exactly the classification in Cortes (2016). Cortes (2016) shows that this occupational classification corresponds well to the task scores defined in Acemoglu and Autor (2011) using the *Dictionary of Occupational Titles* (DOT). Cognitive task content is the average score of 'Mathematics' and 'Direction, control and planning', Routine content is the average score across 'Dealing with set limits, tolerances and standards' and 'Finger dexterity'; and Manual content is the score for 'Eye-hand-foot coordination'.

1.2.1 Stylized facts

Fact A: Job Polarization of prime-aged men and the cognitive wage premium

I use data from the CPS to estimate the average share of the labour force that is employed in each occupational class, as well as the mean and median wages in these groups. The sample is constrained to men aged 40 in full-time employment, and wages are deflated by the CPI index to correspond to 2015 dollars. Figures 1.2a–1.2b shows the timeline of the share of employment in

Figure 1.1: Occupational shares and occupation switch probability by age



Notes: Data on occupational shares are calculated using CPS data on men in full-time employment. Occupational switching probabilities are estimated using PSID data. Figures (a)-(c) show the within-cohort average employment share in each occupation, plotted by age. Occupational switch defined as different broad occupational categories reported for the respondents' main job between two interviews.

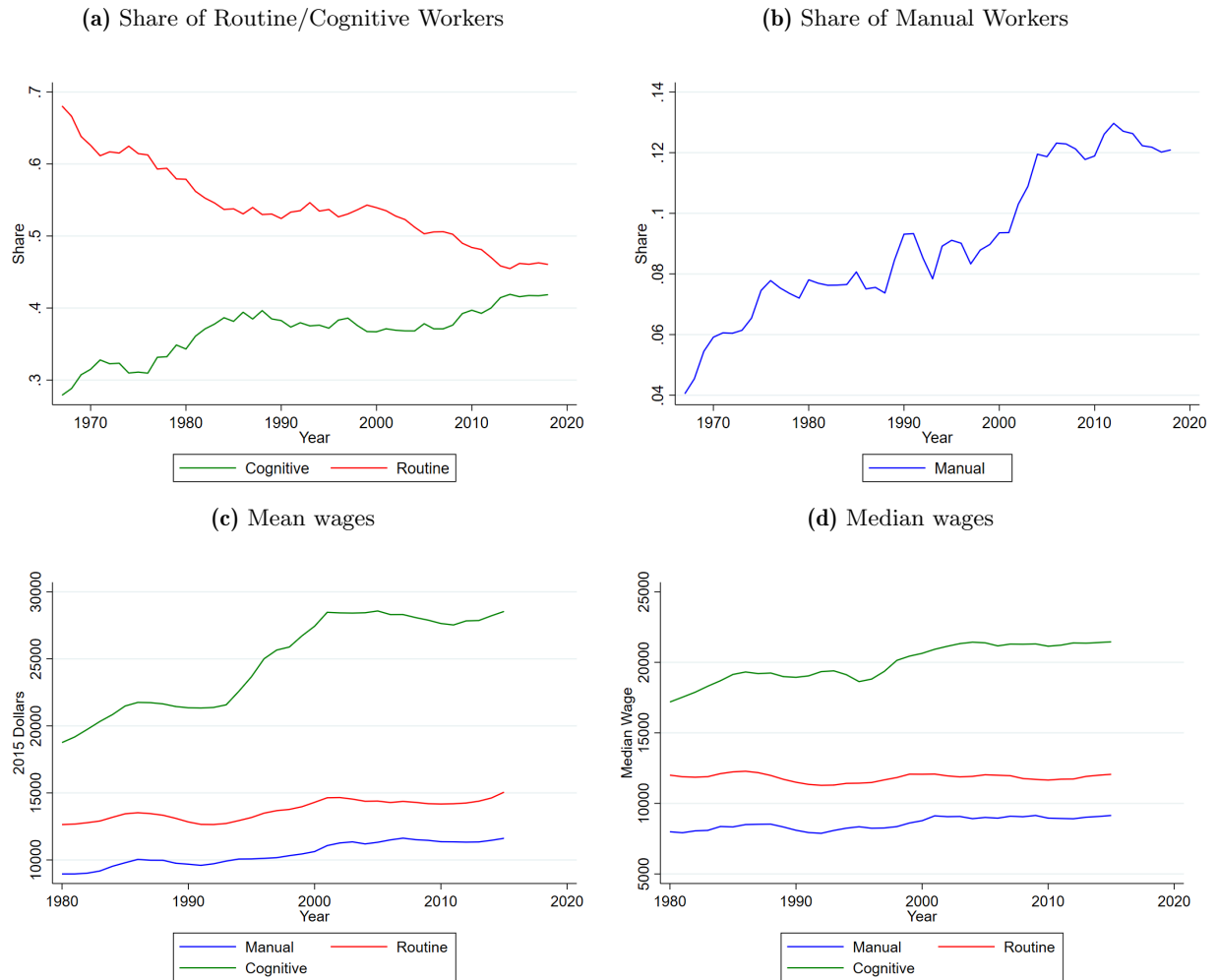
each of the occupational classes and figures 1.2c–1.2d shows the timeline of their respective wages. It is immediately apparent that job polarization, both in shares and in wages, is prominent among prime-aged men. The share of workers in manual occupations increased by 50% over the period considered, from 8% in 1980 to just over 12% in 2018. At the same time the share of workers in routine occupations decreased from nearly 59% in 1980 to 46% in 2018 and the share of workers in cognitive occupations increased from 34% in 1980 to 42% in 2018. In terms of average wages, there was a large dispersion starting around 1990 with a sharp increase in the wage premium paid to cognitive workers; in 1980 a cognitive worker earned 46% more than a routine worker on average, but by 2016 this had increased to 90%. There is a slight convergence of routine and manual wages, with the routine to manual wage premium falling from 39% in 1980 to 30% in 2016. The increasing wage premium is also apparent for median wages, albeit less pronounced.

These estimates are in line with Cortes et al. (2017) who find that the decreasing propensity of prime-aged men, particularly with low education, to work in routine occupations is a key driver of the overall decline in routine jobs. The focus on men means that the increase in the cognitive occupational share is smaller than found in other empirical work since a large share of the overall increase in the cognitive work share is driven by women (see G. M. Cortes, Jaimovich, and Siu 2018). The increase in the cognitive wage premium is widely recognised, however, unlike Acemoglu and Autor (2011), I do not find that average real wages of routine and manual workers have been stagnant or declining, rather they appear to be growing at a relatively stable rate. The larger increase in manual and cognitive wages relative to routine wages has also been noted in earlier literature such as Autor and Dorn (2013) and is sometimes referred to as ‘wage polarization’.

Facts B-D: Intergenerational occupational mobility and its trend over time

I use data from the PSID to parametrically and non-parametrically estimate trends in intergenerational occupational mobility. In total I observe 847 father-son links with occupations recorded at least once between age 39-41. For the non-parametric estimation I place the sons in bins based on their birth year: 1953-1957, 1958-1962, ..., 1973-1978, and, for each bin, estimate the share of workers in occupation $j \in \{\text{Manual, Routine, Cognitive}\}$, with a father in occupation $i \in \{\text{Manual, Routine, Cognitive}\}$, which will be denoted by $\lambda_{i,j}$. Figure 1.3 reports the results

Figure 1.2: Occupational shares and wages over time



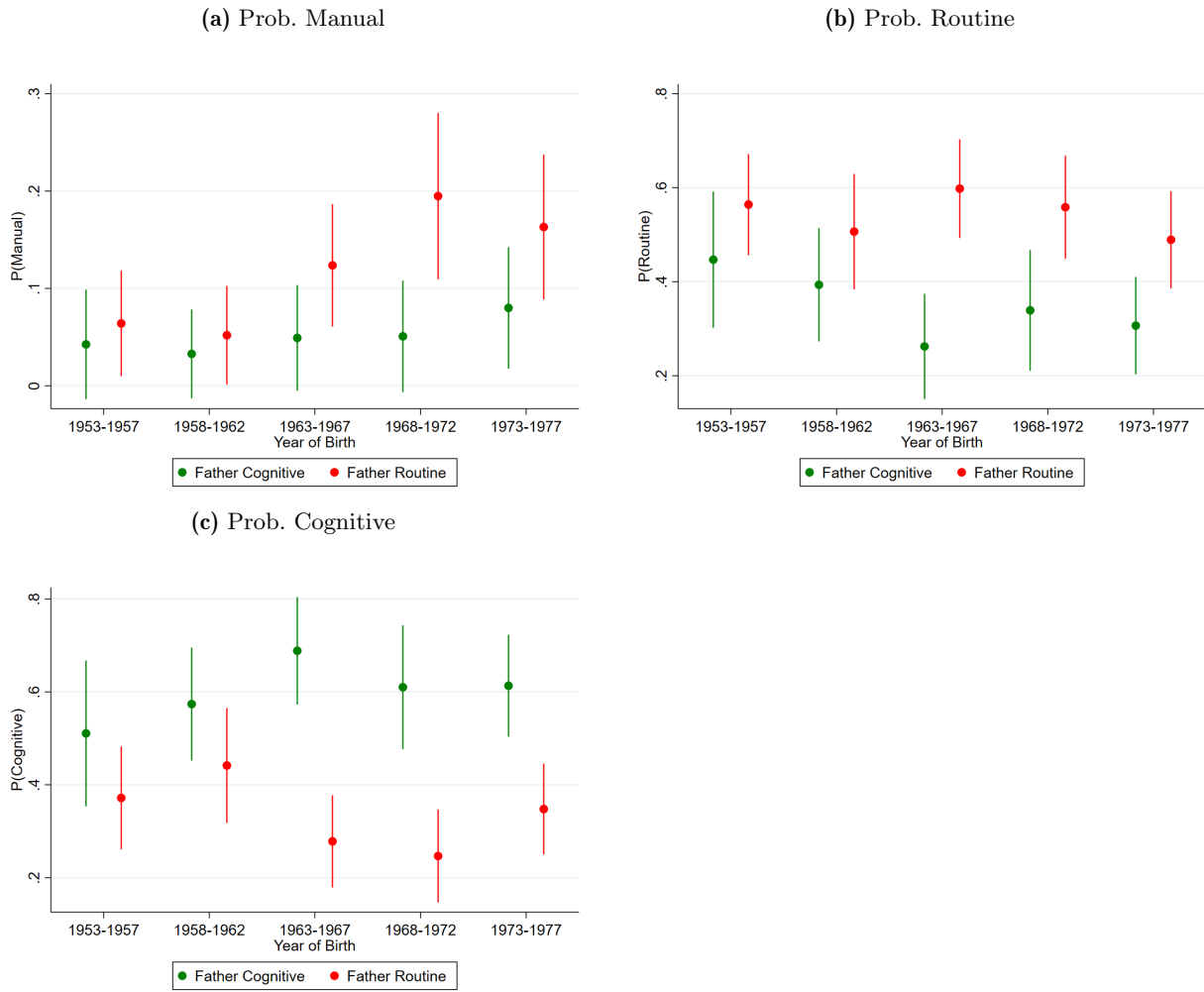
Notes: Data from CPS with 3-year moving averages. Panels (a)-(b) plot average employment share in each occupational group among 40-year-old men in full-time employment. Panels (c)-(d) plot average/median annual wages and salary in each occupational group among men in full-time employment. Wages are deflated by the CPI to correspond to 2015 dollars.

including 95% confidence intervals for the estimates based on standard errors clustered at the father level. Since very few individuals have fathers employed in manual occupations (only 52 individuals across the 5 cohort bins) the estimated probabilities for those with manual fathers are very imprecise and hence relegated to the appendix (figure 1.A1).

Mobility to cognitive occupations: The estimates point at a significant amount of occupational persistence across generations. Estimates for the cohorts born between 1953-1962 indicate that individuals with cognitive fathers were around 10 percentage points more likely to work in a cognitive job relative to those with routine fathers, and similarly those with routine fathers were around 10 percentage points more likely to work in a routine job. For later cohorts the gap between $\lambda_{R,C}$ and $\lambda_{C,C}$ increased, suggesting that there was more intergenerational persistence in mobility to cognitive occupations. For individuals born between 1963-1972 the propensity of working in a cognitive job, conditional on having a routine father, had fallen to below 30% from a level of around 40% for the earlier cohorts, whereas for individuals with cognitive fathers the probability increased from around 55% to over 60%. Although the persistence in occupational outcomes is perhaps not so surprising, the dynamic path poses an economic puzzle. The wage premium for cognitive workers increased sharply between 1980-2000, which corresponds to the time when these cohorts entered the labour market. Hence, we may have expected that the supply of cognitive workers would increase over this time period. This is indeed what we see for individuals with cognitive fathers, but seemingly not for those with routine fathers. Explaining this ‘intergenerational supply response’ to the RBTC-driven increase in the cognitive wage premium will be one of the key challenges for the model to explain.

Mobility to manual occupations: Turning to the propensity of downwards mobility to the lowest wage, manual occupational category, the estimates provide new insights into the rise in the aggregate share of manual workers: it appears that this increase is largely driven by workers with routine fathers, where the share of workers with routine fathers working in manual jobs going up from around 5% for the earlier cohorts to nearly 20% for the later ones. For those with cognitive fathers, the propensity to work in a manual job remains relatively stable over the considered cohorts at around 5%, although there is a slight uptick for the last cohort bin, born between 1973-1977.

Figure 1.3: Intergenerational occupational mobility



Notes: Data from PSID. Father's and son's occupation taken at highest observed age between 39-41. Bars display 95% confidence intervals and standard errors are clustered at the father level.

Parametric estimation: I also estimate the time trend in the relationship between fathers' and sons' occupations parametrically, which allows for significance testing of the diverging trends and helps control for potential compositional changes in the data that may bias the results. To this end I fit the following logistic regression equation

$$\text{logit}(y_i) = \beta_0 + \beta_1 \times \mathbb{1}\{f_occ_i = \text{Cog}\} + \beta_2 \times \text{birthyear} + \beta_3 \times \text{birthyear} \times \mathbb{1}\{f_occ_i = \text{Cog}\} + \eta \times X_i + \epsilon_i.$$

where y_i denotes the occupation of the son (a dummy variable that takes value one if the son works in a cognitive/routine/manual occupation in three separate estimations) and f_occ_i denotes the occupation of the father (both as observed in the PSID data at age 40 and excluding manual fathers). X_i is a vector of individual characteristics (region of birth and race) which accounts for possible changes in the demographic composition of the data over time. The key coefficient of interest is β_3 , which represent the difference in the time trend of the propensity of working in a cognitive occupation for those with cognitive relative to routine fathers. Using a dummy for having a cognitive occupation as the dependent variable the estimates show that β_3 is positive and strongly significant ($p < 1\%$), which confirms the findings of the non-parametric estimation – there has been a divergence in the probability of son working in a cognitive occupation by family background over this time period. For the dependent variable of manual occupation β_3 is negative, which again suggest that sons with routine fathers mainly accounted for the rise in manual occupations, however this divergence is not significantly different from zero when looking over the entire time period. The full regression results are presented in the appendix table 1.A2.

Facts E-F: Sorting by ability

Using data from the National Surveys of Youth (NLSY79 and NLSY97) I estimate the average cognitive ability of the different occupational groups. The respondents of the NLSY79 survey were asked specifically about the occupations of their fathers, which allows me to also estimate the average cognitive ability of workers conditional on their father's occupation. These moments will turn out to be useful in estimating the structural model, as the conditional abilities help identify the relative importance in the inheritance of cognitive ability relative to monetary transfers. To proxy cognitive ability, I follow Abbott et al. (2019) and use the AFQT89 percentile score. For

the NLSY97 sample I use the ASVAB math and verbal percentile score, which is designed to mimic the AFQT score in the NLSY79 sample as best possible. In order to make the results more consistent with the quantitative part of the paper I replace the percentile scores to the percentile score *among men*. In the most recent wave of the NLSY97 survey which I have access to (2017) the oldest individuals are 37 years old, so to make the two surveys comparable I here use 37 rather than 40 as the the age at which I make the comparison. For individuals who are not interviewed at age 37 I use age 36 instead. In both the NLSY79 and the NLSY97 interviews respondents had the option of reporting several jobs, and their corresponding occupations. As a convention I use the first job reported in each interview as the ‘main’ occupation.

Table 1.1 displays the average ability percentile in each occupational group, split by the NLSY79 and NLSY97 samples. There is evidence of occupational sorting by ability; in both surveys cognitive workers score higher than routine workers on average – ranking near the 70th percentile relative to routine workers who rank around the 45th percentile. There is also a difference in rank between manual and routine workers. In NLSY79 routine workers rank 4 percentiles higher than manual and in NLSY97 the difference is 6 percentiles. Although much smaller than the gap between routine and cognitive workers this difference is statistically significant ($p=0.0018$ in a two-sided t-test using the NLSY79 sample).

Turning to dynamics, the difference between occupational shares in the NLSY79 and NLSY97 are consistent with the job polarization observed in the CPS data. There was an increase in the manual and cognitive occupational shares and a fall in the routine share between the two cohorts. Despite this, there was not a large change in sorting by ability; the only discernible difference in average ability across the samples was a two percentile fall in the average ability of cognitive workers and a 2 percentile increase in the average cognitive ability of routine workers. These dynamics are qualitatively consistent with a change in sorting following the technology-induced wage premia. For cognitive workers, the increasing cognitive wage premium causes lower ability workers to select into cognitive occupations, leading to a fall in the average ability rank. For routine workers, there are two opposing effects: lower ability workers are more likely to sort into manual occupations, causing the average ability to increase, while higher ability workers are more likely to sort into cognitive occupations, causing the average ability to fall.

Table 1.1: Average AFQT/ASVAB percentile in NLSY79 and NLSY97, by occupational group.

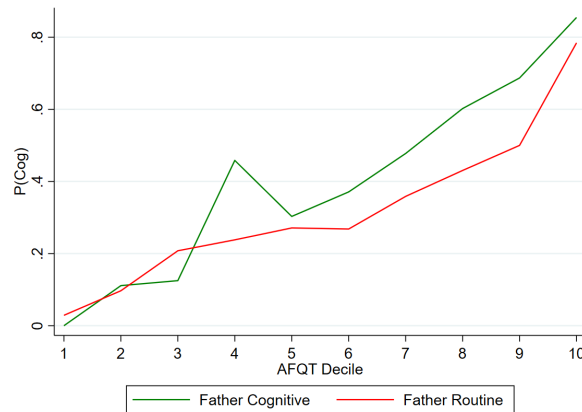
	NLSY79			NLSY97		
	Manual	Routine	Cognitive	Manual	Routine	Cognitive
Ability percentile	0.39	0.43	0.70	0.39	0.45	0.68
Occupation share	10%	57%	33%	13%	49%	39%
N	344	1,926	1,109	112	432	345

Next we turn to occupational sorting by ability, *conditional on family background*. The respondents in NLSY79 (cohorts born 1957-1964) were specifically asked about their father’s main occupation when they were 14 years old, but unfortunately NLSY97 does not include any information about the parents’ occupations.³

Two stylized facts from this section will be important for the remainder of the analysis. First, *conditional on ability*, individuals with cognitive fathers are around 10 percentage points more likely to work in a cognitive occupation compared to those with routine or manual fathers. This is suggestive of untapped potential among the pool of individuals with lower-skilled fathers, as it is consistent with some friction keeping youths with high cognitive ability from poorer backgrounds from investing in the skills required to work in a cognitive occupation. In the model this difference will be attributed to differences in financial means depending on the occupation of the father, although it is also possible that other factors play a role, such as differences in access to contact networks, differences in parental expectations, or differences in risk preferences conditional on family background (in case education is considered a risky investment). Figure 1.4 illustrates this result by plotting the share of cognitive workers split by ability deciles and the occupation of the father (once again manual fathers are omitted as the small sample size makes the estimation imprecise). A regression analysis using a dummy variable for cognitive occupation as the dependent variable, controlling for a cubic in ability percentile and with dummies for the father’s occupation on

3. Backward looking questions about parental occupations are known to have some inherent bias, which is why the key intergenerational moments in this paper are estimated using PSID data, where both the father and son’s occupations are directly observed. Still, the NLSY data is able to provide some useful stylized facts about the ability distribution conditional on parental background.

Figure 1.4: Share of workers in cognitive occupations, by ability decile and occupation of father



Note: Data from NLSY79. Occupational classes defined as in Cortes (2016). Information on father's occupation taken from survey question on father's occupation at age 14.

the right-hand side shows that the the average ability conditioned gap in the probability of working in a cognitive occupation between those with cognitive and routine fathers is 10.8 percentage points, and that this difference is strongly significant ($p < 0.1\%$). The full regression output is reported in appendix table ??.

Second, *conditional on occupational class* individuals with cognitive fathers are on average around 20 percentiles higher in the ability distribution than those with routine or manual fathers. To reach this conclusion, I use the NLSY sample to estimate the average AFQT percentile score of 40-year old men in each occupational group, conditional on the occupation of their father. Table 1.2 shows these estimates in a matrix where the rows correspond to the occupation of the father and the columns correspond to occupations of the sons. A clear stylized fact stands out: regardless of the occupation of the son, those with cognitive fathers tend to score around 20 percentiles higher on the AFQT scale on average relative to those with routine or manual fathers. There is a potential concern that this difference is due to the fact that the manual-routine-cognitive dimensions do not perfectly capture the skill of the individual. For example, individuals with cognitive fathers in routine occupations may have higher wage jobs within the group of routine occupations than those with routine fathers. However, I argue that this is likely not the explanation for this stylized fact as controlling for wages does not dramatically change the observed discrepancy. This is shown in appendix figure 1.A2, which sorts cognitive workers into bins based on their wage decile (within the

Table 1.2: Average AFQT score by father's and own occupation.

		Son's Occupation		
		Manual	Routine	Cognitive
Father's Occupation	Manual	0.396	0.405	0.632
	Routine	0.394	0.416	0.639
	Cognitive	0.580	0.611	0.808

Note: Data from NLSY79. Occupational classes defined as in Cortes (2016). Information on father's occupation taken from survey question on father's occupation at age 14. Son's occupation defined at age 40.

group of cognitive workers), and compares AFQT scores for individuals with routine and cognitive fathers. Within almost every wage decile cognitive workers with cognitive fathers have significantly higher AFQT scores than those with routine fathers, and the magnitude is typically similar to the aggregate; having a cognitive fathers is associated with being roughly 20 percentiles higher up in the ability distribution.

The fact that workers with cognitive fathers are positively selected by ability within all occupational categories is difficult for a standard OLG model with intergenerational transfers and a financial constraint to rationalize: if individuals follow a threshold strategy where they invest in more skills if their ability is above some limit, one would expect upwards socially mobile workers, such as cognitive workers with routine fathers, to be selected with *higher* ability on average and downwards mobile workers, such as routine workers with cognitive fathers, to be selected negatively by ability. However, in calibrating the model it is found that an appropriate weighting of persistence in ability and idiosyncratic occupational preference is able to fit these moments well, as both of these forces causes the father's occupation to be a stronger predictor of a person's ability than their occupation choice.

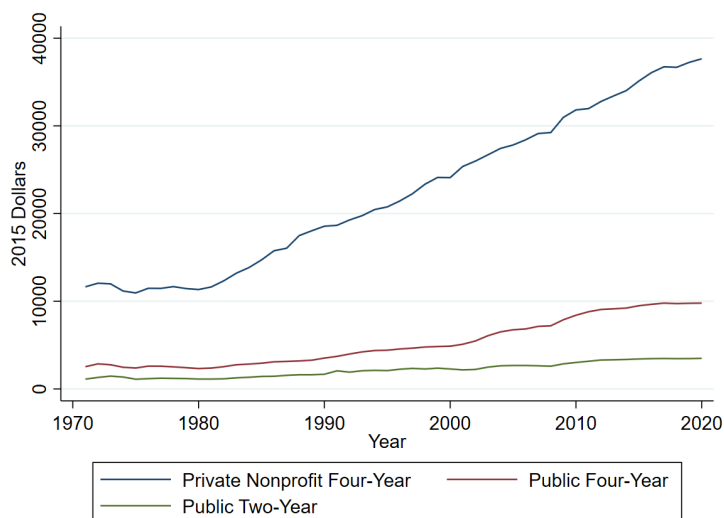
Fact G: Sorting by education

The final empirical facts concern the education levels of the occupational groups. It is a well established fact that cognitive workers are more likely to have a college education, and indeed that an increase in the share of college-educated workers is a key driver of the increase in the cognitive share (Cortes et al. 2017). In this section I confirm these two findings, but also investigate the trend in education levels and education costs within occupational classes over time.

A stand-out feature of the data is that between 1980 and 2000, i.e. under the era when the cognitive wage premium was increasing sharply, the cost of college in terms of tuition fees increased sharply. Figure 1.5 shows the average annual tuition fees across public two-year, public four-year and private nonprofit four-year colleges using data from The College Board (2021) and deflated by CPI to represent 2015 dollars. It is clear that tuition fees increased significantly from year 1980 and beyond – in particular for private four-year colleges where real tuition fees increased by 232% from \$11,380 in 1980 to \$37,650 in 2020, but also for public four-year colleges, which saw a 421% rise in real tuition fees from \$2,510 in 1980 to \$10,560 in 2020.

To add to this trend in increasing annual tuition fees there is also a clear trend towards longer, and hence more costly, educations within workers of all occupational groups, but for cognitive workers in particular. This can be seen in table 1.3 which shows the share of full-time employed 40 year old men who have at least a high-school degree, some college, a finished college degree, or a postgraduate degree, split by year (2000, 2010 or 2020) and occupational class. Since these workers are age 40 approximately 20 years have passed since they were in school/college, hence these three year categories should roughly correspond to individuals making their college decisions in 1980, 1990 and 2000, i.e. under the same era that the cognitive wage premium grew rapidly.

Two features in the data are particularly relevant for the model. First, there is little evidence of routine workers having more years of college than manual workers. In neither year was the share of college graduates higher among routine workers than among manual workers. There does appear to be a gap in high-school attainment, however. In year 2000 manual workers were 4 percentage points less likely to complete high school than routine workers, although this gap closed to just 1 and 2 percentage points in year 2010 and 2020 respectively. Since high school is publicly financed in the US, the model will interpret this, together with the finding in the previous section that manual worker have lower cognitive ability than routine workers on average, as evidence that acquiring the skills necessary for a working in the routine sector requires an investment that is costly psychically, but not financially.

Figure 1.5: Annual tuition fees

Notes: Data from The College Board (2021). Price is deflated using the CPI index to represent 2015 dollars.

Second, the share of workers with a college degree or a postgraduate degree has increased in all occupational groups but for cognitive workers in particular, where the share of workers with a college degree increased from 59% in 2000 to 69% in 2020, and the share with a postgraduate degree increased from 24% to 32% over the same time. Taken together with the fact that annual tuition fees have increased sharply over the same time this suggests that cognitive workers of later cohorts have undertaken a much more costly financial investment to obtain their skills. This correlation could be rationalized in at least two ways. Either the added years of education have increased the amount of human capital among cognitive workers, which has caused their productivity, and hence wages, to increase. Or, alternatively, the skills of cognitive workers remained the same over this time period, but acquiring proof of these skills became more expensive (e.g. due to an increasing role of signalling in the labour market). The model will take the second view and assume that cognitive workers' productivity only increased due to the technological change, but that the cost of education required to obtain cognitive skills increased as the cognitive wage premium grew.

Table 1.3: Education levels by occupational class and year

	2000			2010			2020		
	Man	Rou	Cog	Man	Rou	Cog	Man	Rou	Cog
HS grad	0.81	0.85	0.99	0.86	0.87	0.98	0.86	0.88	0.99
Some college	0.38	0.37	0.81	0.48	0.43	0.87	0.50	0.46	0.87
College grad	0.10	0.10	0.59	0.17	0.15	0.67	0.20	0.16	0.69
Postgraduate	0.0	0.1	0.24	0.2	0.2	0.29	0.3	0.3	0.32
N	536	3,036	2,021	887	3,635	3,061	716	2,956	2,700

Note: Data from CPS. Sample includes men aged 37-43, in full-time employment in the given occupation. Omitted category is ‘High-school dropout’ and reported values denote share of workers with *at least* the given amount of education.

1.3 Model

The facts outlined in section 1.2 are rationalized through an overlapping generations model with endogenous skill acquisition in the presence of technological change, with intergenerational money transfers and ability persistence generating a link between parents’ and children’s occupational choices.

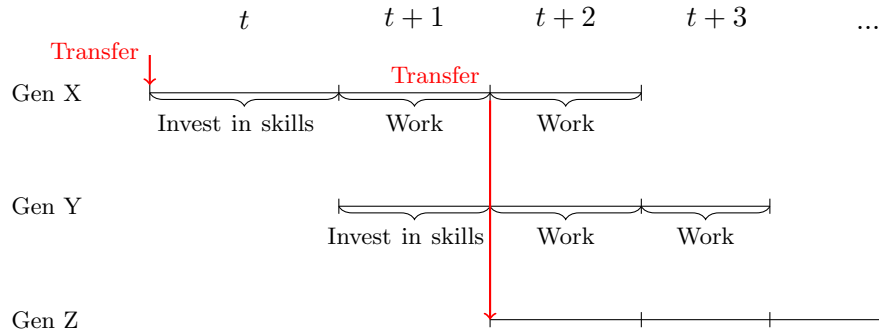
The cross-sectional facts – i.e. the sorting into occupation by education, ability and family background – are generated by demanding a costly initial investment to obtain the skills necessary to work in the different occupations. These investments have a financial component, which can only partly be financed by a loan, and a psychic cost component, which depend negatively on ability. Hence, *ceteris paribus*, wealthier and higher ability individuals will be more likely to invest in skills. Furthermore, an individual’s starting wealth is obtained through an altruistically motivated inter-vivos transfer from their parents, which means that those with higher-paid parents will have a larger initial wealth.

The dynamic facts – i.e. the divergence in intergenerational mobility rates and the increasing financial cost of skills accumulation – are driven by an exogenous gradual fall in the price of ‘automation capital’. On the production side, this price fall causes firms to immediately purchase more capital, which drives the routinization process. The capital substitutes routine workers and complements cognitive workers, which, holding labour shares fixed, increases cognitive wages and lowers routine wages. Furthermore, the cost of education depends positively on the cognitive

wage rate, which means that the financial costs of skill investment increases. This process affects children of the different occupational groups differently: cognitive workers are now able to transfer more money to finance their children's education, while children of routine (and manual) workers face higher education costs, at the same time as their parents received a negative income shock. This creates a divergence in the propensity to work in cognitive occupations. Furthermore, since many children of routine workers are unable to invest in cognitive skills, and the technological transition adversely affects routine wages, many children of routine workers' instead choose to seek employment in the manual sector, which is how the model generates an increase in manual workers that is mainly driven by individuals with routine parents.

1.3.1 Environment

The model environment consists of an overlapping generations structure where each individual lives through a three period long life-cycle. In the first period agents are 'young' (age 15-30) and invest in skills using a transfer they receive from their parent, as well as a psychic investment which depends on their *learning ability*, which is partly inherited. In the second period agents are 'prime-age' (age 30-45) and use their skills to supply labour in exchange for an income which they share between own consumption, a transfer to their child, and potentially savings for later life. The child will use the transfer to invest in skills in the following period. In the final, 'late-life' period (age 45-60), individuals continue working in their chosen occupation and consume all their income. Since parents are in late-life when their child is young there is one generation in-between the parent and child, so that if the parent belongs to generation X, the child belongs to generation Z. Figure 1.6 gives an overview of the model's life-cycle dynamics. In the value functions that follow the three periods in the life-cycle will be denoted by a superscript. The model assumes that each parent has exactly one child, and is set in an open economy general equilibrium framework, i.e. interest rates are exogenous, but wages and the price of the sole consumption good adjust so that all agents (firms and workers) act optimally and markets clear. This section will first set up the households' problems, leading to their value functions at different ages, and then the firm's profit-maximizing objective function. Together these allow for the construction of a competitive equilibrium.

Figure 1.6: Overview of lifecycle dynamics

The households' problem

Agents are born with a money endowment, a , which they have received as a transfer from their parent; an innate learning ability, ℓ , which is inherited from their parent through a stochastic process; and preference endowments $\nu = (\nu_M, \nu_R, \nu_C)$ for each of the three occupations, which are independently drawn from Gumbel distributions with mean zero and identical scale parameters α . The learning ability should be thought of as capturing any influence a parent has on their child that does not depend on financial transfers, which of course will be a combination of reasons including both nature and nurture. The rationale for introducing extreme value preference shocks is that it allows for imperfect sorting from ability and parental background to occupations, which will enable the model to match the fact that the sorting from ability and parental background to occupation is imperfect. The calibration section (1.4) discusses this in greater detail.

The young-age agent chooses how much of their initial wealth to spend on consumption and how much to spend on investment in skills. Skill investment is discrete and will determine the agent's occupation, and hence wage, in their entire working life.⁴ In the value function formulation below possible skill investments are captured by subscripts $s \in \{M, R, C\}$, which denote manual, routine and cognitive skills respectively. Investment in any of these skills comes with a psychic cost, captured by the function $\kappa_s(\ell)$, as well as a monetary cost, $T_s(w_t^c)$ which may depend on the aggregate cognitive wage rate. The financial cost of skill investment is in part financed by a

4. Modelling the occupational choice as a one-off decision in early-life is motivated by the findings in Cortes et al. (2017), who finds that job polarization is mainly driven by new labour market entrants – rather than outflows to occupational classes. The same modelling assumption is made in recent papers by Guerreiro, Rebelo, and Teles (2021) and Brinca et al. (2022).

loan, which will be paid back as an adult, and in part by a payment out of the agent's endowment (a fraction τ of the cost). Apart from the student loan there is no borrowing in the economy (i.e. the borrowing constraint is zero). Taken together, this means that both the agent's monetary endowment and learning ability endowment will affect their decision of which skills to acquire. The agents make their investment decision without knowing the learning ability or preferences of their future child, so take an expectation of the value at old age given their child's learning ability ℓ' and preferences ν' , which are the two state variables at prime age. The stochastic process that determines the child's ability is known and has an AR(1) structure:

$$\ell' = \rho\ell + \epsilon, \quad \epsilon \sim N(\mu_\ell, \sigma_\ell). \quad (1.1)$$

Letting the price of the consumption good be the numeraire, the full first-period maximization problem faced by an agent can be written as⁵

$$\begin{aligned} V_t^1(a, \ell, \nu) &= \max_{s \in \{M, R, C\}, c} u(c) - \kappa_s(\ell) + \nu_s + \beta E_{\nu', \ell' | \ell} \left[V_{t+1}^2(s, \ell', \nu') \right] \\ \text{s.t.} \quad c &= a - \tau \times T_s(w_t^s). \end{aligned}$$

This formulation assumes that student loans are non-optional, which makes the model more tractable. However, for most parameterizations, including those in section 1.4 when I take the model to the data, all young agents do wish to take as large student loans as possible, since this smooths their life-time consumption. Hence, τ can be thought of as the borrowing limit on student loans. Similarly, this formulation assumes that agents cannot save from their initial wealth for the future. Once again this assumption, which simplifies the solution greatly, turns out to be innocuous: in all calibrations and counterfactual analyses it is the case that no-one wants to save from their initial transfer for the future. It is the case, however, that agents would like to borrow more, hence an alternative reading of this maximization problem is that agents are maximizing early age consumption and skills investment subject to a strict borrowing constraint.

5. I have assumed that the preference shock associated to a particular occupation, ν_s is received at young rather than old age. This does not influence the agents' decisions in any way.

As an adult the agent learns the ability and preferences of their child, which they factor in when deciding how much of their disposable income to gift, and how much to use for own consumption. They are also allowed to save for the final period, but in equilibrium will typically opt not to do so (the borrowing constraint is binding), so I suppress the savings choice from the maximization problem. The value function at age 2 is therefore given by

$$V_t^2(s, \ell', \nu') = \max_{c, a'} u(c) + \beta \left[\phi V_{t+1}^1((1+r)a', \ell', \nu') + V_{t+1}^3(s) \right]$$

$$\text{s.t.} \quad c = w_t^s - (1-\tau)(1+r) \times T_s(w_{t-1}^c) - a',$$

where the ϕ -parameter governs how altruistic the parent is towards their child and r is the interest rate on student loans. In the final period of life the agent will simply consume their income, yielding

$$V_t^3(s) = u(w_t^s)$$

Solving the household's problem: Although the household's problem is eventually solved numerically, significant simplifications are possible, and some properties can be derived analytically. First I show how only 9 intergenerational transfers are possible equilibrium, which means that the state space of the young agents can be reduced to just 9 levels of starting wealth. To see this, it is first useful to define the young agents objective functions absent preference shocks, which will be denoted by $W^1(a, \ell, s)$ and can be interpreted as the value of an individual of type (a, ℓ) choosing occupation s , before their idiosyncratic preference is accounted for. We have

$$W_t^1(a, \ell, s) = u(a - \tau \times T_s(w_t^s)) - \kappa_s(\ell) + \beta E_{\ell'|\ell} \left[E_{\nu'} \left[V_{t+1}^2(s, \ell', \nu') \right] \right], \quad (1.2)$$

where I have made use of the fact that the idiosyncratic preferences and ability are drawn from independent distribution to break up the expectation.

Next, consider a hypothetical transfer decision facing a parent in occupation s , who knows that the occupational choice of their child is s' . Assuming that utility functions are concave and satisfy the Inada conditions, this choice must solve the first-order condition of a prime-aged individual with respect to transfer size, giving

$$u'(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a') = \beta \frac{\partial [\phi(W_t^1(a', \ell', s') + \nu_s) + u(w_t^s)]}{\partial a'}. \quad (1.3)$$

Substituting in for $W_t^1(a', \ell', s')$ and differentiating yields

$$u'(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a') = \beta \phi u'(a' - \tau \times T_{s'}(w_{t+1}^c)), \quad (1.4)$$

which states that the marginal utility of the parent is equated to the (altruistically weighted) marginal utility of consumption of their child. Denote the solution to this equation by $a_{s,s'}$. Proposition 1.3.1 says that any equilibrium transfer must satisfy this first-order condition, and that a parent will only give a transfer $a_{s,s'}$ if the optimal choice of their child at this transfer is to choose occupation s' .

Proposition 1.3.1. (a) Any equilibrium transfer must satisfy equation 1.4, hence $a_{s,s'} \quad \forall s, s' \in \{M, R, C\}$ gives all possible equilibrium transfers. (b) A parent will only give a transfer $a_{s,s'}$ if the optimal occupational choice of their child at this transfer is s' .

The proof, which is given in the appendix section 1.7.3, hinges on the fact that the model features ‘true altruism’ – which means that utility is dynastic and hence any decision that makes the child better off also makes the parent better off. Proposition 1.3.1 allows for a significant simplification of the optimization problem facing a parent in occupation s with a child of ability ℓ' and with preferences ν' . Given that only three transfers are possible, this problem can now be written as a discrete choice over $\{a_{s,M}, a_{s,R}, a_{s,C}\}$. The optimal solution is then simply the transfer that obtains the highest second-period value, given by

$$V_t^2(\ell', s, \nu') = \max_{s' \in \{M, R, C\}} \{u(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a_{s,s'}) + \beta [\phi V_{t+1}^1(a_{s,s'}, \ell', \nu') + u(w_{t+1}^s)]\}$$

where I have substituted in for the final period value function. Furthermore, since the proposition states that a parent will only choose to transfer $a_{s,s'}$ if the child's occupational choice is indeed s' , we can replace the value function of the child by their objective function at occupational choice s' , giving

$$V_t^2(\ell', s, \nu') = \max \left\{ u(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a_{s,s'}) \right. \\ \left. + \beta \left[\phi \left[W_{t+1}^1(a_{s,s'}, \ell', s') + \nu_{s'} \right] + u(w_{t+1}^s) \right] \right\}_{s' \in \{M, R, C\}}.$$

From this point we can use well-known properties of the Gumbel distribution to construct the expectation of $V_t^2(\ell', s, \nu')$ with respect to ν' , as

$$E_{\nu'} \left[V_t^2(\ell', s, \nu') \right] = \alpha \phi \log \left\{ \sum_{s'} \frac{1}{\alpha \phi} \exp \left\{ u(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a_{s,s'}) \right. \right. \\ \left. \left. + \beta \left[\phi \left[W_{t+1}^1(a_{s,s'}, \ell', s') \right] + u(w_{t+1}^s) \right] \right\} \right\} + \lambda \beta \phi \alpha, \quad (1.5)$$

where λ is the Euler-Mascheroni constant ($=0.57721\dots$) and α is the Gumbel scale parameter.⁶ Substituting this equation into (1.2) yields an equation for $W_t^1(a, \ell, s)$ that can be solved numerically by iterating on an initial guess. The computational appendix (section 1.7.4) outlines this in more detail.

Finally, given the solution to $W(\cdot)$, Gumbel distribution properties yields a simple expression for the law of motion from father to son occupation, as a function of the son's learning ability, given by equation (6) below

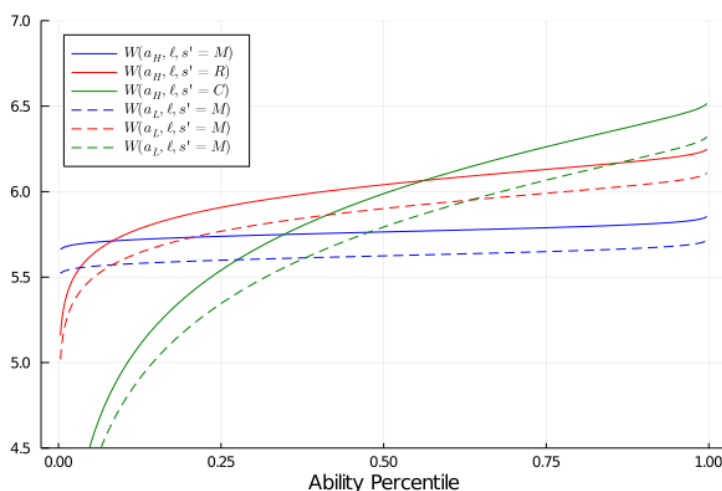
$$P(s'|s, \ell') = \frac{\exp \left\{ \frac{1}{\alpha \phi} u(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a_{s,s'}) + \beta \left[\phi \left[W_{t+1}^1(a_{s,s'}, \ell', s') \right] + V_{t+1}^3(s) \right] \right\}}{\sum_{j \in \{M, R, C\}} \exp \left\{ \frac{1}{\alpha \phi} u(w_t^s - (1 - \tau)(1 + r) \times T_s(w_{t-1}^c) - a_{s,j}) + \beta \left[\phi \left[W_{t+1}^1(a_{s,j}, \ell', j) \right] + u(w_{t+1}^s) \right] \right\}}$$

The computational appendix shows how equation (6) allows for the solution of a stationary distribution over occupations and ability in case wages are fixed; as well as the dynamic path of this distribution over a transition where wages change.

6. This result goes back to McFadden (1974). See e.g. Chatterjee, Corbae, Dempsey, and Ríos-Rull (2020) for a more recent application.

Properties of the households' problem: The model gives rise to a sorting pattern where early-life individuals sort according to a threshold strategy in terms of their learning ability: two ability thresholds determine the cutoffs at which agents choose to invest in routine/cognitive skills respectively. Since agents have an incentive to smooth consumption, and are borrowing constrained, a low level of initial wealth will increase the level of each of these ability thresholds – as a greater payoff in older life is needed to offset the low consumption level early in life that comes from investing in skills. Hence, individuals from wealthier backgrounds, who receive larger transfers from their parents, will be more likely to invest in education even if they are of the same ability. Figure 1.7 exemplifies the optimal household policy by plotting the youths' net preference objective functions $W(\cdot)$ for two levels of initial wealth: a_H and a_L where $a_H > a_L$. In the case when $\alpha \rightarrow 0$ (i.e. when preference shocks do not affect behaviour) the early-age value function is simply the upper envelope of the three functions drawn, and the optimal investment policy is clearly visible as the discrete choice rule given by a threshold strategy where the agent's occupation choice changes at the lines' crossing points. In this example there is only a financial cost associated with cognitive skill investment, but not with routine skill investment. This can be seen in the figure by noting that the ability threshold above which agents invest in routine skills is similar for the two types, whereas the threshold above which they invest in cognitive skills is higher for those with lower starting wealth.

Figure 1.7: Value in first life period, conditional on initial wealth, ability percentile and occupational choice.



The firm's problem

A competitive firm produces the sole consumption good, Y using a production function which draws on that of Autor and Dorn (2013). Cognitive and routine workers combine with automation capital to produce a ‘manufactured’ good Y_g , which is used as an intermediate input together with a ‘service’ good Y_s using a CES production technology

$$Y = A(Y_g^\eta + Y_s^\eta)^{1/\eta} \quad (1.7)$$

where A is a Hicks-neutral aggregate productivity parameter. The manufactured intermediate good is produced using a Cobb-Douglas technology by combining an ‘abstract’ input, T_A , and a ‘routine’ input, T_R , where the parameter ξ determines the factor income shares.

$$Y_g = T_A^\xi T_R^{1-\xi}. \quad (1.8)$$

The abstract input can only be produced by cognitive labour C , such that $T_A = C$, but the routine input is produced using a combination of ‘automation capital’, K , and routine labour, R , with a constant elasticity of substitution σ such that

$$T_R = (\mu_R R^\sigma + (1 - \mu_R) K^\sigma)^{1/\sigma}, \quad (1.9)$$

where μ_R denotes the relative factor share. Finally, the service good is produced using only manual labour M , with a constant factor-augmenting productivity α_M such that

$$Y_s = \alpha_M M. \quad (1.10)$$

Firms are price-takers, and choose the quantity of each input good to purchase, yielding the maximization problem

$$\max_{M, R, C, K} Y(K, M, R, C) - p_t^K K - w_M M - w_R R - w_C C \quad (1.11)$$

which gives rise to the standard solution of each input being used at the level where its marginal product equals its price.

The routinization process will be driven by an exogenous fall in p_t^K , which causes the firm to purchase more capital K .

1.3.2 Equilibrium

A stationary equilibrium is defined as a vector of prices (w_M, w_R, w_C) such that the firm's and households' solve their respective maximization problems and labour demand equals labour supply in each occupation. I assume that workers of different ages are perfectly substitutable, so the total labour supply in each occupation is simply the aggregate over the two working generations. Note that the market clearing conditions only apply to the labour inputs, which means that we can think of the economy as a small open economy that only trades labour domestically but purchases capital at the international market rate p_t^K , which is taken as exogenous. Since the production technology features constant returns to scale firms will make zero profits in equilibrium. The rents accrued by capital owners will be outside the model; we can think of the owners of capital as full-time capitalists who do not enter the labour market and hence do not matter for the analysis that is at the core of this paper. In the dynamic version the price of capital changes. The change takes the form of a so-called 'MIT'-shock, which means that, following the unexpected shock, the dynamic equilibrium requires households and firms to maximize with respect to the full future stream of prices. Labour supply adjusts sluggishly to the change, with only new cohorts of labour market entrants being able to choose their occupation. Capital, on the other hand, responds immediately, thus a fall in the price of capital increases the amount of capital used by the firm, which under the assumption that capital and routine workers are sufficiently substitutable (σ is high enough) lowers routine wages and increases cognitive wages, due to the complementarity between routine and abstract inputs in the Cobb-Douglas formulation. The equilibrium over such a transition is defined by a fixed point where agents optimize given the full stream of future wages, and where their labour supply decisions lead to exactly the same stream of wages.

One way to view the model dynamics is to think of the fall in the price of automation capital as setting off a ‘race between education and technology’.⁷ Complementarity between routine and cognitive inputs, and substitutability between automation capital and routine workers both work to increase the cognitive to routine wage premium ($w_C \uparrow$ and $w_R \downarrow$), which increases the incentive for new generations to invest in education. However, since education must be partly financed by parental income, and since the cost of education depends positively on the cognitive wage, ‘poverty trap’ dynamics may arise, which slows down the education supply response to the increasing cognitive wage premium. Furthermore, the CES structure between the ‘manufactured’ and ‘service’ goods ensure that M and Y_g are q-complements, hence manual wages will increase on impact as the fall in the automation capital price causes Y_g to increase (how much manual wages increase depends on the elasticity of substitution η). Thus, manual jobs serve as a ‘point of refuge’ for new labour force entrants who are unable or unwilling to invest in cognitive skills. Yet, in equilibrium manual jobs will pay less than routine jobs, as there is a higher psychic cost associated with routine skill investments. Thus, the increased flow to manual jobs can also harm the supply to cognitive jobs in the future, which adds more sluggish dynamics to the system. In this sense, the model generates job polarization dynamics that are intrinsically linked to the race between technology and education, which is how the framework here differs from the two sector ‘skilled-biased’ technological change with endogenous education decisions.

1.4 Calibration

The model is calibrated to the US economy from 1980 to 2010. 1980 is assumed to be a steady state, but following periods are subject to technological change. Technological change is initially introduced as an unexpected shock, but follows a perfectly predictable path thereafter, which the agents’ internalize when making their decisions. The within-period timing of the shock is that it occurs *after* the young cohort (who will enter the labour market the following period) choose their education level, but *before* wages have been earned and transfers has been decided. This means that agents fully internalize the future stream of wages when deciding the inter-vivos transfers, and

7. See Tinbergen (1974) and Goldin and Katz (2007).

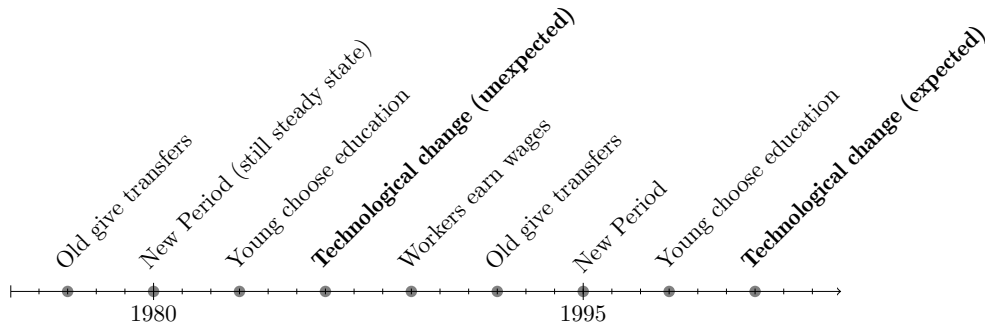


Figure 1.8: Timeline of technological change in baseline version

that each parent has the correct belief of what education their child will undertake when deciding how large a transfer to give. Figure 1.8 gives a timeline of the shock as assumed when estimating the model parameters. The analysis will distinguish between three generations: the cohort born in 1950, who make their education decision in 1965 and enter the labour market in 1980; the cohort born in 1965, and the cohort born 1980. Notice that both the 1950 and 1965 cohorts choose their skill investment prior to the realization of the technological shock, whereas the 1980 cohort make their skill investment decision while aware of the new technology.

In order to quantitatively evaluate the model a number of functional form assumptions need to be imposed, and the model parameters must be chosen. I will calibrate some model parameters using standard conventions in the literature, some will be estimated outside the model and some will be estimated while solving the model using a method of moments procedure.

First consider the parameters set externally. I assume a CRRA utility function, $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ with the γ -parameter set to 1.6, which is within the standard range in the literature. I parameterize the psychic cost function as $\kappa_R(\ell) = -\gamma_R \log(\ell)$ and $\kappa_C(\ell) = -\gamma_C \log(\ell)$, where ℓ is the ability percentile of ℓ . This particular functional form has some convenient properties: it is bounded by 0 and 1, and costs go to infinity as $\ell \rightarrow 0$ and costs go to zero as $\ell \rightarrow 1$, which means that some agents will always prefer the manual/cognitive job in equilibrium (as long as the wage premium exceeds the cost of education). Furthermore, defining the cost function in terms of percentiles means that the mean and variance of the ability generating process do not affect any dynamics. This means that I can, without loss of generality, set $\mu_\ell = 0$ and $\sigma_\ell = 1$, and thus only need to

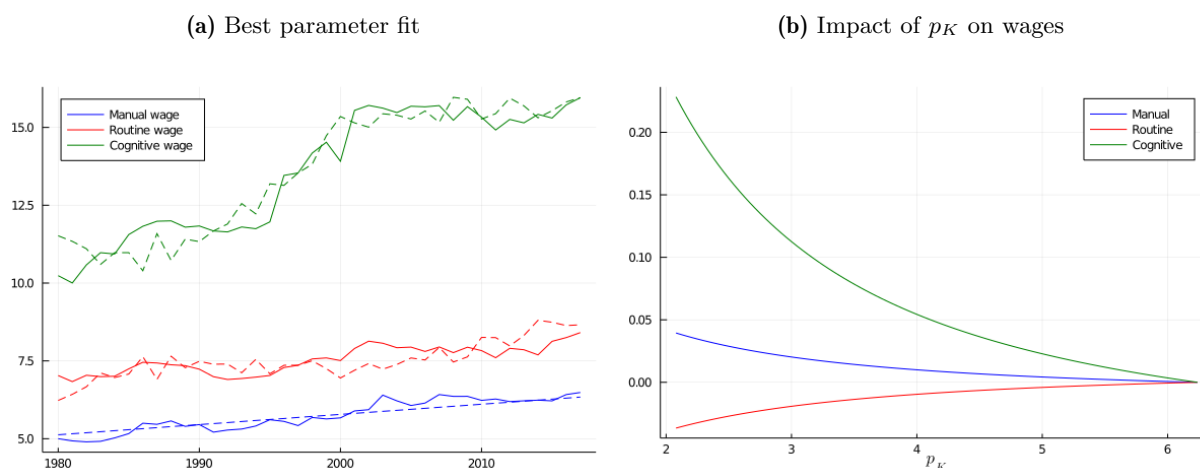
choose the model parameter ρ to characterise the ability generating process. Finally, since neither the discount factor nor the interest rates play crucial roles in the economy (the model is already discounted through the altruism factor, and there are typically no savings in equilibrium) I simplify the model by setting $\beta = 1$ and $r = 0$.

Next, I turn to the parameters that are estimated without solving the model. These are the ones governing the monetary costs of education and the production function parameters.

Production function: Due to limited micro-evidence on the elasticities of substitution between Manual, Routine and Cognitive workers I estimate these key production function parameters using aggregate data on wages and employment shares of the three occupational groups. I limit the estimation to the years 1980–2000, which correspond to the period of rapid increase in the cognitive wage premium. I assume that two exogenous technological forces were active in this period: first, a constant increase in Hicks-neutral productivity; second, a fall in the price of automation technology. While the growth rate of Hicks-neutral technology is estimated I assume a fall in the price of automation capital of $2/3$, which is consistent with the ICT price series derived from the BEA’s detailed fixed-asset accounts in Eden and Gaggl (2018). Since Hicks-neutral technological change cannot, *ceteris paribus*, generate changes in wage premia this identification strategy effectively loads the entirety of observed *wage polarization* (i.e. the increase of cognitive and manual wages relative to routine) on the fall in the price of automation capital, while taking out a linear increasing trend in real wages due to neutral technological growth. The parameters to be estimated are thus the elasticities and factor shares in the production function ξ , σ , η , μ_R , g_p , α_M , as well as the starting value and growth rate of Hicks-neutral technology A_{1980} , g_A , and the starting value of the price of automation technology p_0^K .

The parameters are estimated non-linearly by minimizing the distance between the observed wages in the data to those induced by the firm’s first-order condition given observed worker shares. Table 1.4 shows the vector of the estimated parameters and figure 1.9a shows how well these fit the data. The key elasticities driving wage polarization – the elasticity between automation capital and routine labour and the elasticity between the manufactured and service good – are given by $\frac{1}{1-\sigma}$ and $\frac{1}{1-\psi}$ respectively. Their estimated values correspond reasonably well to the earlier literature. The estimated value of $\psi = 0.805$ corresponds to an elasticity of 4.12, which is higher than the

Figure 1.9



Notes: In panel (a) solid line represents data points and dashed line model-induced values. In panel (b) the range of the x-axis represent the values of p_K in the estimation, with 6.23 corresponding to the 1980 value and 2.08 to its 2000 value. In panel (b) worker shares are held fixed at their 1980 levels and the y-axis measures percentage deviation in wages from their 1980 level.

elasticity in Albertini et al. (2017) and Hartmann and Föll (2020) of 1.86 but within the range of estimates in vom Lehn (2020) who finds an elasticity between 1.49-10.18. The estimated elasticity of substitution between automation capital and routine workers is $\frac{1}{1-0.60} = 1.50$, which can be compared values of 2.85 in Albertini et al. (2017) and Hartmann and Föll (2020) and 1.30-1.50 in vom Lehn (2020). The production function elasticities are important for the analysis to come as they capture the impact of a fall in the price of automation capital on worker wages, which will affect counterfactual welfare analyses where the pace and extent of the fall in p_K is varied. To develop more insight of how the price of automation capital impacts wages in this setting, figure 1.9b shows the effect of p_K defined on the range of values it takes in the calibration on wages of occupational group, while holding worker shares fixed at their 1980 level. It is clear that p_K has a mildly negative effect on routine cognitive wages, a mild positive effect on manual wages and a strong positive effect on cognitive wages under this parameterization.

Cost of education: To estimate the cost of college I use information on annual tuition fees from The College Board (2021) together with information on average years of education within the occupational group from the CPS. Appendix table 1.A3 shows how education groups in the CPS are mapped to years of college. I assume that cognitive workers are required to attend a 4-year college, but since I do not have information on whether individuals attended public or

private college I follow Lee and Seshadri (2019) and assume that the annual price of college is the average between the tuition fees of private non-profit and public four-year colleges. I do not include the cost of room and board in my estimated price of college since these costs should be captured in consumption. Occupation is defined at age 40, but the cost of college is assumed to be paid at age 20. Empirically, there is a strong correlation between the cognitive wage premium and the cost of college – as the cognitive wage premium started increasing around 1980 so did the cost of college. In the baseline calibration this is treated as a *causal* relationship between the cognitive wage premium and the cost of college (although I also run robustness exercises where this assumption is relaxed). I parameterize this relationship as one with constant price elasticity so that $\log(T_{C,t}) = \chi_0 + \chi_1 \log(w_t^c)$. The parameters, χ_0 and χ_1 , are estimated using OLS on data from year 1980-2000 (since the main occupation is defined at age 40 there are no consistent estimates for the length of education after year 2000). The elasticity parameter χ_1 is estimated to be 2.60, and the fit is good with an R-squared of 0.83. I do not explicitly model how the link between college costs and the cognitive wage arises but there are many potential micro foundations. For example, the increase in cognitive wages should increase the salary of college professors – who are cognitive workers themselves – and thus increase the cost of education.⁸ Finally, I assume that manual jobs do not require any financial investment, and since there is no evidence that more formal education is required to perform a routine job relative to a manual job, I set $T_R(w) = T_M(w) = 0$ for all w .

The final education cost parameter to be estimated is the share of college that must be paid upfront. The parameter governing this, τ , is set to 0.56, which was the share of college expenses financed by parents on average for the academic year 2019-2020 (Sallie Mae 2020). This is a simplification: in reality there are a multitude of ways to finance an education even for poorer background students, such as using student loans or working through college (Abbott et al. 2019), but to model these as state dependent decisions would require a richer model. Instead, the goal of the calibration exercise will be to capture the *financial friction* facing young agents by letting the data on conditional abilities across occupations and family background inform the model of the experienced financial constraint across family background. It turns out that the model can capture these conditional

8. The link between income inequality and college costs has been studied extensively. See, for example, papers by Jones and Yang (2016) and Cai and Heathcote (2022).

ability distributions well either by changes in τ or by changes in the altruism parameter ϕ , as the smaller transfers induced from lower altruism affects the young agents' decisions similarly to a stricter borrowing constraint. Because of this these parameters seemingly cannot be separately identified. Since the share of educational expenses financed by parental transfers has a closer data analogy I therefore choose to calibrate this parameter, whereas the altruism parameter is estimated in the method of moments procedure.

Method of moments: The remainder of the parameters are estimated while solving the model over the technological transition. These are the parameters governing the psychic cost of education: γ_R and γ_C , the ability persistence, ρ , the Gumbel distribution parameter, α , and the altruism parameter ϕ . The data moments that are targeted are: the intergenerational transition rates – from the perspective of young individuals – from routine/cognitive to routine/cognitive in 1980 and 1995 (PSID); the average cognitive ability of prime-aged workers conditional on routine/cognitive father and own occupation in 1995 (NLSY79); average ability of prime-aged workers by occupation in 1995 and 2010 (NLSY79 and NLSY97); aggregate shares of workers in each occupational class in 1980 and 2010 (CPS); the 10% higher propensity to invest in cognitive skills for cognitive relative to routine sons, conditional on ability of prime-aged workers in 1995 (NLSY79). This gives a total of 27 independent targeted moments. To save on computational burden I estimate the model using a three-step procedure. First, I solve for a well-fitting parameter vector when solving the model in partial equilibrium – assuming that wages track the data exactly and are already in steady state in 2010. Second, I re-estimate some production function parameters, in order to ensure that model-induced wages from the partial equilibrium transition track the data as closely as possible. To this end I allow the manual-augmenting technology α_M and Hicks-neutral technology A to vary over the transition period and thus estimate four additional parameters: $\alpha_{M,1995}$, $\alpha_{M,2010}$, A_{1995} and A_{2010} . Third, I solve the model in general equilibrium and make minor adjustments to the parameters to improve the fit. The full list of parameter values is given in table 1.4. Below I outline some intuition on how the data moments are informative of the model parameters, and show how well the best estimates match the data.

Table 1.4: Parameter values and descriptions

Description	Parameter	Value
<i>Calibrated within model</i>		
Learning ability persistence	ρ	0.49
Routine psychic cost parameter	γ_R	0.02
Cognitive psychic cost parameter	γ_C	0.42
Extreme value parameter	α	0.17
Altruism Parameter	ϕ	0.51
<i>Production function parameters</i>		
Cognitive income share	ξ	0.49
CES substitution parameter in routine good	σ	0.60
CES substitution parameter in final good	η	0.81
CES factor share parameter in T_R	μ_R	0.73
Price of automation capital in 1980	p_0^K	6.60
Annual change in price of automation capital in 1980-2000	g_p	-0.19
Manual-augmenting technology in 1980	$\alpha_{M,1980}$	0.12
Manual-augmenting technology in 1995	$\alpha_{M,1995}$	0.11
Manual-augmenting technology in 2010	$\alpha_{M,2010}$	0.13
Hicks-neutral technology in 1980	A_{1980}	19.38
Hicks-neutral technology in 1995	A_{1995}	22.29
Hicks-neutral technology in 2010	A_{2010}	22.86
<i>Other parameters</i>		
Discount factor	β	1.0
Interest rate	r	0.0
AR(1) parameter in ability process	μ_ℓ	0.0
AR(1) parameter in ability process	σ_ℓ	1.0
Relative risk aversion	γ	1.6
Share of college cost paid upfront	τ	0.56
College cost parameter	χ_0	-15.33
College cost parameter	χ_1	2.60

1.4.1 Model fit

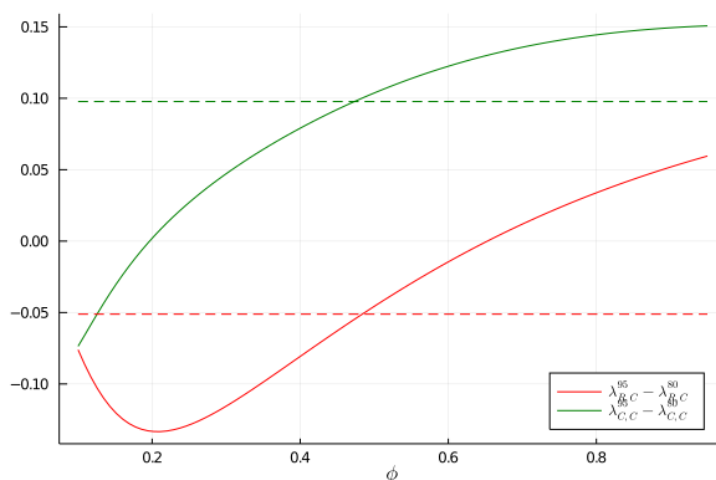
This section shows how the model fits the targeted (and some untargeted) moments. It also discusses the intuition behind how each parameter helps the model fit the data.

Estimating the altruism factor

The main role of the altruism parameter, ϕ , is to determine the size of the financial friction facing young agents. There are two moments in particular which speak to this friction. The first is the intergenerational occupational supply response to changes in wages and education costs, and the second is the probability of investing in cognitive skills conditional on parental background.

As for the first of these, recall that from 1980 to 2000 the cognitive wage premium grew rapidly, such that an investment in cognitive skills was highly profitable despite an increase in the cost of college. The supply response from new labour market entrants suggested that sons of cognitive workers responded to this change by being more likely to invest in cognitive skills, whereas sons of routine workers were less likely to do so. The only way this behaviour can be rationalized, in the context of the model, is that the size of the financial friction was impeding the sons of routine workers enough that the utility loss associated with an early skill investment (through a less smooth consumption) was not enough to offset the later utility gains from a higher income. For the sons of cognitive workers, however, the opposite must have been true. A well-calibrated ϕ -parameter is able to capture both of these facts. Figure 1.10 illustrates the heuristics of how ϕ alters the new cohorts' occupational choice by comparing the change in the probability of investing in cognitive skills following an increase the college premium and the cost of education equal to that observed in the data between 1980 and 2010. In this example we see that, for low levels of altruism, individuals with either type of parent respond to the change by decreasing their investments, whereas for high altruism it is worthwhile for both types to increase their investment. Figure 1.11 shows how well the model fits the intergenerational mobility rates in the data as well as the dynamic path of aggregate occupational shares.

Figure 1.10: Change in intergenerational mobility following a change in the college wage premium and cost of education as observed in the model.



Note: $\lambda_{i,j}^y$ refers to the intergenerational transition rate from occupation i to occupation j in year y . The dashed lines represent the data moments.

The second way in which the data can inform the size of the experienced financial friction, and hence the size of ϕ , is by directly comparing the likelihood of skills investment among individuals with the same ability but different family background. The intuition behind this is clear: in the model the only reason that sons of cognitive fathers would be more likely to invest in cognitive skills than sons of routine fathers, conditional on having the same ability, is that the financial friction is inhibiting the individuals with routine fathers. Recall that in the NLSY79 it was found that cognitive workers' sons were 10.8% more likely to become cognitive workers after controlling for ability. The altruism parameter speaks directly to this moment, with a higher ϕ being associated with a smaller gap in the ability-specific propensity to invest in cognitive skills. This is illustrated in figure 1.12a. Figure 1.12b shows that the model induced gap under the estimated parameterization fits this moment well, both in terms of the targeted average but also across the ability distribution.

Separating ability persistence and idiosyncratic preferences

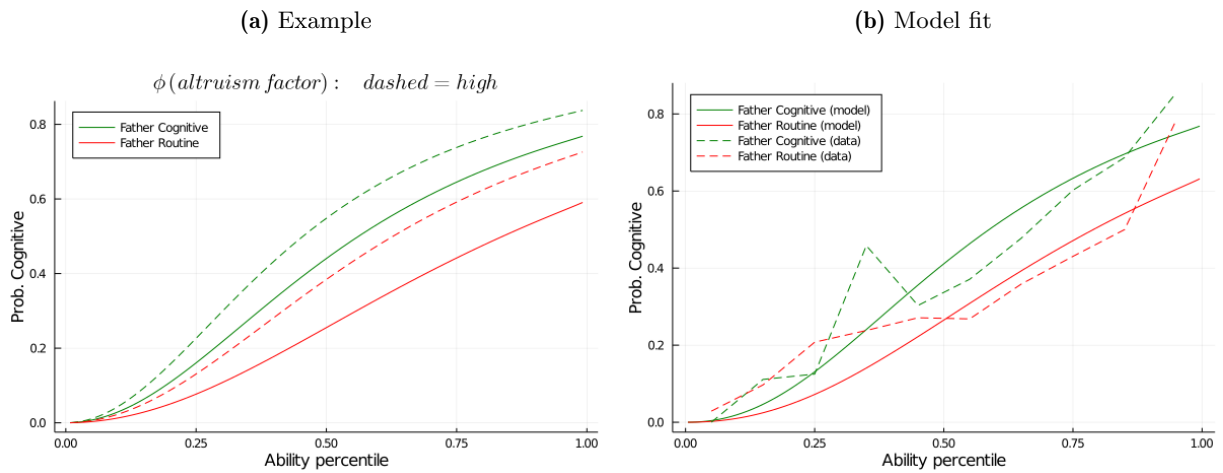
One of the key challenges of the quantitative exercise is to disentangle how much of the observed intergenerational persistence is due to non-financial 'inheritance' of ability, how much is due to financial frictions in skill acquisition, and how much is due to idiosyncratic noise in the workers' preferences. Indeed, the observed intergenerational flows between father's and son's occupations

Figure 1.11: Model fit: occupational shares and intergenerational occupational mobility



Note: Intergenerational mobility rates calculated from the perspective of young individuals. In the data this is taken at age 20, whereas for the model it is for the early-life period (age 15-30).

Figure 1.12: Model fit: probability of cognitive occupation by ability and father's occupation



can be matched well solely with a mix of intergenerational ability-persistence and psychic cost of education, or with an appropriately weighted ‘financial friction’ through the altruism parameter. Furthermore, noise in preferences, which increases the idiosyncratic part of occupational choice for agents of any background and ability will, *ceteris paribus*, decrease intergenerational occupational persistence, which allows an even larger scope for model parameters to match the data in this dimension. Intuitively, having pinned down the altruism parameter as discussed in the previous section, the two other parameters that have important consequences for intergenerational mobility are ρ , which governs the persistence of ability, and α , which governs the size of the preference shocks.

To see why both preference shocks and ability persistence are an important addition to allow the model to match the data, consider the observation made in part 1.2 (fact F): in the NLSY79, cognitive workers with cognitive fathers had roughly 20 percentiles higher ability than cognitive workers with routine fathers. This is surprising since we would expect that individuals from a poorer background require a higher learning ability to find it worthwhile to invest in skills, as seen in the young-age policy function without idiosyncratic preferences in figure 1.7. Allowing for a high persistence in ability can account for some of this data feature, as it shifts the ability distribution of cognitive workers far enough to the high-end of the ability distribution that the mass of their children are well above the threshold at which it is optimal to invest in cognitive skills. However, it turns out that reaching the required gap is not possible using ability persistence alone; we also need some idiosyncratic noise in preferences in order for the model to accurately match the data. Figure 1.13 illustrates this by visualizing the model induced ability gap $\ell_{C,C} - \ell_{R,C}$ for different values of ρ and α (as usual, the first subscript denotes the father’s occupation and the second the son’s). In this example it is clear that achieving a positive gap, as consistent with the data, requires a mix of relatively high ability persistence and some weight on idiosyncratic preferences.

Figure 1.14 shows that the model does a good job at fitting the targeted average ability percentiles conditioned on own and parental occupation. It also shows that the model does a decent job at fitting the full ability distributions of cognitive and routine workers, as well as conditional ability distribution of cognitive and routine workers, by parental background.

Figure 1.13: Difference in ability for cognitive workers with cognitive or routine fathers, $\ell_{C,C} - \ell_{R,C}$, under different parameter values

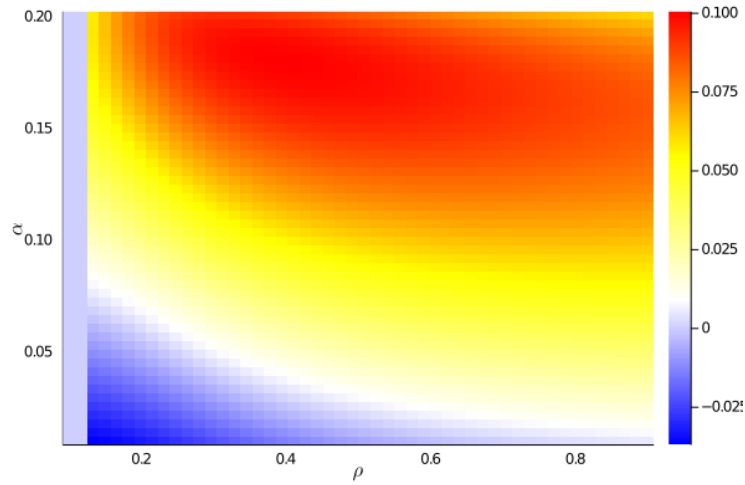


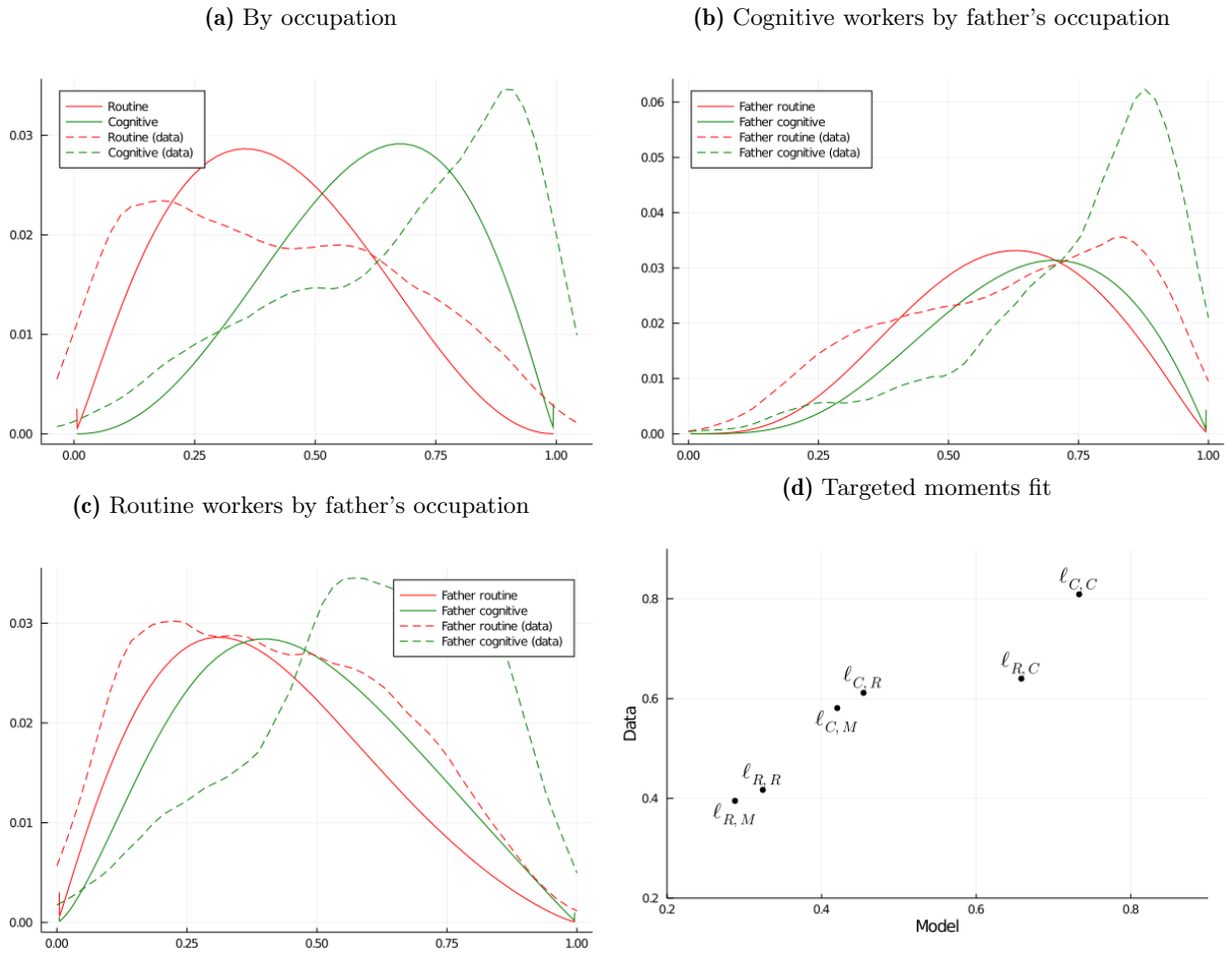
Table 1.5: Model fit: average ability percentile scores by occupation

	1965 cohort / NLSY79		1980 cohort / NLSY97	
	Model	Data	Model	Data
Manual	0.37	0.39	0.36	0.39
Routine	0.40	0.43	0.39	0.45
Cognitive	0.67	0.70	0.67	0.68

The psychic cost parameters

The final two parameters are the ones governing the psychic cost of skill investment, γ_R and γ_C . Although these are also part of the moment matching procedure, and hence estimated jointly with the other parameters, these have more straight-forward corresponding data moments: they mainly help match the average difference in ability in the occupational classes. In the best fit γ_R is estimated to be more than an order of magnitude lower than γ_C , which reflects the fact that the ability gap between cognitive and routine workers is much greater than that between routine and manual. Table 1.5 shows how well the model fits the average ability scores in these two cohorts. Note that these targets would be impossible to fit without idiosyncratic preferences, since the ‘pure’ threshold policy of young agents would mean that only the lowest ability individuals would choose to work in manual occupations.

Figure 1.14: Model fit: ability distribution by own and father's occupation



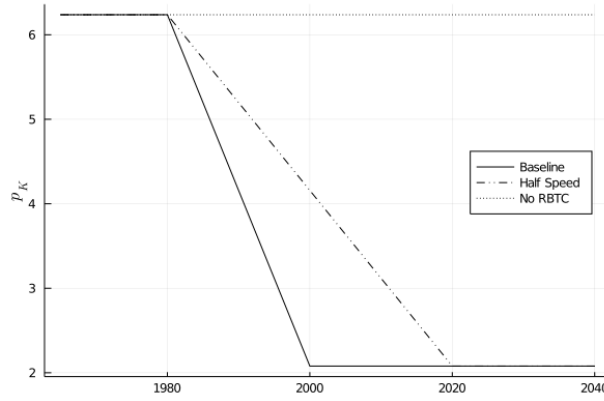
Notes: Data densities are calculated as kernel densities using data from the NLSY79 and Stata's default bandwidth. $l_{i,j}$ refers to average learning ability of individuals with father in occupation i and own occupation j .

1.5 Counterfactual analyses

I use the fully specified quantitative model to perform three counterfactual experiments. In the first counterfactual I calculate welfare under the ‘baseline’ fall in the price of ICT capital (p_t^K), to which the model is calibrated, and compare this to counterfactual technological shifts, where the pace and extent of the fall in p_t^K varies. In the second counterfactual analysis I perform a structural decomposition to investigate the relative importance of financial frictions and ability inheritance in driving intergenerational occupational persistence and aggregate dynamics. To do so I re-evaluate the model while (in turn) shutting down the intergenerational ability persistence and the student borrowing constraint. The main result from this counterfactual is that ability inheritance accounted for the majority of the intergenerational occupational persistence in 1980, but in 2010 the financial constraint was more influential (accounting for two thirds of the gap in the probability of cognitive employment by routine/cognitive father). In the third counterfactual, I explore whether differences in the student borrowing constraints can be a plausible explanation for differences in job polarization in the US and Europe. I find that a lower constraint on borrowing is associated with a smaller rise in the manual occupational share, which provides an indication that this may be the case.

1.5.1 Counterfactual 1: Welfare and the pace of routine-biased technological change

The first set of counterfactuals consider the welfare effects of RBTC, which is introduced at different speeds. The idea is that a slower introduction of RBTC may correspond to a policy where automation is halted, or perhaps a protectionist policy which stops the offshoring of routine tasks. I consider four separate technological transitions: the ‘baseline’ version corresponds to a fall in investment prices as assumed in the calibration, the ‘half speed’ and ‘double speed’ counterfactuals correspond to cases where the fall in routine capital happens at half/twice the speed as in the baseline, and the ‘No RBTC’ counterfactual corresponds to a world where no routine-biased technology occurred. Figure 1.15 plots the timeline of the ICT capital price in each of these counterfactuals. Before turning to the results, I describe how I calculate the consumption-equivalent units which are used to measure welfare changes.

Figure 1.15: Timeline of fall in investment good price in different counterfactuals

Welfare definition

For the 1950 and 1965 cohorts I measure welfare effects in terms of prime-age *expected* consumption equivalent variation. By expected consumption I refer to the average consumption of someone with occupation s and a child with ability ℓ' . Note that consumption is not constant at this point since it will depend on the preference shock of the son, which, together with the ability and father's occupation, determines the son's occupational choice and hence the father's consumption/transfer decision. Fortunately, Gumbel distribution properties allows for an easy way to calculate the expected consumption. Formally, let \mathcal{B} denote the baseline state of the world, the second life-period value function of a type $i := \{s, \ell'\}$ is then given by (dropping time-subscripts)

$$V_{i,\mathcal{B}}^2 = u(c_{i,\mathcal{B}}^1) + \beta \left[\phi V_{i,\mathcal{B}}^1(a'_{i,\mathcal{B}}, \ell', \nu') + u(c_{i,\mathcal{B}}^3) \right],$$

where $c_{i,\mathcal{B}}^2$ denotes the expected consumption in state i under regime \mathcal{B} , which, using the notation from section 1.3, evaluates to

$$\begin{aligned} c_{i,\mathcal{B}}^2(s, \ell') &= \int_{\nu'} w_{s,\mathcal{B}} - (1 - \tau)(1 + r)T_s(w^c) - a'(s, \ell', \nu') dF(\nu') \\ &= w_{s,\mathcal{B}} - (1 - \tau)(1 + r)T_s(w^c) - (P(s' = M|\ell', s) \times a_{s,M} + P(s' = R|\ell', s) \times a_{s,R} + P(s' = C|\ell', s) \times a_{s,C}) \end{aligned}$$

where the conditional probabilities are found using equation (6), and the transfer decisions $a_{s,s'}$ come from the household's optimal policy. Furthermore, let us similarly denote the alternative policy regime or technological change by \mathcal{A} , which has a corresponding prime-age value given by

$$V_{i,\mathcal{A}}^2 = u(c_{i,\mathcal{A}}^2) + \beta \left[\phi V_{i,\mathcal{A}}^1(a'_{i,\mathcal{A}}, \ell', \nu') + u(c_{i,\mathcal{A}}^3) \right].$$

The consumption equivalent variation, denoted by $\Delta_i^{\mathcal{A}}$ is then implicitly defined such that the following equation holds:

$$u\left((1 + \Delta_i^{\mathcal{A}})c_{i,\mathcal{A}}^2\right) + \beta \left[\phi V_{i,\mathcal{A}}^1(a'_i, l'_i) + u(c_{i,\mathcal{A}}^3) \right] = V_{i,\mathcal{B}}^2$$

Table 1.6 compares the mean welfare effects in each of the occupational groups. For the 1950 and 1965 generations, who made their educational choice before the shock was realised, I summarize the welfare effect as the average consumption equivalent variation in that occupational group:

$$\Delta_s^{\mathcal{A}} = \int_{\ell'} \Delta_{\ell',s}^{\mathcal{A}} dF(\ell'|s).$$

For the 1980 cohort, who made their educational decision after the technological shock, I instead report the welfare effects in terms of young-age consumption equivalent variation, which is defined implicitly as $\delta_{s_f,\ell}^{\mathcal{A}}$ such that the following equivalence holds:

$$u\left((1 + \delta_{s_f,\ell}^{\mathcal{A}})c_{i,\mathcal{A}}^1\right) - \kappa_{s_i}(\ell) + E_{\nu',\ell'|\ell} \left[V_{t+1}^2(s_i, \ell', \nu') \right] = V_{i,\mathcal{B}}^1,$$

where $c_{i,\mathcal{A}}^1$ once again denotes expected consumption at $i \in \{(a, \ell)\}$, s_f denotes the father's occupation and s_i the optimal policy at i . I aggregate these welfare effects by father's occupation, since, for the 1980 cohort, the father's occupation does not depend on the technological transition, hence the reported values are given by

$$\delta_{s_f}^{\mathcal{A}} = \int_{\ell} \delta_{s_f,\ell}^{\mathcal{A}} dF(\ell|s_f).$$

Results

Table 1.6 displays the difference in welfare and average lifetime wages for each counterfactual across the different generations and occupational classes. Rows denoted by ‘No RBTC’ represent the counterfactual where the entirety of the routine-biased technological shift is halted (the ‘no RBTC’ counterfactual). The welfare results reveal that all workers are worse off in this counterfactual. In the 1950 cohort, cognitive workers have the largest welfare losses and are 4.47% worse off in absence of RBTC, while routine workers experience the smallest welfare losses of 1.20%. It is of note that routine workers see welfare losses despite the absence of RBTC increasing their wages by 2.03%. The reason for this is that their children (the 1980 cohort) have 5.79% higher welfare in young-age consumption equivalent units, and hence – due to altruistic preferences – the loss in consumption of routine workers are more than offset by the positive impact of technology on the opportunities of their children. In the 1965 cohort a similar pattern emerges; manual and cognitive wages fall in the absence of RBTC while routine wages increase, but the overall welfare impact is negative across all groups.

The rows denoted by ‘Half speed’ represent the counterfactual where the fall in the automation capital price occurs at half the annual rate relative to the baseline. The impact of a slowdown in the pace of technological progress on wages is similar to the effect of a full shutdown of RBTC: routine wages are higher while manual and cognitive wages are lower. However, the welfare impact in this scenario is qualitatively different. Routine and manual workers of the 1950 cohort, as well as routine workers of the 1965 cohort, are *better* off by 0.54-2.94% in prime-aged consumption equivalent units in the half speed counterfactual relative to the baseline. In the case of the 1950 cohort an explanation for this can be seen by considering the impact of the slowdown in technology on the welfare of their children. While children of cognitive fathers prefer a faster technological progress to a slower, those with routine and manual fathers are better off when the pace of RBTC is reduced by half. To add intuition to the sources of these welfare results, figure 1.A3 in the appendix shows how each of these counterfactuals change the intergenerational occupational mobility rates, the aggregate labour shares and the occupation-specific wages over the transition.

Table 1.6: Difference in welfare and lifetime wages in counterfactual exercises relative to baseline.

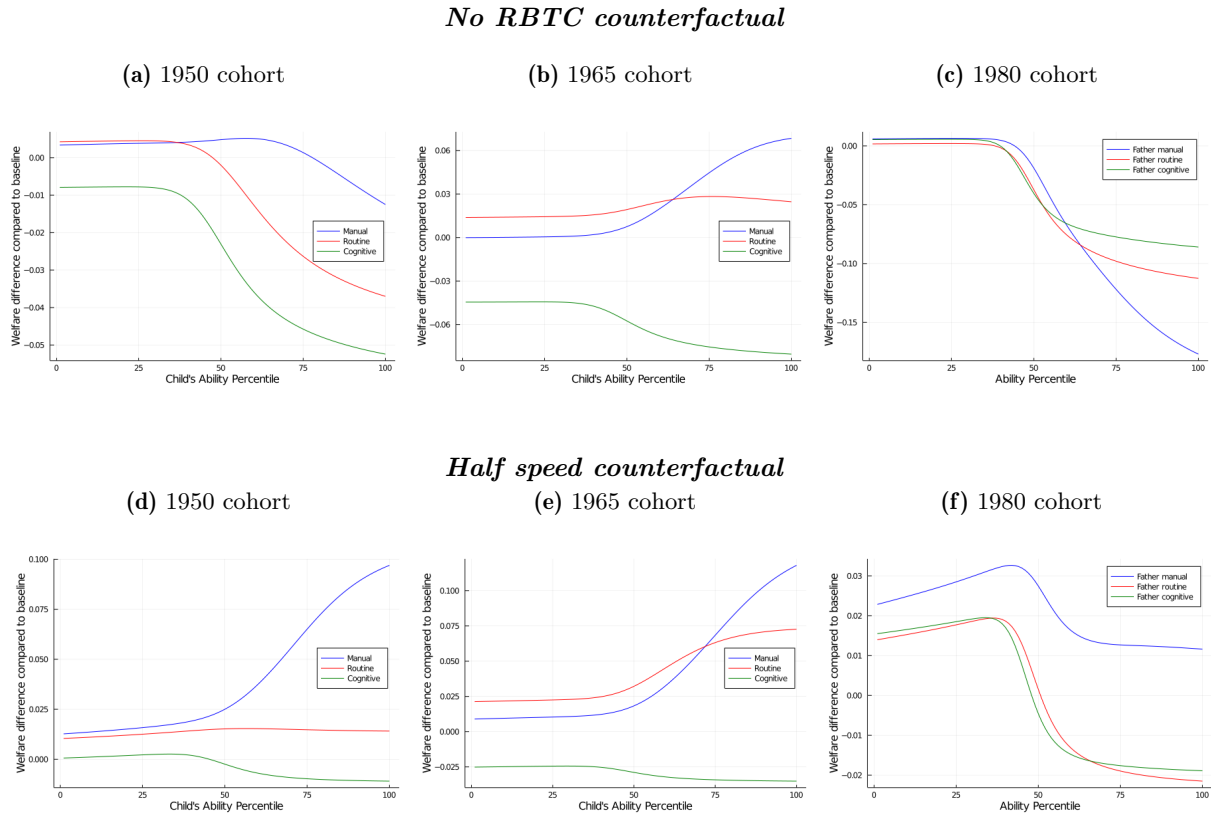
	1950 cohort			1965 cohort			1980 cohort		
	Man	Rou	Cog	Man	Rou	Cog	Fath. man	Fath. rou	Fath. cog
Wages (%)									
No RBTC	-1.68	2.03	-7.17	-3.25	2.86	-17.89			
Half Speed	-1.20	2.02	-5.52	-1.00	4.07	-11.92			
Welfare									
No RBTC	-3.43	-1.20	-4.47	-5.24	-0.24	-7.84	-6.57	-5.79	-7.09
Half Speed	0.54	1.76	-1.33	-0.96	2.94	-3.65	1.50	0.28	-1.34

Note: Wage effects are measured in percentage deviations. Welfare effects are measured in consumption equivalent units, as described in the text. The first six columns are average difference by own occupation, whereas column 6-9 display expected change in welfare by father's occupation.

The model also allows for comparisons of welfare effects across the ability distribution. Figure 1.16 shows this breakdown by reporting the ability-specific consumption equivalent variation (δ_i^A) under each of the counterfactual exercises for the three different cohorts. Panels (a)-(c) compares welfare in a counterfactual without routine-biased technology to the baseline. For all cohorts the results are qualitatively the same across the ability distribution. However, quantitatively there are some differences: cognitive workers with high ability sons prefer the baseline more relative compared to their peers; whereas this difference is not as stark for routine and manual workers with high-ability sons. This makes intuitive sense since one of the key negative effects of RBTC – the increase in education prices – affects poorer workers with high ability children the most. Panels (d)-(f) compares the baseline to the ‘half speed’ counterfactual. Here the results occasionally differ qualitatively across the ability distribution, with, for example, the highest ability individuals of the 1980 cohort of any parental background seeing welfare losses due to the technological slow-down, while lower ability individuals see welfare gains.

In a final exercise I investigate the role of the endogenous college cost for the welfare results. Recall that much of the downsides of technological change for routine and manual workers are driven by the link between the cognitive wage and the cost of education. To quantitatively evaluate the importance of this assumption I also run a model specification where education costs follow the data *exogenously*, which means that counterfactuals where the wage premium of cognitive workers are lower still see the same rise in the cost of education as in the baseline model. In this specification

Figure 1.16: Welfare change relative to baseline calibration under counterfactual exercises, by ability percentile.



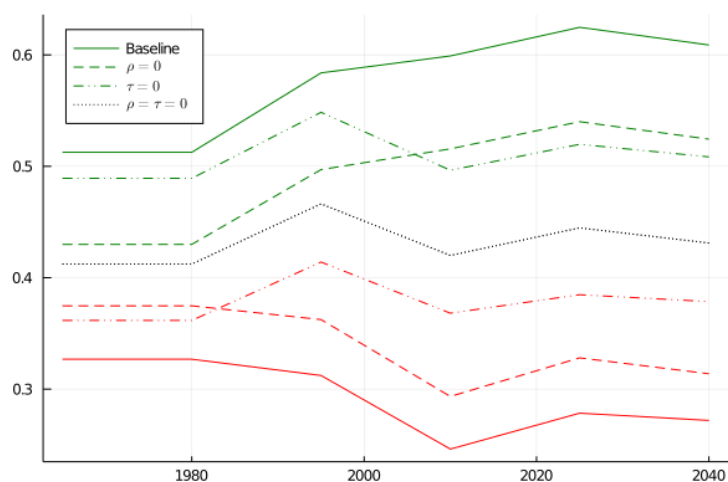
Note: Welfare is measured in consumption equivalent units, as described in the text. Panels (a), (b), (d) and (e) represent differences by child’s ability percentile, whereas panels (c) and (f) display differences by own ability percentile.

the welfare effects of both a removal and a slow-down of RBTC are significantly worse. However, it is still the case that routine workers of the 1965 cohort prefer the half speed counterfactual to the baseline technological change. The full welfare results under this model are reported in table 1.A4 in the appendix.

1.5.2 Counterfactual 2: The role of financial constraints and ability persistence for intergenerational occupational mobility and aggregate dynamics

In a second set of counterfactual analyses I again consider the baseline transition in routine-biased technology, but now shut down certain mechanisms in the model. First I set persistence in the ability generating process to zero (i.e. set $\rho = 0$). Second, I shut down the financial constraints by making the educational choices fully funded by a loan (i.e. set $\tau = 0$). Third, I shut down both of these factors at the same time. The goal of this exercise is to explore the contribution of each of these mechanisms in determining intergenerational occupational mobility.

Figure 1.17 reports the intergenerational transition rates in each of the counterfactuals. Red lines refer to individuals with routine fathers and green lines to individuals with cognitive fathers. The black dotted line is the counterfactual where both ability persistence and the borrowing constraint are set to zero: in this case there is no difference between the two types in the likelihood of investing in cognitive skills, which confirms the intuition that occupational persistence is only driven by the borrowing constraint and the ability persistence. The dashed+dotted lines represent the counterfactual where the financial friction is removed. From this counterfactual it is clear that, although ability persistence does generate a gap in the propensity to work in a cognitive occupation by father's occupation, this gap is largely unchanged throughout the technological transition. It is also clear that, without a borrowing constraint, technological change increases the probability of cognitive skill investment both for those with routine and cognitive fathers. It is therefore the borrowing constraint that enables the model to generate the 'Great Gatsby' effect where the probability of upwards mobility falls following an increase in the wage premium. This can be seen in the dashed line, which represents the counterfactual with ability persistence set to zero. Since these two forces generate all occupational persistence in the model we can decompose the persistence into these two parts. In the initial 1980 steady state the learning ability persistence is the main driver of the father-son correlation in upwards mobility – explaining roughly two thirds of the gap in cognitive skills investment between those with cognitive vs routine fathers. By 2020, after the technological shift has occurred, the reverse is true – now it is the financial friction which explains roughly 2/3 of the gap. One interpretation of this is that the technological shift has made the labour market less meritocratic, and more based on financial resources. In a richer model,

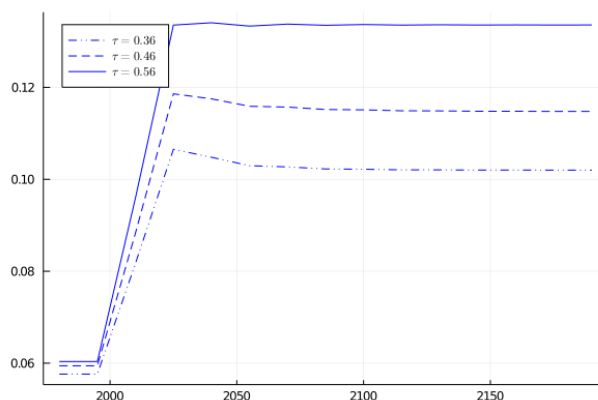
Figure 1.17: Decomposition of intergenerational occupational mobility

Note: Red lines refer to individuals with routine fathers, green lines refer to individuals with cognitive fathers.

which has a notion of match efficiency, we may expect that this force would increase the level of mismatch from ability to occupation in the economy. Figure 1.A4 in the appendix reports the aggregate dynamics of worker shares and wages under each of these counterfactuals. While the ability persistence is an important driver of occupational persistence, it has only a marginal effect on aggregate dynamics.

1.5.3 Counterfactual 3: The role of the financial frictions in the rise of the manual occupation share

In a final counterfactual experiment I investigate the role of the financial constraint in accounting for the increase in the manual share of labour. This analysis is motivated by the observation that the increase in the manual occupation share appears to be larger in the US than in Europe; empirical studies in the US typically estimate that the share of low-skilled jobs have been increasing faster or at least at the same rate as the share of high-skilled jobs (Autor et al. 2006, Cortes et al. 2017), while most estimates for Europe suggest that the share of low-skilled workers has been increasing by less than the share of high-skilled workers (Goos and Manning 2007, Goos, Manning, and Salomons 2009, Adermon and Gustavsson 2015). This begs the question of whether the more generous public education expenditure in Europe can account for this difference. To explore this further I investigate counterfactuals where the share of college costs paid by parents varies. It

Figure 1.18: Transition of manual occupation share under varying degrees borrowing constraint

should be noted, however, that I do not fully calibrate the economy to a ‘European style’ welfare state, thus this exercise is mainly exploratory and should be thought of as a motivation for future research. In particular, we may expect that a model calibrated to a European economy would have counteracting forces: while the public education subsidies spur investment in cognitive skills, a more progressive income tax will discourage skills investment.⁹

Bearing these caveats in mind, I explore the model dynamics in a set of counterfactuals where I vary the student borrowing constraint (i.e. the share of college expenditure paid upfront) and for each value investigate the model dynamics through the technological transition. Apart from the baseline value of $\tau = 0.56$, I consider counterfactuals with $\tau = 0.0$ and $\tau = 0.28$. Figure 1.18 reports the dynamics of the manual occupation share under each of these counterfactual scenarios. It is clear that an easing of the financial constraint (a fall in τ) is associated with a lower response of the manual share to the technological change. In the counterfactual with $\tau = 0.0$ the total increase in the share of manual employment is 3.3 percentage points as compared to 4.7 percentage points in the counterfactual without the baseline borrowing constraints ($\tau = 0.56$). Hence, in the model, the borrowing constraint accounts for 28% of the rise in the manual worker share, which provides an indication that this could be an important channel for explaining cross country differences in polarization.

9. See, e.g. D. Krueger and Ludwig (2016) for a joint analysis of education subsidies and progressive taxation in an overlapping generations model with inter-vivos transfers and inheritable ability.

1.6 Conclusion

This paper analyses the long-run effects of routine-biased technological change, explicitly taking into account parents' altruistic preferences toward their children, as well as frictions stopping children from obtaining the skills that become increasingly valued due to the technological shift. I empirically document that sons of routine fathers were less likely to work in cognitive occupations for cohorts born 1964-1977 relative to those born 1953-1963, whereas those with fathers in cognitive occupations have seen a moderate increase in their probability to work in cognitive occupations. This finding, among others, is rationalized in a general equilibrium model with overlapping generations, where skill investments require an early life investment that is costly both in monetary and psychic terms. The model is calibrated to the US economy between 1980-2010, making use of information on intergenerational occupational mobility, aggregate dynamics, and ability distributions across occupations and parental background to disentangle the relative importance of financial frictions, ability persistence and idiosyncratic preferences in generating intergenerational occupational persistence. The calibrated model is used to perform three counterfactual experiments. The first of these investigates the welfare impact of technological change, and finds that – after accounting for altruistic preferences – advances in automation technology in the 1980s and 1990s came with a welfare increases to workers in all occupational groups; although routine workers would be better off if technological progress occurred at half the rate. The second exercise investigates the role of ability persistence and financial frictions for intergenerational occupational mobility. The results show that, in 1980, ability persistence played a larger role than financial frictions for generating intergenerational occupational persistence, whereas in 2010, financial frictions played the dominant role. The third exercise investigates the role of financial frictions in increasing share of manual jobs. The results show that the increase in the manual worker share is linked to the share of college costs that cannot be financed by a loan, with stricter student borrowing constraints being associated with a larger increase in the manual share of labour.

1.7 Appendix

1.7.1 Mapping occupations to manual, routine and cognitive categories

To sort the occupations to their broad categories I follow exactly the procedure of Cortes (2016), who maps the PSID 3-digit ‘Census Occupation Codes’ (COC) into three broad categories (manual, routine and cognitive). For the CPS and NLSY data the occupational categories are given by 4-digit codes according to the Census Bureau occupational classification system, which is easily mapped to the 3-digit COC system by removing the last digit. Table 1.A1 gives a full list of the mapping, which differs between the two classification system used over the time period considered by Cortes (2016): the 1970 COC codes were used in the PSID until 2001, and were replaced by the 2000 COC codes starting in 2003. In 2017 the classification system changed again to 2010 COC codes. I use the crosswalk provided by the National Institute for Occupational Safety and Health (2022) to map the 2010 COC codes to their 2000 equivalents.

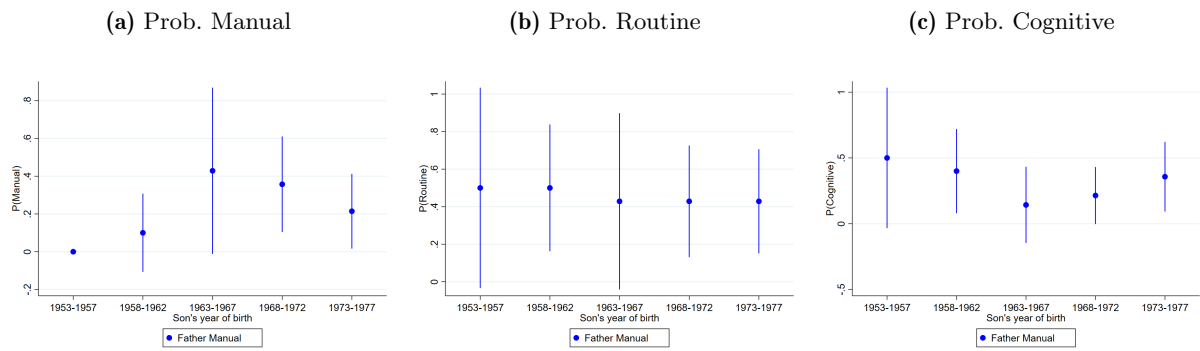
Table 1.A1: Mapping of occupational classifications

Broad class	Occupations	1970 COC	2000 COC
Cognitive	Professional, technical and kindred workers	001-195	
	Professional and related occupations		100-354
	Managers, officials and proprietors, except farm	201-245	
	Management, business and financial occupations		001-095
	Managers of retail and non-retail sales workers		470-471
Routine	Sales workers, except managers	260-285	472-496
	Clerical and kindred workers	301-395	
	Office and administrative support occupations		500-593
	Craftsmen, foremen and kindred workers	401-575	
	Operatives, except transport	601-695	
	Laborers, except farm	740-785	
	Construction and extraction occupations	620-694	
	Installation, maintenance and repair occupations		700-762
	Production occupations		770-896
	Transport equipment operatives	701-715	
Transportation and material moving occupations		900-975	
Manual	Service workers	901-984	360-465
Not classified	Members of armed forces	600	984
	Farmers, farm managers, farm laborers, farm foremen	801-824	
	Farming, fishing and forestry occupations		600-613

Notes: Follows exactly Cortes (2016). For the NLSY and CPS data occupational codes are translated to their COC equivalent by removing the last digit.

1.7.2 Additional figures & tables

Figure 1.A1: Occupation shares for individuals with manual fathers



Notes: Father's and son's occupation taken at highest observed age between 39-41. Bars display 95% confidence intervals and standard errors are clustered at the father level.

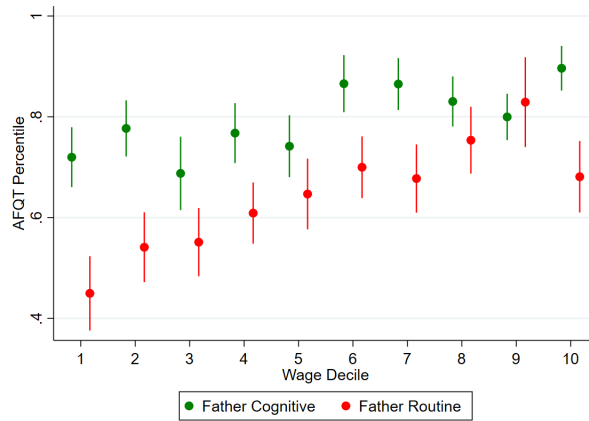
Table 1.A2: Estimated effect of birth year on probability of working in a cognitive occupation, depending on occupation of father.

	Cog	Rou	Man
Birth year	-0.0500 (0.031)	0.0159 (0.029)	0.0949* (0.054)
Birth year × father cog	0.140*** (0.052)	-0.112** (0.050)	-0.0738 (0.107)
Father cognitive	-0.471 (0.517)	0.305 (0.496)	0.310 (1.138)
North Central	-0.405 (0.335)	0.562* (0.328)	-0.614 (0.594)
South	-0.314 (0.361)	0.377 (0.350)	-0.288 (0.551)
West	-0.141 (0.431)	0.308 (0.427)	-0.575 (0.714)
Nonwhite	-1.342*** (0.345)	0.768*** (0.288)	1.107** (0.487)
Constant	0.429 (0.385)	-0.485 (0.378)	-3.336*** (0.710)
<i>N</i>	422	422	414

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Data from PSID. Results from logistic regression. Standard errors in parentheses are clustered at the father level. Omitted geographical region is Northeast. Sample includes men aged 39-41 born between year 1953-1977 with fathers observed in either cognitive or routine occupation.

Figure 1.A2: Average AFQT score for Cognitive workers with Routine/Cognitive fathers, split by wage decile.

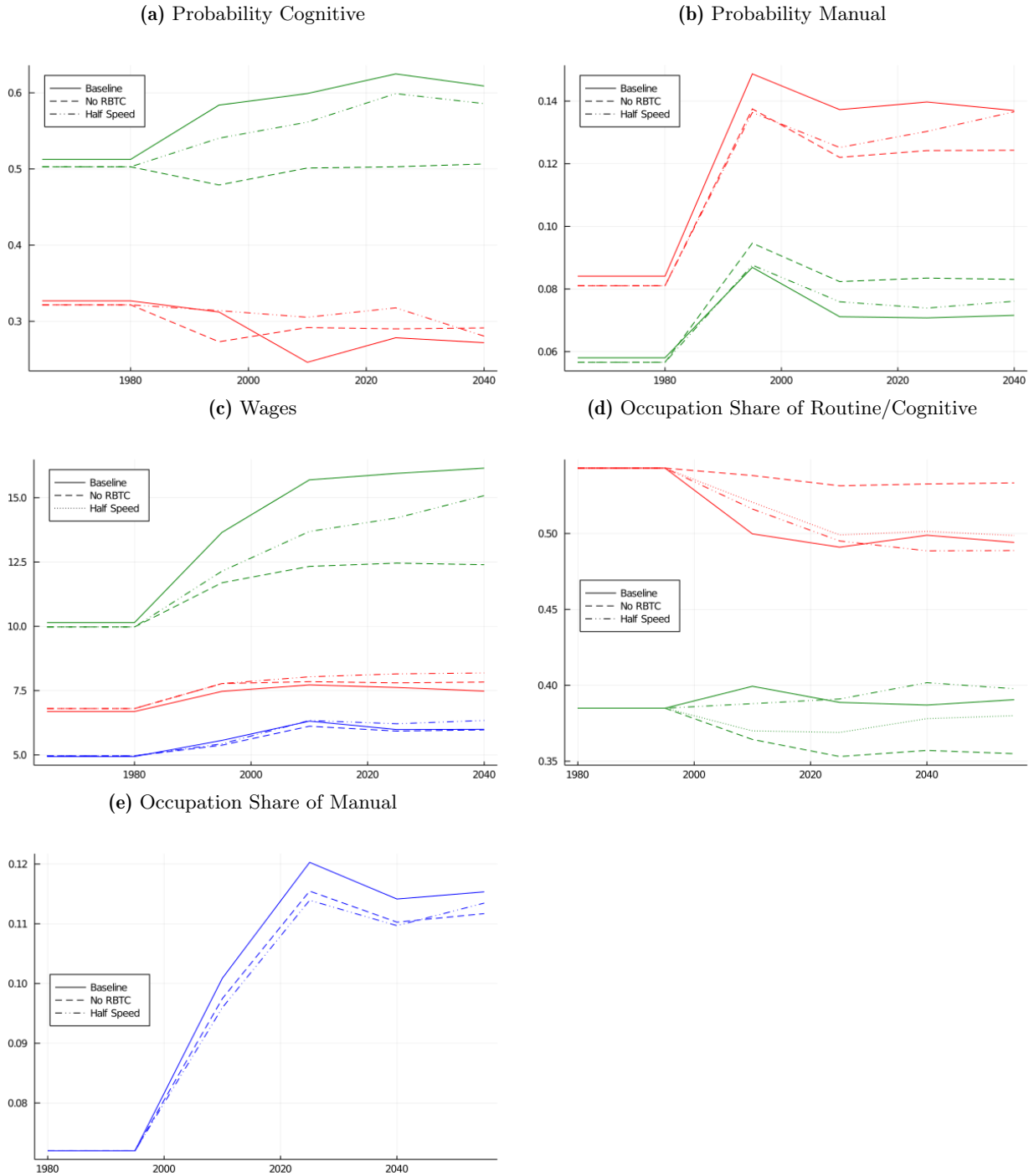


Notes: Data from NLSY79. Bars represent 95% confidence intervals.

Table 1.A3: Mapping from CPS highest educational attainment variable to broad education categories and years of college

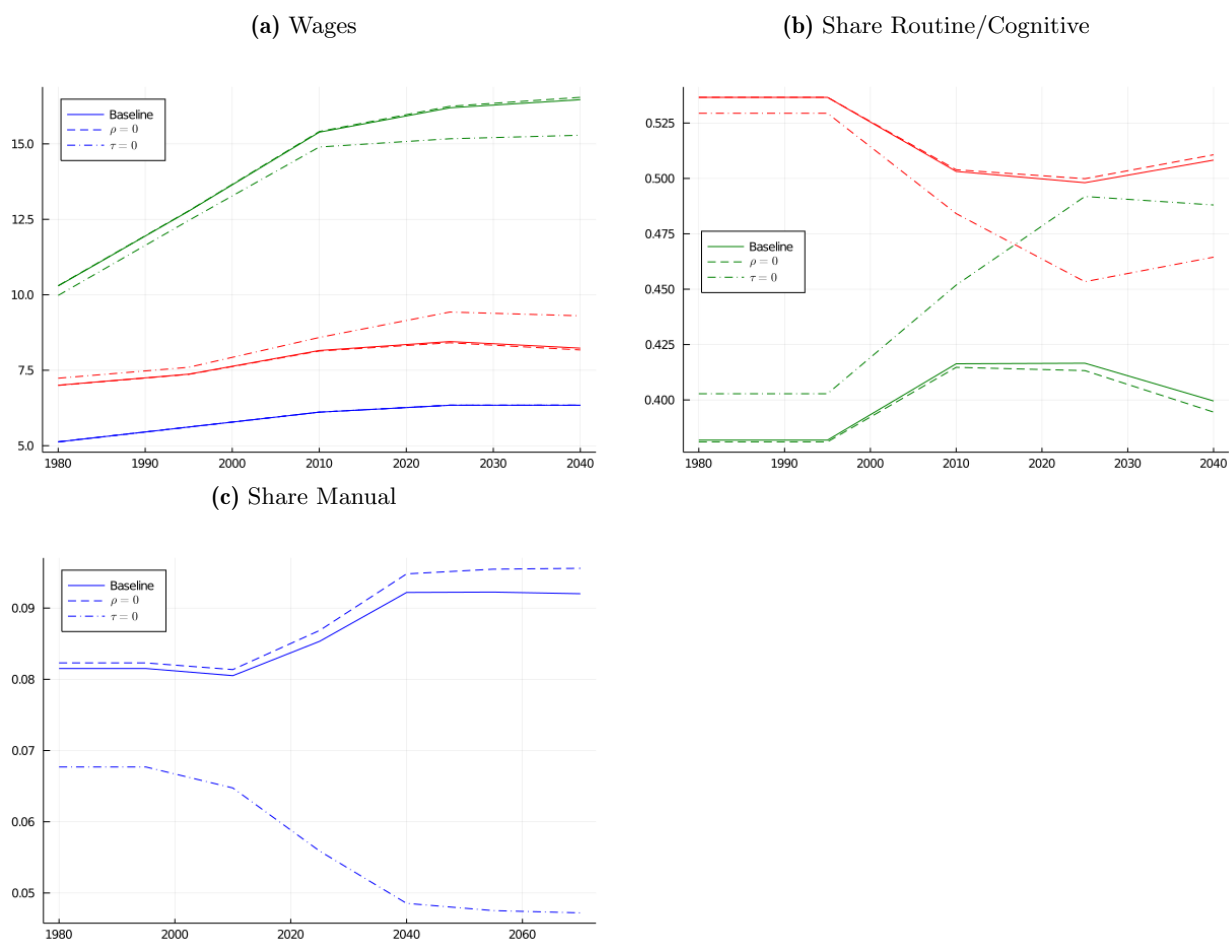
Broad category	Highest educational attainment	Imputed 'Years of college'
HS dropout	None or preschool	0
	Grades 1-11	0
HS graduate	12th grade, no diploma	0
	High school diploma or equivalent	0
Some college	Some college but no degree	2
	Associate's degree, occupational/vocational	2
	Associate's degree, academic program	2
College graduate	Bachelor's degree	4
Postgraduate	Master's degree	6
	Professional school degree	8
	Doctorate degree	8

Figure 1.A3: Comparison of responses to a routine-biased transition in baseline model and in counterfactual exercises with differing technological change



NOTE: Throughout blue lines refer to manual, red lines to routine, green to cognitive. In the first two figures these are the occupations of the father, whereas in the others it is the worker's occupation. The first two figures refers to the probability of entering cognitive/manual occupation at the time of investing in education.

Figure 1.A4: Aggregate dynamics in structural decomposition exercises



Note: Throughout blue lines refer to manual workers, red lines to routine workers, and green to cognitive workers.

Table 1.A4: Welfare change from the baseline estimation under the assumption of exogenous education cost.

	Boomer generation			Gen X			Millenials		
	Man	Rou	Cog	Man	Rou	Cog	Father man	Father rou	Father cog
No RBTC	-1.72%	-1.2%	-3.38%	-2.18%	-0.92%	-6.46%	-7.08%	-6.61%	-6.84%
Double Speed	0.0%	-0.62%	1.31%	0.0%	-1.23%	2.85%	0.02%	-0.06%	0.06%
Half Speed	-0.32%	0.16%	-1.75%	-0.43%	1.11%	-3.69%	-2.25%	-2.32%	-2.44%

Note: The first six columns are average welfare differences in prime-aged consumption equivalent variation units by own occupation, whereas column 6-9 are welfare differences in young-age consumption equivalent variation by father's occupation.

1.7.3 Proof of Proposition 1.3.1

Suppose, for the sake of contradiction, that the optimal transfer is $\hat{a} \neq a_{s,s'}$. Denote the optimal occupational choice of the child at this transfer level by $s_1 = s^*(\hat{a}, \ell', \nu')$, and the value obtained by the parent at this transfer level and given this occupational choice of their child by $U^p(\hat{a}, s_1)$. Compare this to the alternative transfer a_{s,s_1} , which satisfies equation 1.4. Denote the optimal occupational choice of the child at this transfer by $s_2 = s^*(a_{s,s_1}, \ell', \nu')$. Two cases are possible: either the optimal choice of the child at a_{s,s_1} is still occupation s_1 , i.e. $s_1 = s_2$. In this case a_{s,s_1} trivially does better than \hat{a} as it satisfies the parent's FOC. Hence $U^p(a_{s,s_1}, s_1) > U^p(\hat{a}, s_1)$. Alternatively, the child chooses a different occupation at a_{s,s_1} , i.e. $s_2 \neq s_1$. Since preferences are altruistic, any choice that makes the child better off also makes the parent better off, thus $U^p(a_{s,s_1}, s_2) > U^p(a_{s,s_1}, s_1) > U^p(\hat{a}, s_1)$. Since these are all possible cases we conclude that $\hat{a} \neq a_{s,s'}$ for $s' \in \{M, R, C\}$ can never solve the parent's transfer decision, which proves part (a) of the proposition. To prove part (b) note that, in the case when $s_2 \neq s_1$, the parent can do even better than transferring a_{s,s_1} as this transfer does not satisfy the parent's FOC for this occupational choice. Indeed, the best transfer given the new occupational choice is a_{s,s_2} and thus $U^p(a_{s,s_2}, s_2) > U^p(a_{s,s_1}, s_2) > U^p(a_{s,s_1}, s_1) > U^p(\hat{a}, s_1)$. If this transfer makes the child choose yet another occupation the same argument can be repeated indefinitely to conclude that a transfer $a_{s,s'}$ will always be given to a child that chooses occupation s' .

1.7.4 Computational Algorithm

Solving for steady state equilibrium

Solving for a steady state equilibrium involves three iterative procedures: an 'inner loop' takes wages as given and uses a value function iteration procedure to solve for young agents' value at a state space consisting of their starting wealth and ability. A 'middle loop', calculates the stationary distribution over the age one and two state spaces given these value functions. Finally, an 'outer loop' calculates a fixed point of wages and worker shares.

Inner loop:

1. Given wages, calculate education cost $c(w_C)$, as well as a grid over possible starting values of wealth, $a_{s,s'}, \forall s, s' \in \{M, R, C\}$ as argued in section 2.
2. Make an initial guess for the young age objective function function, $W^1(a_{s,s'}, \ell, s')$ over an ability grid of size 100 and for each possible starting asset position.
3. Solve for the expected value at age 2, conditional on child's ability, using equation .
4. Numerically calculate the expectation of value at age 2 with respect to child's ability for each point in the age 1 state space¹⁰.
5. Substitute this expectation into equation 1.2, to update the guess for $W^1(a_{s,s'}, \ell, s')$
6. Repeat until convergence.

Middle loop:

1. Guess a distribution over the age 1 state space.
2. Use the discretized AR(1) markov matrix to update to the distribution over occupation \times child ability in the prime-age generation.
3. Use equation (6) to update to a new age 1 distribution
4. Update until convergence

Outer loop:

1. Guess a distribution of worker shares M_0, R_0, C_0 , which gives rise to wages w_M, w_R, w_C
2. Using the inner loop, calculate value functions at these wages, and then use the middle loop to calculate the stationary distribution over occupations, denoted M_1, R_1, C_1 .
3. If $\sum_{s \in \{M, R, C\}} |s_0 - s_1| < 10^{-5}$ stop, otherwise update guess to some linear combination $s_0^{new} = k s_0 + (1 - k) s_1 \quad \forall s \in \{M, R, C\}$, where $k \in (0, 1)$, and repeat algorithm from step 1.

10. I use the Tauchen (1986) method to approximate the AR(1) process by a Markov transition matrix.

Solving for a transition

Solving for an equilibrium transition involves solving for a fixed point of a series of wages using a similar procedure to the algorithm for solving for a steady state equilibrium. First assume a length, T of the transition before it reaches a new steady state (I assume a new steady state is reached after $T = 15$ periods). Then use the following iterative procedure:

1. Solve for steady state value functions and distributions at initial and final steady states.
2. Guess a transition path of worker shares over some specified length, T , where the end point is as in the new steady state, $\{M_{0,t}, R_{0,t}, C_{0,t}\}_{t=1}^{T-1}$.
3. Find age one value functions along the transition path by iterating on an initial guess similarly to how we solve for steady state.
4. Starting at the initial period steady state distribution of the young age state space, use the AR(1) approximation together with equation (6) to iterate forward to find the distribution of worker shares in each generation and time period.
5. From this distribution calculate an updated transition path $\{M_{1,t}, R_{1,t}, C_{1,t}\}_{t=1}^{T-1}$. If this is close to initial guess stop, otherwise repeat from step 1 with an updated guess given by a linear combination of $\{M_{0,t}, R_{0,t}, C_{0,t}\}_{t=1}^{T-1}$ and $\{M_{1,t}, R_{1,t}, C_{1,t}\}_{t=1}^{T-1}$.

Intergenerational Transfers, Wealth, and Job Search Behaviour

This article was co-authored with Ludo Visschers, who have agreed that it can appear as a chapter of this thesis, and that it represents a significant contribution on my part.

2.1 Introduction

The role of wealth in job search behaviour has become of increasing interest in labour economics. When coupled with the realistic assumptions of decreasing absolute risk aversion (DARA) and a constraint on borrowing, standard theories of job search – including both the random search and directed search frameworks – predict that wealth should affect a job seeker’s optimal decision in terms of search effort, target wage and reservation wage.¹ In this paper we investigate how findings of the effects of individual wealth on job search may generalize to *parental* wealth. Noting that much of an individual’s career trajectory is determined in early-life, and that many individuals at this point still receive support from their parents, we suggest that findings on the importance of individual wealth may also apply to family wealth. However, to further our knowledge on the link between parental wealth and job search decisions of (adult) children, more empirical research is

1. In the random search literature: Danforth (1979) show that reservation wages are increasing in wealth; Lentz and Tranæs (2005a), Chetty (2008) and Lentz (2009) analyze interactions between wealth and search intensity. In the directed search literature: Griffy (2021), Eeckhout and Sepahsalari (2021) and Chaumont and Shi (2022) analyze the tradeoff between higher job finding and higher wages.

needed. In particular, two key links must be established: (i) how does individual wealth affect job search? And (ii) how is wealth transferred across generations. In this paper we contribute new knowledge into both of these questions, as well as novel findings on the direct impact of parental income on children's job search behaviour.

To analyze the effect of individual wealth on job search we make use of the quasi-random allocation in the timing of the 2008 US stimulus payments, which were paid out to most US households as a means of averting the impending recession. These transfers were largely based on the last two digits of an individual's social security number, and hence represent a plausibly exogenous wealth variation, which we use to analyze the effects on recipients' job search behaviour. To do so, we use data from the 2008 Survey of Income and Program Participation (SIPP), which is a nationally representative survey. The broad reach of the stimulus payments, as well as our dataset, allows us to analyze effects of wealth on job search in a more theoretically relevant setting than previous empirical literature. Earlier work on effects of unconditional wealth transfers on job search (i.e. not state-dependent transfers, such as unemployment insurance) has typically relied on variation in severance payments (Card, Chetty, and Weber 2007, Chetty 2008). We believe that studying a broader wealth shock provides important new insights, as receivers of severance payments belong to a select group that are likely to be further from their borrowing constraint, and whose job search behaviour is therefore theoretically less likely to be impacted by added liquidity. Our main results regard the job search behaviour of those who were unemployed when receiving their stimulus payments: we find that the contemporaneous effect of the liquidity injection was a fall in the job finding rate of around two percentage points, and that this effect was larger for groups that we expect to be closer to their borrowing constraint – younger and lower earning individuals. We also investigate how the added wealth affected the match quality at the subsequent employer. Here the results are less clear, but suggest that those who found a job in proximity to their transfer tended to find work in occupations associated with higher wages on average, and tended to stay with the new firm longer. All-in-all these findings are in line with the prediction of the directed search framework and suggest that wealth can have important career consequences, in particular for young and low-wage individuals.

Next, we turn to the analysis of intergenerational wealth transfers. We note that the theoretical predictions of the effects of parental wage on the child's job search behaviour crucially depend on the nature of intergenerational transfers; it is particularly important whether parental help is need-specific or unconditional. In a sense, the question we are asking is: should parents be thought of as wealth, or as insurance? This question links us to another strand of literature that analyzes the motives of parent to child wealth transfers, and asks whether these are best described as altruistic, and hence varying by the need of the child, or unconditional, as described by, for example, a 'warm glow' or 'joy-of-giving' assumption². Answering this question empirically has proved difficult, as data on inter-vivos transfers from parents to children are scarce. The most concrete contribution of this section is to add to this knowledge by analyzing a dataset that has so far been overlooked in this literature: the 1979 National Survey of Youth (NLSY79) and its follow-up Child and Young Adult sample (CNLSY79). These datasets have several desirable features: the respondents in the CNLSY79 are the children of all women in the NLSY79, which means that we have detailed longitudinal information on labour market outcomes linked across two generations. The CNLSY79 also contains information on transfers from parents to children through a set of questions that asks the child sample how large a share of their personal expenditure is covered by their parents. We find that the majority of expenditures paid by parents to their children that are above 18 years old and not in college occur when cohabiting, but parents continue to pay a significant share of expenditures even after the child has moved away from home – around 10% on average for 18-19 year olds, but then declining with age. Furthermore, we find that a small but statistically significant share of expenditures can be explained by the labour market status of both the parent and child: parents are more likely to give transfer when their income is high, and children are more likely to receive transfers when they are out of employment. These results hold both in the cross-section and when limiting the analysis to within-individual time-varying variation. Qualitatively, these results suggest that an altruism model may be appropriate in describing inter-vivos transfers, although only a smaller fraction of transfer variation can be attributed to state-dependent transfers, while a larger part appears to be unconditional.

2. Many papers investigate the motivation behind gifts within the family. See, for example, Becker (1974), Altonji, Hayashi, and Kotlikoff 1997 or Barczyk and Kredler 2021.

We also make use of the detailed labour market history in the CNLSY sample to investigate directly how parental income affects the child's job search behaviour. Contrary to the theoretical prediction, we find that higher parental income is associated with a *higher* job finding rate, as well as reemployment wages. This result is robust to controlling for a host of individual characteristics, but not significant when only using within individual time-varying variation. To bring the analysis of intergenerational insurance and job search closer to an exogenous change in parental income, we also study the effect of a job loss (defined as a transition from employment to unemployment) of the mother on their child's job search behaviour. In line with theoretical predictions, we find that a job loss of the mother is associated with an 1.5 percentage point increase in the contemporaneous job finding rate of the child. Focusing on the subsample of individuals who either have deceased fathers or report having no contact with their father this effect is significantly larger and more persistent, with an employment loss of the mother being associated with more than a 3 percentage point increase in the job finding rate of the child both in the same month as the mother's job loss and the month following. These findings are consistent with a liquidity effect on job search in line with the theoretical predictions. We also analyse whether the increase in the job finding hazard following the job loss of the mother was associated with sorting into lower-paying occupations, and find that individuals who found a new job in relation to a job loss of their mother tended to do so in a lower-ranked occupation, which once again is in line with the predictions of the standard model.

Finally, we estimate the direct impact of a transfer from parent to child on job search behaviour. We find that receiving transfers is associated with worse labour outcomes; job finding rates as well as re-employment wages tend to be lower, and long-term wage effects seem to be negative as well. However, we are cautious not to interpret this correlation causally, as there is likely reverse causality whereby the person needing a transfer is subject to a worse shock, which in itself may have lasting effects on labour market outcomes. We attempt to control for such reverse causality by instrumenting transfers by transfers to siblings. Once again we find that a sibling receiving a transfer, which should correlate with the individual receiving 'family insurance', correlates with

worse labour market outcomes. To the extent that this evidence can be taken as causal, this suggests that the moral hazard dimension of intergenerational insurance may be important for labour market outcomes, although we cannot rule out that the correlation is explained by other factors, such as synchronized local labour market shocks.

Since the two pieces of analysis presented in this paper – one on the effects of individual wealth on job search and the other on the effect of intergenerational transfers – are quite separate from each other we organize the paper in two main parts, each of which can be read independently of the other. The first part – section 2.2 – reviews the literature on individual wealth and job search behaviour before reporting our new estimates of the causal effect of wealth on labour market outcomes using the natural experiment of the 2008 tax rebates. The second part – section 2.3 – reviews the literature on intergenerational transfers and job search models with family insurance before introducing the CNLSY dataset and reporting the empirical results on how intergenerational transfers interact with parent’s and children’s labour market outcomes. Finally, section 4 concludes with a discussion of potential avenues for future work.

2.2 Wealth effects on job search: A natural experiment

In this section we analyze the effect of wealth on job search behaviour through a natural experiment – the stimulus payments (tax rebates) received by most US households following the 2008 financial crisis. The timing of these transfers, which in large were determined by social security number³, means that the month in which an individual received their transfer was close to random, and hence makes them ideal to study wealth effects. Indeed, a multitude of research papers have exploited these tax rebates to study the effect of wealth on various economic issues such as consumption pass-through (e.g. Parker, Souleles, Johnson, and McClelland 2013, G. Kaplan and Violante 2014, Broda and Parker 2014), the effect on earnings (Powell 2020), consumer bankruptcy (Gross, Notowidigdo, and Wang 2014) and subjective well-being (Lachowska 2017). However, as far as we are aware, we are the first to focus on the effects of the tax rebates on unemployed individuals, and in particular, on their job search behaviour. This fills a gap in the literature: while there has been

3. See Powell (2020) for more detail about the arrangements of the tax rebates, and how they depended on social security number.

quasi-experimental studies made to investigate the effect of unemployment insurance on hazard rates and re-employment wages (e.g. Card and Levine 2000, Lalive, Van Ours, and Zweimüller 2006), the literature on wealth effects is more scarce and have typically only considered wealth effects through severance payments (e.g. Card et al. 2007). Since workers covered by severance payments is naturally a selected group the focus of the tax rebates in 2008, which had a large reach in eligibility, will provide an important addition to this literature.

2.2.1 Theoretical foundation and earlier empirical work

Empirical work

One of the contributions of this section is to add to the knowledge of the effects of insurance on individual's job search behaviour. The role of insurance, either through own accumulated wealth or government provided unemployment insurance (UI), in worker's job market outcomes has a long tradition of being studied in labour economics. A robust finding in the empirical literature is that an increase, or lengthening, of UI lowers the job finding rate. In one of the studies most relevant to our setting Card et al. (2007) use sharp cut-offs of severance payments and unemployment insurance (UI) extensions in Austria to find that a lump-sum payment equivalent to two months of income reduced the job-finding rate by 8%-12% on average, and that an extension of UI from 20 to 30 weeks lowered the job finding rate in the first 20 weeks by 5%-9%. However, they do not find any significant effect of either extended UI or severance payments on the quality of the subsequent job, as measured by the re-employment wage or job duration. Several other papers document similar relationships between UI and unemployment duration, both using cross-sectional correlations (e.g. Moffitt and Nicholson 1982, Katz and Meyer 1990) and quasi-experimental variation (e.g. Card and Levine 2000, Lalive et al. 2006). There is also some empirical evidence of the *mechanism* through which UI affects unemployment and wages: for example Marinescu and Skandalis (2021) use rich French panel data that contains detailed information on job applications and find that job search intensity goes up, and the target wage falls, when UI is nearing an end.

One of the key aims of this literature is to separate the ‘moral hazard’ and ‘liquidity’ components of the UI-caused distortions in job finding. The moral hazard effect can be seen as the insured agent inefficiently substituting search effort for leisure, as the marginal tax rate on labour is particularly high when job finding is coupled with a loss of UI. A liquidity effect, on the other hand, is active if the agent is borrowing constrained, and therefore – from a life-time income perspective – would have preferred a longer spell of unemployment, either because this would allow for more time to search for a better job, or to optimize their labour/leisure tradeoff. Chetty (2008) (henceforth Chetty) use a revealed preference framework to estimate that 60% of the increase in unemployment duration caused by UI is due to the liquidity effect rather than moral hazard. For identification Chetty relies on two types of variation: one exploits geographically differential changes in UI duration across the US, which is coupled with information on households’ capability to smooth consumption, as measured by asset holdings and single- versus dual earner status. Here the finding is that ‘constrained’ (low-wealth, single earner) households responded more strongly to the duration increase than unconstrained household, suggesting that the liquidity effect is important. However, since both wealth and dual earner status are endogenous outcomes, and hence likely correlated with other potentially important characteristics, Chetty also use another empirical strategy, by exploiting variation in lump-sum severance payments. Lump-sum payments do not affect the marginal tax-rates and hence should only have an income effect, but no substitution effect, on the tradeoff between job search and leisure. If the severance pay is small relative to life-time income this wealth effect should be particularly relevant for credit constrained individuals. Chetty finds that job losers who receive severance payment tend to spend longer time in unemployment, and that this effect is stronger for those closer to their borrowing constraint, again suggesting that the liquidity effect is important.

Theory

To inform our analysis of the role of wealth in job search behaviour we draw on theoretical insights from job search theory. A number of papers have analyzed the finding that wealth impacts job search behaviour through random search models where agents have some combination of a search effort decision, curved utility (risk-aversion), and a savings decision subject to a borrowing

constraint. Common to all of these papers is that missing markets for credit (self-insurance) and private unemployment insurance creates a role for the government to provide unemployment insurance that allows agents to smooth their consumption. Lentz (2009) use such a framework to study optimal UI policy, finding that it is very sensitive to both the subjective discount rate, and the interest rate. In this model the wage offer distribution is degenerate, so there is no relevant impact of wealth on the quality of the new match. The government's tradeoff is therefore only to provide unemployment insurance, which allows for better consumption smoothing, at the expense of distorting agents' search effort motives. Similar models are analyzed in Lentz and Tranæs (2005a), Card et al. (2007) and Chetty (2008). Lise (2013) extends this framework by incorporating on-the-job search, which endogenously creates a large wealth dispersion, as workers on different parts of the wage ladder have vastly different optimal savings behaviour.

A more recent literature has incorporated the empirical positive correlation between wealth and unemployment duration into directed search models. Here the correlation has a natural interpretation as wealthier individuals may be more willing to search for higher-paying jobs despite a lower job-finding rate, thus generating a positive correlation between wealth and both re-employment wages and unemployment duration without the need of either a reservation wage choice or a search effort choice. One challenge for the directed search literature to explain is that there is a well-established negative correlation between wages and unemployment duration; high-wage individuals tend to find a job faster (e.g. Van den Berg and Van Ours (1996)). The canonical directed search model is unable to explain this *negative duration dependence* as higher-wage postings always attract more applicants and thus should be associated with lower hazard rate from unemployment. Eeckhout and Sepahsalari (2021) shows how introducing a savings decision and decreasing absolute risk aversion into the directed search model can reconcile this – as unemployed workers run down their savings they become increasingly likely to apply for lower-paying jobs with higher job finding probability. Thus, this model can generate both a positive association between wealth and job finding and a negative correlation between unemployment duration and re-employment wages.

Griffy (2021) also studies a directed search model with a savings decision and a borrowing constraint, but extends the framework to allow for endogenous human capital formation in the spirit of Ben-Porath (1967), where agents face a tradeoff between labour earnings and human capital investment. The model is used to analyse the impact of initial conditions at labour market entry on life-time earnings. It is shown that feedback effects between directed search and human capital investment creates a stronger link between initial wealth and life-time earnings than what earlier literature, notably Huggett, Ventura, and Yaron (2011a), has suggested. The reason for this is that, in a directed search model with risk aversion, borrowing constraints and a savings decision, a job separation is particularly costly for a low-wealth individual, as they choose to search for lower-paying jobs with higher job finding probability. This means that upon labour market entry a low-wealth individual devotes more of their resources to building up precautionary savings, rather than to human capital accumulation, which has long-lasting effects on life-time income. An interesting extension to this framework, which is not done in this paper, would be to consider how differences in *parental wealth* upon labour market entry affect life-cycle earnings.

The mechanism through which wealth affects income in the aforementioned papers is through the borrowing constraint. Much like it is the borrowing constraint that generates precautionary savings in the Bewley (1977), Huggett (1993), Aiyagari (1994) class of incomplete market models, as low-wealth individuals are unable to smooth consumption when receiving a negative income shock, it is the borrowing constraint that gives low-wealth individuals a *precautionary job search motive* in directed search models with risk aversion. Herkenhoff (2019) develops a model in this class that directly hones in on this mechanism. Noting that access to non-secured debt (e.g. credit card debt) has increased sharply, Herkenhoff builds a directed search model that explicitly models unsecured borrowing and a default decision. Analysing the impact of unsecured credit over the business cycle Herkenhoff finds that increasing access to credit coupled with the end of a recession leads to a slower recovery, as the increase in credit access causes individuals to search for higher-paying, but harder-to-find, jobs.

2.2.2 Institutional background

The wealth variation used in this paper will come from the tax rebates that were paid out as unconditional cash transfers (check in the mail or wire transfer) in the US in 2008 as part of a stimulus program. The stimulus program was named ‘The Economic Stimulus Act of 2008’ and was passed by the senate in February 2008 and signed into law by President Bush in the same month. A large part of the stimulus package – which was designed to avert a feared recession – took the form of direct economic stimulus payments (ESPs) to individuals through tax rebates. Any person who filed a 2007 income of at least \$3000 in 2007 were eligible for a tax rebate, which amounted to at least \$300 per individual or \$600 for a married couple filing jointly, even if this amount was below the household’s tax liability, and then equal to the entirety of tax liabilities up to a cap of \$600 per individual or \$1,200 per couple. Rebates were gradually phased out for individuals earning above \$75,000, or couples earning above \$150,000, at a rate of 5% of income above this threshold.

The first stimulus payments were made on the 28th of April 2008, and the rest were scheduled between April and July. The timing of the transfers were based on two factors: the last two digits of the recipient’s social security number and whether the recipient reported a bank routing number in their 2007 tax return, which determined whether the rebate was received via electronic transfer or by a check in the mail. Although all payments were scheduled between April-July, in the data we also observe individuals receiving their payments in August-December, Powell (2020) hypothesize that this is because these individuals filed their 2007 tax returns late.

2.2.3 Data description

To analyse the effect of the tax rebates on job search behaviour, we use the 2008 panel of the Survey of Income and Program Participation (SIPP). SIPP is a panel survey representative of the US noninstitutionalized population where just over 42,000 households were interviewed every 4 months for a maximum of 16 rounds – making the interview dates span from September 2008 to December 2013. Our key variables of interest are the employment, earnings and tax rebate status

of individuals: respondents provided earnings at the monthly level and employment at weekly level going back to May 2008 and were asked specifically about the 2008 tax rebates – which month they were received and what they amounted to – making SIPP an ideal sample to analyse the labour market effects of the stimulus payments.

In the data we observe stimulus payments between April 2008 and December 2008. Table 2.1 reports some summary statistics; the first column uses the full sample, which includes those who never received a transfer, whereas the rest of the columns report the sample split by which month transfers were received. Clearly, and as mentioned previously, there is some nonrandom variation in individual characteristics depending on which month the transfer was received. For this reason, our preferred specification uses individual level fixed effects to account for unobserved heterogeneity. Using individual fixed effects, which has been the norm in the studies using this variation, also has the advantage of controlling for nonrandom attrition in the sample, although this is less of an issue as all rebate payments occurred in the first two waves. The selection issue mainly arises from transfers that were received after July, as transfers in this period were not based on social security number. However, since transfers between April-July should be close to randomly allocated we also estimate models on data restricted to people who receive transfers in these months without including individual fixed effects. We make few restrictions on the data, although we run through a number of different specifications as robustness checks, and to elicit information on which subgroups seem to have been most affected by the transfers.

2.2.4 Results

Our main objectives are to investigate the effect of the tax rebates on the job finding rate and re-employment wage rate of individuals. We also report results of some other labour market outcomes such as job destruction rates and job-to-job switches. To do so we estimate a linear model, which allows for both anticipation and lagged effect of transfers, while controlling for individual, age,

Table 2.1: Summary statistics by month of stimulus payment.

	(1) Full Sample	(2) April	(3) May	(4) June	(5) July	(6) August-December
Labour market statistics						
Earnings	2215.59	2729.76	2706.70	2550.86	2429.88	2505.67
Wealth	240764	267730	216316	231032	215879	259923
Employed	0.66	0.75	0.75	0.74	0.73	0.72
Unemployed	0.12	0.08	0.07	0.08	0.08	0.08
UE-transition	0.30	0.30	0.32	0.32	0.31	0.31
Tenure	76.91	90.30	96.26	97.10	96.94	94.46
EU-transition	0.02	0.01	0.01	0.01	0.01	0.01
Individual characteristics						
Age	39.94	43.57	44.50	44.95	45.26	46.65
Married	0.47	0.63	0.64	0.63	0.63	0.63
Female	0.51	0.52	0.53	0.53	0.53	0.52
Months observed	37.39	44.66	45.03	44.94	44.24	44.23
Observations	87910	3418	14313	15951	10880	3707

Note: Each variable is first averaged at the individual level, and table reports the cross-individual mean of these averages.

month, and ‘months from survey’ fixed effects⁴. Following the literature we do not make use of the information of the size of tax rebates, as this variation is non-random and may create bias, hence we only use a dummy that takes value one if a transfer was received in a given month on the right-hand side. The model can be written as

$$Y_{i,t} = \alpha_i + \beta_0 \times Reb_{i,t+1} + \beta_1 \times Reb_{i,t} + \beta_2 \times Reb_{i,t-1} + \beta_3 \times Reb_{i,t-2} + \gamma \times X_{i,t} + \delta_t + \epsilon_{i,t}, \quad (2.1)$$

where $Y_{i,t}$ is the outcome variable of interest. β -coefficients, which are estimated using ordinary least squares, denote the forward-lagged, twice lagged and contemporaneous effects of tax rebates (denoted $Reb_{i,t}$). α_i , δ_t and η_j denote individual and month fixed effects respectively, and $X_{i,t}$ is a vector of time-varying individual characteristics (fixed effects for age, marital status, and years from survey).

Since our key dependent variables of interest; job finding rates and re-employment wages; are only defined when an individual transitions into employment, the individual fixed effects are only identified for individuals with more than one non- or unemployment spell. Table 2.2 shows the distribution of such transitions for our estimating sample. For the majority of individuals we observe zero or one transition, hence they will not contribute to the estimation. For this reason we must be careful when interpreting the results from individual fixed effects as they will only apply for the selected sample of individuals who frequently transition in and out of employment. To address this issue we also run estimations without individual fixed effects, but here focusing only on individuals who received transfers in April-July, as this should be a more randomly selected group given that transfers in this period were mainly based on social security number.

4. Months from survey is a variable that measures how far the interview month is from the observation month. Controlling for this is important since it correlates both with the outcome variable – for example, reported job finding is highest in the earliest month asked about – and with the rebate timing, as the majority of transfers were made in the very earliest months of the survey and hence correlated with being far from the interview months. Failing to control for this can thus create a bias where the job finding rate appears to be greater in transfer months. Furthermore, since not all individuals were interviewed in the same month, this variable can be identified separately from month fixed effects.

Table 2.2: Distribution of number of UE-transitions per individual.

	0	1	2	3	4+
N	65,331	15,292	4,757	1,663	867

Effect of transfers on job finding rate

Our first results consider the effect on job finding rates of individuals. We define an unemployment spell as any spell of non-employment during which the individual reports actively searching for a job in at least one week. The job finding rate only includes individuals who transition from an unemployment spell to employment. This includes month-to-month transitions, but also within-month transitions, i.e. if the individual reported being without employment for some weeks of the months after which they started a job. Individuals who were with a job, but absent with or without pay, did not count as job finders once they reappear as employed. This means that the effect noted by Powell (2020), who finds that a higher likelihood of taking an unpaid absence was one of the significant effects of transfers, will not be picked up by our estimation strategy. Using this definition of job finding we construct a binary variable *jobfind*, which takes value one if an individual transfers from an unemployment spell to employment in a month and zero if the month is part of an unemployment spell but no job was found. Using this binary variable as the dependent variable we estimate equation 2.1 under some different sample selections. Figure 2.1 reports the results for the coefficients of interest; corresponding to the tax rebate dummy as well as its lags and forward lag.

Panel A reports the result for the main specification, which uses the full sample of individuals. The pattern that emerges is consistent with a liquidity effect: receiving a tax rebate is on average associated with a 2 percentage point contemporaneous drop in the job finding rate, which subsequently fades away – consistently with the liquidity effect vanishing. There also appears to be an anticipation effect, where the job finding rate is lower in the month preceding a transfer. This could easily be rationalized in a standard search model with a savings/borrowing decision, as individuals expecting a cash payment in the following month have less motive to save and hence are effectively moved away from their borrowing constraint.

Panel B reports the result from the specification that does not condition on individual level fixed effects and only uses the subsample of individuals who received their transfers from April to July, when payments were mainly based on social security number and hence more randomly allocated. These estimates show a similar pattern to the main specification – which serves as a robustness check on the results. It appears that the anticipation effect is smaller and that the persistence of the shock is lower in this sample, suggesting that these effects may not be as robust as the contemporaneous effect of the transfer.

Panels C-E hone in on subsamples of the population whose job search behaviour theoretically should be more affected by the rebate. In Panel C the sample is restricted to only include young individuals, who were between age 18 and 35 in 2008. Since these individuals tend to have lower wealth and are more likely to be borrowing constrained we would expect the transfers to have a larger impact for this group, and indeed that is also what we find, with the contemporaneous effect of the transfer being associated with a 4 percentage point fall in the job finding rate for this subgroup. Since these individuals are the ones that are most likely to receive support from home this suggests that differences in family support in this group could lead to significant differences in job search behaviour, although we unfortunately cannot test this hypothesis in the SIPP data as it does not contain any information on family background. Panel D focuses on another group which we expect to be more liquidity constrained: low-wage individuals. We define this group by running a regression of log monthly earnings on individual fixed effects as well as controls for month and age, and define a person as ‘low-wage’ if their individual intercept coefficient falls below the median. Once again the result is consistent with the theory; we find that low-wage individuals responded stronger to the transfer than the full sample average. Finally, panel D looks at the intersection of young and low-wage individuals. We find that this is the group that responds strongest to the rebates, although the smaller sample size means that this finding should be treated with some caution.

All-in-all there is a robust finding of a negative contemporaneous effect of transfers on the job finding hazard. Our results are broadly the findings of Card et al. (2007), who use a regression discontinuity design exploiting a sharp cut-off in Austrian severance payments, which only applied to workers who spent 36 months in employment, to estimate a 8%-12% average fall in the job

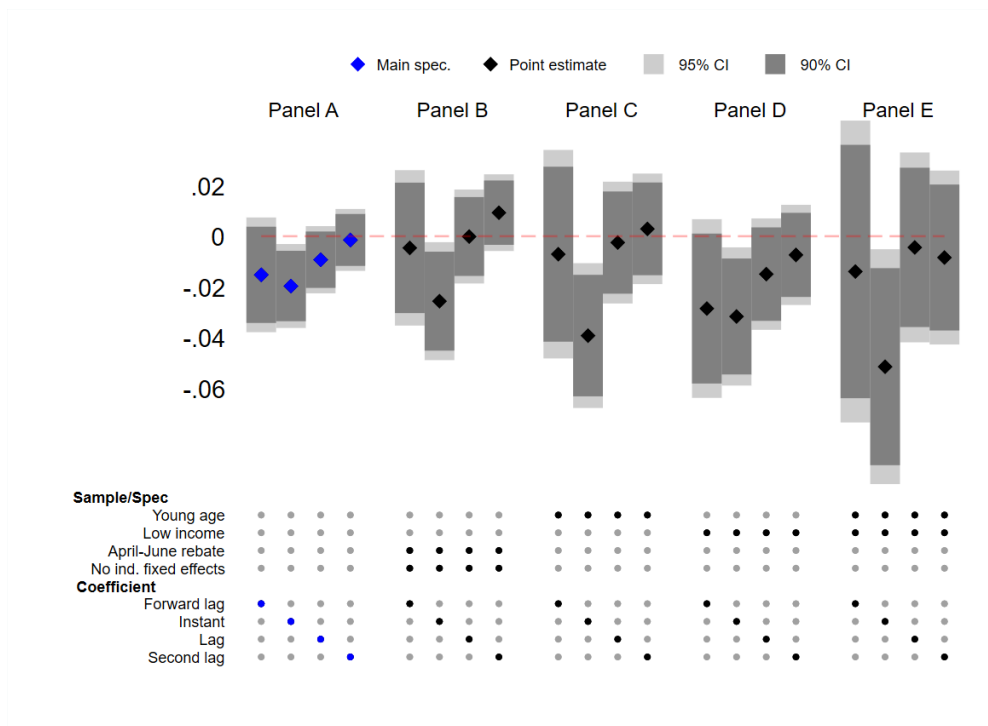
Table 2.3: Effect of transfer on job finding rate relative to baseline rates.

	Panel A	Panel B	Panel C	Panel D	Panel E
Job finding rate	8.37%	13.13%	10.81%	11.80%	14.07%
Monthly income	\$1,794	\$2,194	\$1,542	\$1,145	\$1,001
Transfer amount	\$905	\$917	\$954	\$928	\$996
β_1 -coefficient	-1.96%	-2.56%	-3.92%	-3.16%	-5.15%
Relative effect	-23.5%	-19.5%	-36.2%	-26.8%	-36.6%

Note:- Data from 2008 SIPP. Results control for month, months from interview and age fixed effects. Standard errors are clustered at the individual level. Regressions are weighted using the SIPP sampling weights.

finding rate during the 20 week period following a lump-sum payment equal to two months salary. In our case, transfers are typically equal to between 30%-50% of an individual's average monthly salary and we estimate a drop in the job finding rate between 2 to 5 percentage points. In table 2.3 we report the exact coefficients for the contemporaneous estimated effects for each of the estimation samples A-E in figure 2.1 together with their baseline job finding rate, average monthly income in years 2008-2010, and average tax rebate size conditional on receiving a rebate. Although our methodologies are not directly comparable, job finding seems to respond stronger to the liquidity injection in our estimates relative to Card et al. (2007). In our estimation the relative *contemporaneous* effect (which is different from Card et al. (2007) who report average effects over a 20 week period) is associated with a 19.5%-36.6% relative fall in the job finding rate, depending on the sample and methodology used. We suggest two explanations for the discrepancy in our results. First, the results here are estimated using a representative sample of the US population, which is likely to contain more individuals close to their borrowing constraint relative to those identifying the results in Card et al. (2007), which are workers who have been employed in proximity to 36 months. Second, we may expect that unemployed workers in the US are more financially constrained than in Austria, in the sense that a smaller welfare state means that the consequences of running down one's assets are greater.

Figure 2.1: Estimated effect of tax rebate on job finding rates.



Note:- Data from 2008 SIPP. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results control for month, months from interview and age fixed effects. Standard errors are clustered at the individual level. Regressions are weighted using the SIPP sampling weights.

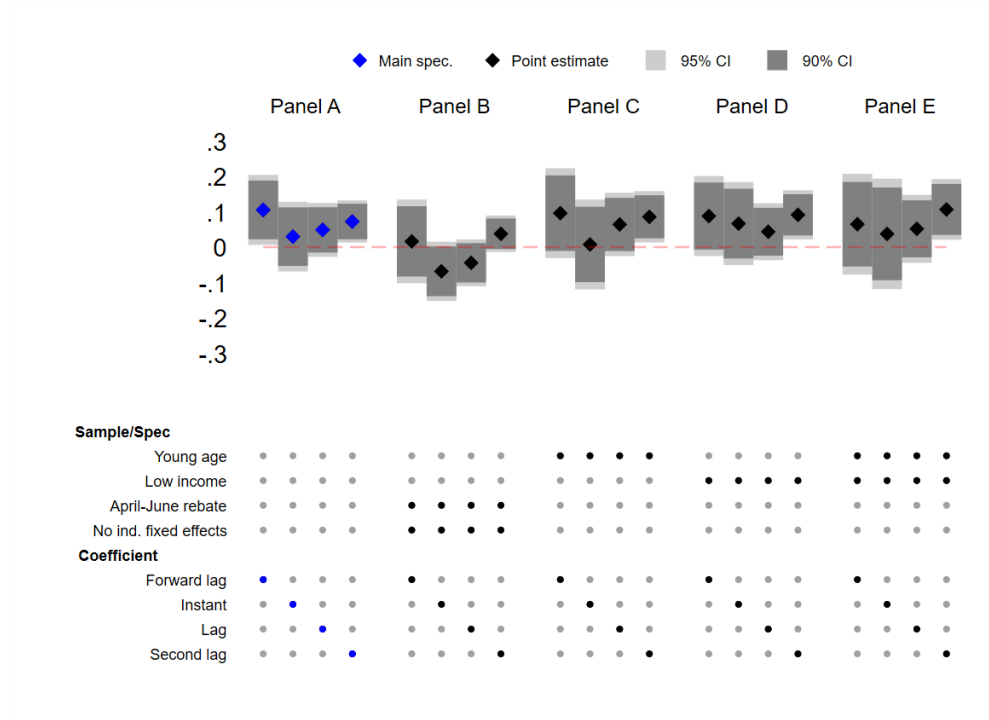
Effects of transfers on re-employment wages and duration of next job

Next, we consider the effect of transfers on re-employment wages. To best capture wages in the job that a worker enters we use as dependent variable the average wage in the occupation associated with a UE-transition. We classify occupations into 21 ‘major’ groups, as given by their two-digit disaggregation in the 2000 Census Occupational Classification. The results are given in figure 2.2a. Our preferred specification once again uses the full panel and individual fixed effects. The findings are consistent both with an increase in the reservation wage of job finders, or with a directed search model where the now less liquidity constrained individual applies for a higher wage job with lower job finding probability: the selected group that find a job in the same month as receiving a transfer tended to find work in an occupation associated with a higher wage. The effect appears to be fairly equally spread around the transfer timing, with anticipation effects and lagged effects being of the same magnitude as the contemporaneous effect. Although not clearly statistically significant, the effect is sizable; in the preferred specification the re-employment wage is 0.05-0.1 log points higher in proximity to a transfer month than otherwise. Interestingly, when focusing on the plausibly random sample and dropping the individual fixed effects the result changes sign, with receiving a transfer now being associated with a *lower* re-employment wage. When interpreting this coefficient it is important to notice that, while the timing of the rebate is mostly random, re-employment wages are only defined for job finders, which is a selected group. Yet, we cannot rationalize this finding by looking at how the effect of job finding affects different groups: we find that the negative effect of transfers on job finding is stronger for low-wage individuals, hence the group of job finders in a transfer month should be positively selected by income and hence, if anything, bias the results in a positive direction. We also do not find any heterogeneous effects; younger and lower-wage individuals see similar increases in their reemployment wage as other groups.

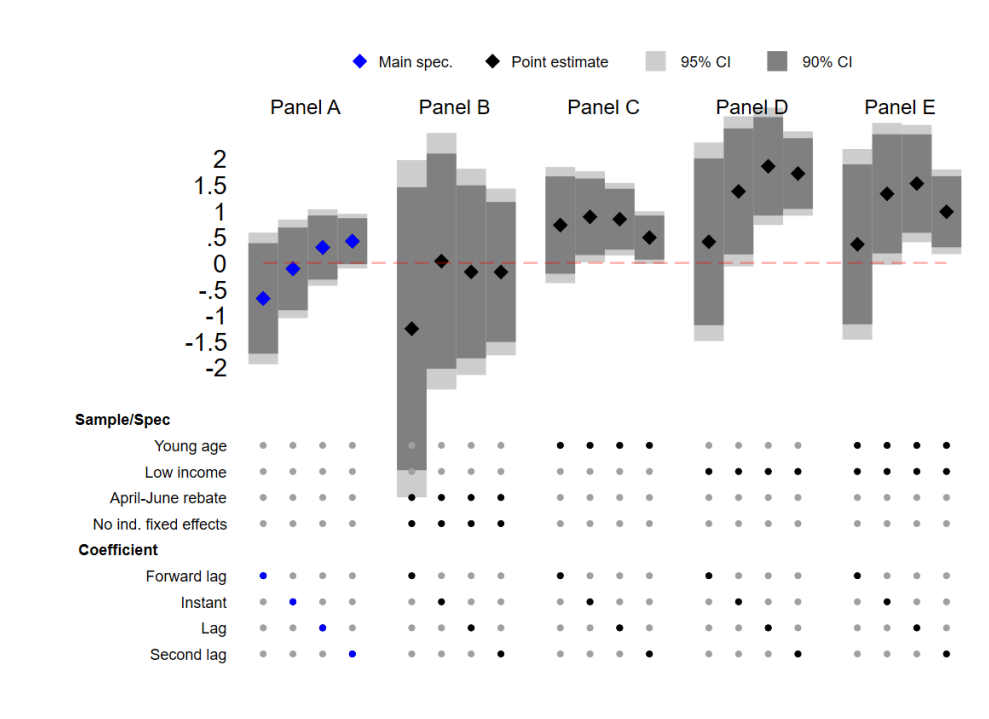
Since a successful job match is not only captured by the wage rate at the new job we also look at an alternative measure of match quality: duration of the next job. One would expect a better match to have a longer duration (see e.g. Jovanovic 1979). We thus also estimate equation 2.1 using duration (in months) of the new match as a dependent variable. The results are reported

Figure 2.2: Estimated effect of tax rebate on match quality of next job.

(a) Occupation-specific re-employment wage.



(b) Job duration (months).



Note:- Data from 2008 SIPP. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results control for month, months from interview and age fixed effects. Standard errors are clustered at the individual level. Regressions are weighted using the SIPP sampling weights.

in figure 2.2b. We cannot establish any significant effects in the main sample. However, for the young and lower-wage individuals we do find a significant and positive relationship: matches that were formed in close proximity to the transfer were associated with between 0.5-2 months longer duration of tenure.

Effect of transfers on job transitions

We also consider some auxiliary outcomes where liquidity may affect individuals' labour market outcomes. In particular, we consider the effect of wealth on career, or job, changes. Since changing careers is a risky decision – for example through layoff rates being higher for low-tenured workers (see e.g. Marinescu 2009) – we hypothesize that a wealth injection, insofar as it changes the risk preferences of individuals may affect this dimension. We consider two outcome variables where this effect may appear in the data: job destruction into unemployment and job-to-job moves. Both of these measures are readily available from the data. For moves into unemployment we separate the effects into moves to unemployment and moves into non-employment, as wealth may also affect the decision to take an unpaid leave or to retire, which should result into a move into non-employment. For job-to-job switches we follow the same methodology as Menzio, Telyukova, and Visschers (2016), who also calculate job-to-job transitions from SIPP data, and define it as any move from one employer to another without a gap in between.

We find no significant effect of the stimulus transfers on job-to-job transitions. If anything point estimates suggest a marginal negative effect, although these results are highly insignificant. For transitions to non- or unemployment we do find an effect, although this seems to be mainly driven by transitions to non-employment, suggesting that the effect on the decision to retire or take unpaid leave are stronger than that for transitions to a new career via an unemployment spell. The full results are found in the appendix; figure 2.A1 displays the results for job-to-job transitions and figure 2.A2 for job destruction.

Concluding remarks

To summarize this section, we find suggestive evidence that the liquidity injection of the 2008 stimulus payments affected job searchers in a consistent way to the predictions of the standard theoretical job search frameworks. Our finding that the job finding rate responded negatively to the transfers was qualitatively similar to other research using quasi-experimental variation in liquidity, notably Card et al. (2007), although our results were stronger in magnitude. We also find some evidence of an improvement in the match quality among those who found a new job in relation to their transfers, although these results are less robust to changes in the econometric specification and sampling. We also find that the effect sizes – both in terms of job finding and in terms of duration of the next job – were stronger for young individuals. This serves as further motivation for the analysis of intergenerational insurance and job search behaviour, as many young individuals still receive support from home at this point in life.

2.3 Intergenerational insurance and job search behaviour

In this section we use data from two of the US ‘National Surveys of Youth’ to investigate the effect of parental wealth on job search behaviour. In particular, we are interested in (i) whether richer background individuals are more likely to financial help from their parents when facing a negative labour market shock, (ii) whether parental income changes the job search behaviour of a child, and (iii) whether transfers from parents to adult children have the same effect on the child’s job search behaviour as the wealth effects estimated in the previous section. Before turning to the empirical analysis, we summarize the earlier literature on family insurance and job search.

2.3.1 Earlier literature

The role of family insurance for labour market outcomes

The role of family background has received some attention in studies of savings and job search over the life-cycle, although not as much as government-provided insurance (UI) or self-insurance through precautionary savings. Kaplan (2012) uses data from NLSY97 to reveal that young men often respond to adverse labour market shocks by moving home, and that those with opportunity to move home are less scarred by job losses early in their career. These findings are incorporated into a structural model where young agents choose their level of savings, whether to move home, and face stochastic job offers, which they choose whether to accept or to reject. The model can rationalize the empirical findings and also explain the low precautionary savings behaviour of young, low-skilled workers, as the family-provided insurance replaces the need for self-insurance through savings.

Unlike this paper and Kaplan (2012), the largest literature on the role of family insurance on labour supply has not considered intergenerational insurance from parent to child, but instead the role of spousal insurance. Blundell, Pistaferri, and Saporta-Eksten (2016) find that endogenous responses of spousal labour supply is an important factor that enables individuals to smooth consumption in the presence of earnings risk. Blundell, Pistaferri, and Saporta-Eksten (2018) and Wu and Krueger (2021) extend this framework to analyse the labour supply choices of families with children and the these interact with child-specific grants and progressive income taxation. While

these papers analyse spousal insurance through a labour supply response they do not use a search-and-matching framework and hence do not analyse the effects of spousal insurance on job search behaviour. There is a literature that also considers this dimension; Guler, Guvenen, and Violante (2012) analyse theoretically the job search choice of a couple, finding that, under the assumption of concave joint utility in income, joint search generates similar behaviour as an increase in wealth – on average unemployment spells tend to be longer as couples where one is employed can afford to be more selective in their search. In a calibrated version of the model the authors find that couples who search jointly therefore have between 1%-2% higher life-time income than single households. Flabbi and Mabili (2018) extends on this analysis to allow for fertility decision, on-the-job search, labour supply and gender heterogeneity. One of the aims of this section is to build towards a joint theory of parental insurance and job search behaviour, which would fill a gap in this literature.

Altruism and inter-vivos transfers: theory and previous empirical findings

Another contribution of this section is to shed more light on the motivations behind transfers from parents to children. For our application this will be an important factor when choosing whether to think of parental transfers as state-dependent insurance or as unconditional transfers, which will have implications on the search model's prediction of the effect of parental wealth on children's job search behaviour. This links us to another literature that investigates the motives behind parent to child transfers. Two competing theories are particularly relevant to our setting. If transfers are motivated by a 'joy of giving' assumption, they should be independent of the labour market status of the child, and hence parental wealth enters the child's decision in a similar way to own wealth. On the other hand, if transfers are described by an altruism model, they should act more as insurance, which for example may mean that the child only receives family support if they are unemployed. This would be the outcome of the standard static setting of the altruism model, as in Becker (1974), who find that altruistic parents choosing how much money to share with their child should transfer enough to equate the marginal utility of own consumption with the weighted marginal utility of consumption of the child. The weight on the child's marginal utility is determined by an 'altruism parameter', which measures how much the parent cares about their child's utility relative to their own. Three simple testable implications arise from this model: transfers should be (i) increasing in

the income of the parents, (ii) decreasing in the income of the child, and (iii) conditional on the parent giving a positive amount of money, a reallocation of wealth from child to parent should be exactly offset by an increase in the transfer. In a dynamic setting the problem becomes more complicated, as strategic interactions arise if there is lack of commitment from the child's side. In particular, a *samaritan's dilemma* may arise where the child consumes too much, and saves too little, in earlier periods as they trust that the altruism of their parents will guarantee help in later period. Internalizing this, parents will backload their transfers as much as possible, but may still give transfers in earlier period in the case where their child is severely liquidity constrained, and hence have a large marginal utility of consumption⁵.

Testing the appropriateness of the altruism model is cumbersome since data on transfers from parents to adult children are scarce. The 1988 and 2013 waves of the cross-generational survey 'Panel Study of Income Dynamics' (PSID) contains information on gifts, loans and support from parents in the preceding year and have been used extensively in research (Altonji, Hayashi, and Kotlikoff 1996, Altonji et al. 1997, Schoeni 1997, Wiemers and Park 2021). Another set of papers use data from the Health and Retirement Survey (HRS). Depending on the wave, the HRS asks respondents if they gave any transfers above \$500 to their children or parents, and if so how much these amounted to. The HRS has been used to study uneven transfer between siblings (McGarry and Schoeni 1995), investment in children's education (Brown, Karl Scholz, and Seshadri 2011), dynamic aspects of family transfers (McGarry 2016), and the relative sizes of inter-vivos transfers and bequests Barczyk, Kredler, and Fahle (2019). Finally, the 1997 NLSY survey asks respondents about financial transfers in the past year as well as co-residence. NLSY97 has, for example, been used to study the impact of parental transfers on part-time work during college (Kalenkoski and Pabilonia 2010). However, as far as we are aware, no papers have previously used the transfer information in the CNLSY79 dataset, which we believe have some useful unique properties, as we outline in more detail below.

5. See Barczyk and Kredler (2021) for an in-depth analysis of the altruism model in a dynamic setting.

2.3.2 Data description

We use data from two of the National Longitudinal Surveys of Youth: the 1979 sample (NLSY79) and the children and young adult sample (CNLSY79). NLSY79 is a longitudinal survey that in 1979 started interviewing a sample of 12,686 young individuals, born between 1957-1964, who have since been interviewed annually until 1994 and after that biennially. CNLSY79 is a follow-up survey that interviews all the biological children of the women in the NLSY79 sample starting from the age of 12, thus allowing for intergenerational comparisons. Excluding individuals born later than 1997 (so that each person is interviewed at least once after their 18th birthday) the CNLSY79 sample consists of 7,934 unique individuals, born between the years 1971-1997. Interviews occurred biennially starting (at earliest) in 1994 and with the latest round of interviews being in 2016. CNLSY79 contains detailed labour market information; each interview object is asked to list up to 5 jobs that they have held since the last interview date, along with information such as start/end date, occupation, wage etc. Unfortunately, since the second survey wave in 1996, respondents were not asked about whether they were actively searching for jobs in between employment spells, hence we cannot separate non-employment spells from unemployment spells in this data. Since the two surveys occur concurrently we can couple the labour market information of youths with detailed labour market information and other characteristics of their mothers, for whom we observe labour market status at a weekly frequency. We also observe some information about their father's labour market outcomes and other characteristics, as the mother answers a number of questions about their spouse such as how many weeks they worked last year, as well as their occupation and earnings.

Apart from labour market outcomes our main object of interest is inter-vivos or in-kind transfers from parents to their children. The data does contain some information on transfers from parent to child, although this is more scarce. To infer information on family transfers we make use of the responses to the following survey questions:

- During [last year], did anyone [(other than your spouse/partner)] pay part of your living expenses?
- Does this person live (here in this household/in your home)?

- What is this person's relationship to you?
- About how much of your living expenses did this person cover?

Since these questions refer to yearly averages we only have information on transfers for every second year, making it harder to interpret results for shorter unemployment spells. This caveat should be taken into account when considering the analysis to come.

Relative to previously used datasets the CNLSY79 survey has two advantages. First, the intergenerational structure means that there is detailed information about both the givers of transfers as well as the receivers, this is a feature that only the PSID has among the previously mentioned datasets, but here there is a limited panel dimension to the transfers as only two waves contains detailed transfer information. Second, the phrasing of the question, which refers to 'the share of living expenses paid for' rather than pure cash transfers can be a strength or a downside depending on the question of interest. Although being less precisely asked it is possible that many transfers from parents to children are in-kind, for example by buying things for ones child, rather than direct inter-vivos transfers. Hence, this question may pick up a broader range of transfers. Since the CNLSY survey also contains information on co-habitation, just as NLSY97, it is also possible to separately identify in-kind transfers through cohabitation, which has been deemed perhaps the most important form of in-kind transfers (Johnson 2013).

Another advantage of the NLSY surveys is that we can control for a very rich set of covariates; apart from information on labour market outcomes, education, race etc. of both parents and children the NLSY surveys also include tests on cognitive ability. The mother sample undertook the Armed Services Vocational Aptitude Battery tests, and in the youth sample each respondent undertook the Peabody Individual Achievement Test (PIAT) tests for maths and reading comprehension. In the estimations that follow we proxy the mother's cognitive ability by their approximate Armed Forces Qualifications Test (AFQT) percentile score, which is derived from their ASVAB test scores, and the youths' cognitive ability by the average of their maths and reading PIAT scores.

2.3.3 Results

The aim of this section is to investigate whether family background affects labour market outcomes either through an insurance effect or through a wealth mechanism. In particular, we investigate whether wealthier background individuals – in line with predictions from directed search models – apply for higher paying jobs with lower job finding probabilities. Armed with data from the cross-generational NLSY surveys we approach this question in three ways.

First, we investigate whether transfers from parents to children correlate with employment status and parental income as described by an altruism model, i.e. whether wealthier parents are more likely to pay for part of their children’s living expenses, and whether these transfers are larger when the child is unemployed.

Second, we investigate whether intergenerational insurance has implications for job search behaviour by estimating the effect of parental income on the job finding probability and re-employment wages of youths, controlling as best possible for observable characteristics. The rich set of covariates increases confidence that we can identify the effect of family income or wealth separately from other determinants of job search behaviour. However, as there is likely still some unobserved heterogeneity that both affects job search and is correlated with family income, we also use the panel structure of the data to exploit within-individual variation in parental income to investigate whether individuals change their job search behaviour based on time-specific family resources.

Third, we attempt to measure directly the impact of transfers from parent to child on job search behaviour. A reverse causality issue makes this estimation difficult: even if receiving transfers helps the receiver search for a higher-paying job, having lack of success in the labour market is likely associated with receiving more help from parents, hence disentangling the effect of transfers on job search behaviour from the reverse causality is difficult. We attempt to solve this issue by considering transfers in earlier periods and transfers to siblings, however, we cannot rule out that reverse causality cause bias in these settings as well.

Table 2.4: CNLSY79 summary statistics

	Mean	Min	Max	Individuals	N
Job finding rate	0.13	0	1	5,213	29,908
Mother's hh income	56,406.59	0	922,631	6,109	26,217
Mother's hh wealth	161,338	-2,489,667	5,526,252	5,339	12,874
Siblings	1.69	0	7	6,921	73,306
Age	26.92	18	47	6,921	73,306
Years observed	13.68	1	23	6,921	73,306

We make some restrictions on the sample. Since the object of interest is not a college decision, or indeed help from family while in college, we exclude individuals who are either in college, or are yet to complete their first college spell. A small number of individuals report having a college degree despite never having reported attending college. To avoid college transfers to these individuals we omit any person with a college degree below the age of 25 from the sample. We also discard individuals serving in the military, those under the age of 18, and those who are never observed in paid employment. Table 2.4 provides some descriptive statistics of the estimating sample at the annual level. Note that some information, such as the transfer information, is only available biennially, hence the actual estimating samples are often smaller than that in table 2.4.

Effect of employment status and parents' income on inter-vivos transfers

We first summarize how common it is for parents to pay part of their children's expenses, how transfers vary with age, and whether they depend on the income of the parents. The share of living expenses paid is reported as a multiple choice question with alternatives 'less than 1/4', 'At least 1/4 but less than 1/2', 'At least 1/2 but less than 3/4' and '3/4 or more'; we re-code these to numerical values as the middle points 12.5%, 37.5%, 62.5% and 87.5%. Those who reported not receiving any help for living expenditures, and those who do not report that it was either their mother or father that paid part of expenses get imputed a value of 0%.

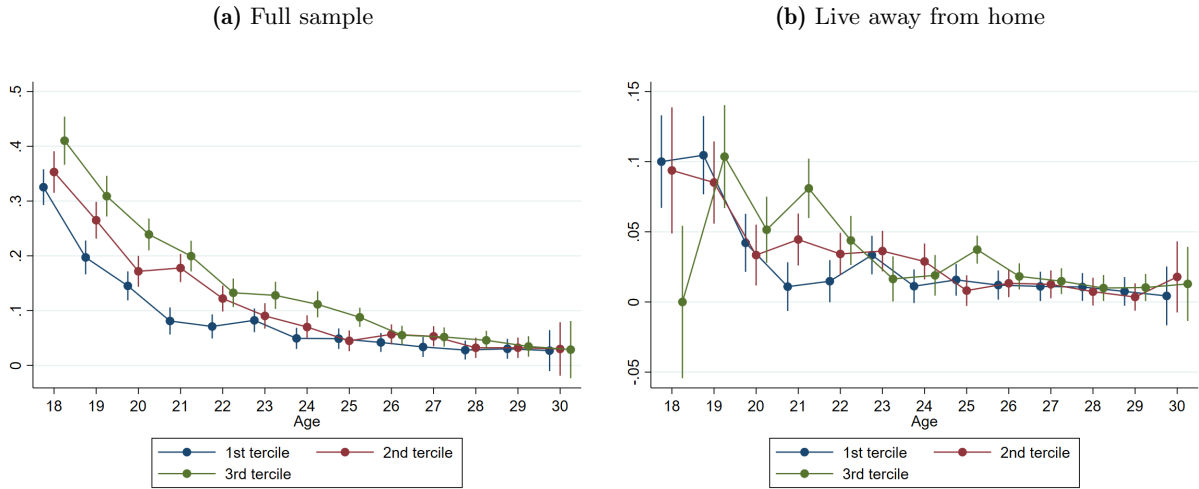
As a first visualization of the data, we plot the size of transfers by age, split by the income tercile of the mother's household, which is observed directly from the NLSY79 sample. We calculate the mother's mean household income across all waves that the respondents are observed above the age of 18, and split into three equal-sized bins. Figure 2.3a displays the results. It is clear that the share

of expenses paid is rapidly decreasing in age – on average 18 year olds have between 30%-40% of their living expenses paid by their parents, but this share declines steadily to around 5% at age 26, where it stabilizes until age 30. Up until age 25 richer-background individuals see a higher share of their living expenses paid, but after this age the shares are similar across groups. Although the intergenerational transfers seem to fade out at a relatively young age it is worthwhile to note that the findings of section 2.2 suggest that it is the young and low-wealth individuals that see the largest impact of liquidity on job search, hence the group for which we do observe intergenerational transfers is the one where we may expect such transfers to have the largest impact on the receivers' job search behaviour and career choice.

To investigate how much the transfers are accounted for by individuals living with their parents, which Kaplan (2012) notes to be an important factor in household insurance, we repeat the analysis excluding those who reported living in the same household as the person paying part of their living expenses, as well as household who (regardless of transfer status) live with their parents⁶. Figure 2.3b displays the results. It is clear that cohabitation explains a large share of inter-vivos transfers, especially for individuals aged between 18-20, where transfers to independent youths are only around 1/3 of the size relative to the overall average.

Next, we investigate whether the share of expenditure paid for by parents correlates with labour market indicators. We ask the following questions: (i) Are individuals more likely to receive transfers when they are unemployed? and (ii) Are parents more likely to give transfers when their income is higher? We choose to focus on parents' income rather than wealth since – despite wealth being the theoretically more relevant dimension – income is typically more precisely measured. Results using wealth instead of income are reported in appendix A. To address the two questions we run regressions with transfer size as the dependent variable. We use three different specifications, each using different variation in the data. First is an OLS regression, which uses both cross-sectional and within-individual variation. Here we control for a battery of household characteristics, in an attempt to avoid omitted variable bias if household characteristics determine transfer sizes in a way that is correlated to, but not caused by, family income or employment status. We thus

6. We observe whether youths cohabit with their parents at the interview date, which is in the calendar year after which the transfer questions refer to, so it is possible that some youths with zero transfer reported remain in this sample despite living at home in the relevant period, if they only recently moved out.

Figure 2.3: Share of living expenses paid by age and tercile of mother's household income.

Notes: Data from NLSY79 and CNLSY79. Mother's household income terciles refers to the tercile bin of the mother's average household income across all waves in the CNLSY79.

control for the education level of the mother and youth (high school dropout, high-school graduate, some college and college graduate), race of the youth (white, hispanic or black), quadratics in cognitive test scores of mothers and youths, age fixed effects, and gender. Nonetheless, there may still be unobserved characteristics that create bias in the estimates. For this reason we also run specifications where we condition on mother, or individual level, fixed effects. Using mother fixed effects means that we do not consider between family variation, but only time-varying and *within-family* variation, i.e. differences in transfers to siblings depending on their income or employment status. Individual-level effects only consider within-individual, time-varying variation. Letting (2.2) be the cross-sectional regression, (2.3) be the family fixed effects specification and (2.4) be the individual fixed-effects specification we can write the models as

$$\text{Exp. Share}_{i,t} = \alpha + \gamma^Y \times \text{Emp. share}_{i,t} + \gamma^M \times \log \text{Inc}_{m(i),t} + \eta X_i + \delta_t + \epsilon_{i,t} \quad (2.2)$$

$$\text{Exp. Share}_{i,t} = \alpha_{m(i)} + \gamma^Y \times \text{Emp. share}_{i,t} + \gamma^M \times \log \text{Inc}_{m(i),t} + \delta_t + \epsilon_{i,t} \quad (2.3)$$

$$\text{Exp. Share}_{i,t} = \alpha_i + \gamma^Y \times \text{Emp. share}_{i,t} + \gamma^M \times \log \text{Inc}_{m(i),t} + \delta_t + \epsilon_{i,t}, \quad (2.4)$$

Table 2.5: Regressions of annual employment share of youth and income of mother's household on the share of child's living expenses paid for in a year.

	Full Sample			Live away from home		
	(1)	(2)	(3)	(4)	(5)	(6)
Youth employment share	-0.0580*** (0.005)	-0.0515*** (0.006)	-0.0434*** (0.007)	-0.0188*** (0.003)	-0.0170*** (0.004)	-0.0139*** (0.005)
Log(Mother's hh income)	0.0100*** (0.002)	0.00601* (0.003)	0.00721** (0.003)	0.00371*** (0.001)	0.00226 (0.002)	0.00205 (0.002)
<i>N</i>	14378	14366	13469	9806	9576	8651
<i>R</i> ²	0.116	0.340	0.484	0.032	0.275	0.433
Individual fixed effects	No	No	Yes	No	No	Yes
Mother fixed effects	No	Yes	No	No	Yes	No
Age & year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	No	No	Yes	No	No

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses are robust for heteroskedasticity and clustered at the individual level. Time-invariant controls: quadratics in ability of youth and mother, education of youth and mother (four groups), race and gender of youth. Age fixed effects refer to age of both mother and youth.

where i denotes an individual, t a year, $\text{Emp. share}_{i,t}$ the fraction of the year that the individual was employed, $\log \text{Inc}_{M_{i,t}}$ the log of mother's annual household income, and $X_{i,t}$ is the vector of control variables. The coefficients of interest are γ^Y and γ^M , which will inform us of how transfer sizes correlate with the employment status of the youth and the income of its parents.

Table 2.5 reports the results. Columns 1 to 3 uses the full sample, including individuals who live at home, whereas columns 4 to 6 only use the sample of individuals who live away from home. Both the cross-sectional and time variation imply an effect of the youths employment status on transfers. The results indicate that a youth who spends the entire year unemployed receives 6 percentage points higher share of living expenses paid for in the cross section and 1-2 percentage points more when using either family-specific or individual-specific variation. There is also evidence that richer-background youths are more likely to receive transfers in the cross-section, although this correlation is not statistically significant for the subsample that lives away from home. Qualitatively, these results support an altruism model, as transfers depend positively on the need of the receiver. Whether the altruism effect is quantitatively important is a more difficult question, and may benefit from placing these estimates in a structural model.

To put these results in perspective, we compare them to the results of McGarry (2016), who also investigates the dynamic aspects of inter-vivos transfers, but using data from the Health and Retirement Survey. The finding in McGarry (2016) that relates most closely to ours is the finding that a \$10,000 increase in the income of the child is associated with a one percentage point fall in the probability of receiving a transfer. In appendix 2.5.2, we run the same regression as McGarry (2016) and find that this results holds up almost exactly using the CNLSY dataset. That this result is so similar using two distinct datasets adds confidence to the accuracy of the estimate of this elasticity, and suggest that the transfer information in the CNLSY79 sample is roughly consistent with that in the HRS.

Effect of parental income on job search behaviour

Next we turn to the effects of family background and transfers on job search behaviour. The goal is to study whether individuals with higher-income parents, who should receive better ‘family insurance’ following a job loss, have lower job finding rates and higher re-employment wages, as a directed search framework would predict. To do so we make use of the detailed employment history information in the CNLSY79 to construct monthly job finding rates as well as re-employment wages, which are defined as the occupation-specific wage rate at the job associated with a job finding. Since information on the mother’s income and transfers are at a biennial frequency we aggregate job finding rates and re-employment rates to their annual averages. Using these as dependent variables we estimate models similar to 2.2 and 2.4, although without the youth’s employment share as an independent variable. The regressor of interest is the log of the mother’s contemporaneous household income.

Table 2.6 reports the results. We find that the job finding hazard goes against the directed search intuition; both in the OLS and fixed effects specifications there is a positive correlation between family income and the job finding rate, although only in the OLS specification is this relationship statistically significant. Re-employment wages, on the other hand, go in the expected direction,

Table 2.6: Regressions of income of mother's household on youth's annual average job finding rate and log re-employment wage.

	Job finding rate		Log(Re-employment wage)	
	(1)	(2)	(3)	(4)
Log(Mother's hh income)	0.00924*** (0.002)	0.000976 (0.003)	0.0549*** (0.011)	0.0132 (0.029)
Individual fixed effects	No	Yes	No	Yes
Age controls	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	No	Yes	No
N	9539	8657	3374	1540
R^2	0.030	0.382	0.090	0.653

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses are robust for heteroskedasticity and clustered at the individual level. Time-invariant controls: quadratics in ability of youth and mother, education of youth and mother (four groups), race and gender of youth. Age fixed effects refer to age of both mother and youth.

with higher family income being associated with a higher re-employment wage. We also consider regressions where we compare the role of parental income to other forms of self-insurance that have been emphasized in the literature, including spousal income and credit card debt. These results are reported in appendix C.

We conclude that, even after controlling for a rich set of covariates, richer-background individuals tend to have higher job finding rates and higher re-employment wages. That these two objects move together is not in itself a surprising finding; it is well-established in the literature that individual job search behaviour exhibits *negative duration dependence*, i.e. a negative correlation between unemployment duration and re-employment wages. Our results contributes to the understanding of this finding by noting that there is one covariate that predicts which individuals fall into the high wage, high job-finding probability group – those with richer parents. A natural interpretation for this finding is that the effect of richer parents on job search behaviour is two-fold: a wealth (or insurance) effect contributes to a lower job finding rates and higher re-employment wages, in line with the literature on severance pay and unemployment insurance, while perhaps a network effect, or some unobserved inheritance effect explains the higher job finding rate, counteracting the wealth/insurance effect.

To remove the bias from these types of unobservable household characteristics, we would ideally want to study a situation where the income of the parents falls for an exogenous, and unpredictable, reason. To this end we make use of the monthly labour market information on both the mother and the child to estimate whether a change in the mother's income is associated with a changes in the job search behaviour of the child. As a wealth 'shock' on the mother side we use a transition from employment to unemployment (an EU-transition). We cannot establish that such a transition is unexpected or unwanted, but constraining ourselves to EU-transitions at least means that the mother reported searching for a job after the job loss, which should mean that retirement decisions or a choice of taking unpaid leave, both of which could be associated with a comfortable financial situation, are not included. Thus, an EU-transition on the mother side provides a suitable proxy for a adverse liquidity event in the parental generation. In the full sample we observe 2,291 EU-transitions for mothers. To estimate the effect of such an event on the job search behaviour of the child we estimate the same model as in section 2.2 (equation 2.1), allowing for one forward lag and three lags as well as the contemporaneous effect of the mother's EU-transition. As dependent variables we use both a dummy for job finding and the log of the occupation-specific mean wage associated to the job find. A downside of the detailed employment history measures is that we only observe the monthly employment status of the mother – but not of the father. For this reason we also limit our analysis to the subsample of individuals who report either having a deceased father or who report that they have no contact with their father⁷. Around 9% of the sample fall into this subcategory, which is denoted with an 'absent father' marker in the results figures below. As in section 2.2 we run both a specification that includes individual, month and year fixed-effects as well as one without individual fixed effects that instead controls for a host of individual characteristics (age of mother and child, cognitive ability of mother/child, education and income of mother, own education and income, gender, race). We also follow exactly the methodology of section 2.2 and estimate the effects focusing on a 'low-income' sample, which is defined as having a below-median individual fixed effects in a standard mincer equation controlling for age and month dummies.

7. Specifically, those who report that they never see their father in response to the survey question: "About how often do you see your father?"

The results are reported in figure 2.4, where panels D-F report the results for the subset with absent fathers. In both the fixed effects (figure 2.4a, panel A) and OLS (2.4a, panel B) specification we observe a spike in the child's job finding rate of approximately 2 percentage points in the same month the mother's EU transition. While this is in line with the theoretical prediction the effect disappears immediately after the first month, which casts some doubt on the robustness of the result – we would expect a persistent effect, as the mother's job loss should be associated with a persistence loss in family income rather than a sudden negative wealth shock. We do not find evidence of a stronger effect for low-wage individuals (figure 2.4a, panel C). Focusing on the subsample without contact with their fathers the effects are much larger, albeit not statistically significant except for the contemporaneous effect in the specification without individual fixed effects. For this subsample all specifications suggest a contemporaneous effect of an increase in the job finding rate of around five percentage points, and that this effects stays at this level even the month after the mother's EU-transition. The baseline job finding rate is very similar across the two samples, so this effect is larger both in absolute as well as relative terms.

In terms of reemployment wages we do not find clear evidence that the uptick in the job finding rate was associated with individuals sorting into occupations associated with lower average wages. These results are reported in figure 2.4b, and although the majority of the points estimates are negative many are not, and none of the results are statistically significant. Note that the confidence intervals are typically rather large, spanning around 0.1 log points in the full sample and at least 0.2 log points in the subsample with absent fathers, hence we cannot rule out that an economically important effect exists that we cannot pick up due to lack of power in the estimation.

In a final analysis, we look at the effect of the mother's job loss on the probability of the child moving up or down the 'occupational ladder'. The reason for considering this dimension is that a higher propensity to move to a lower-wage occupation in recession has been linked to much of the scarring effects of recessions (Huckfeldt 2022), hence this dimension provides important insight into the role of the scarring effects of loss of intergenerational insurance. Thus, we estimate equation 2.1 using two alternative dependent variables. First is a dummy that takes on value one if the individual finds a new job in a lower-paying occupation, and zero if they find a new job in the same occupation as previously, or in a higher-paying one. The results of this regression are reported

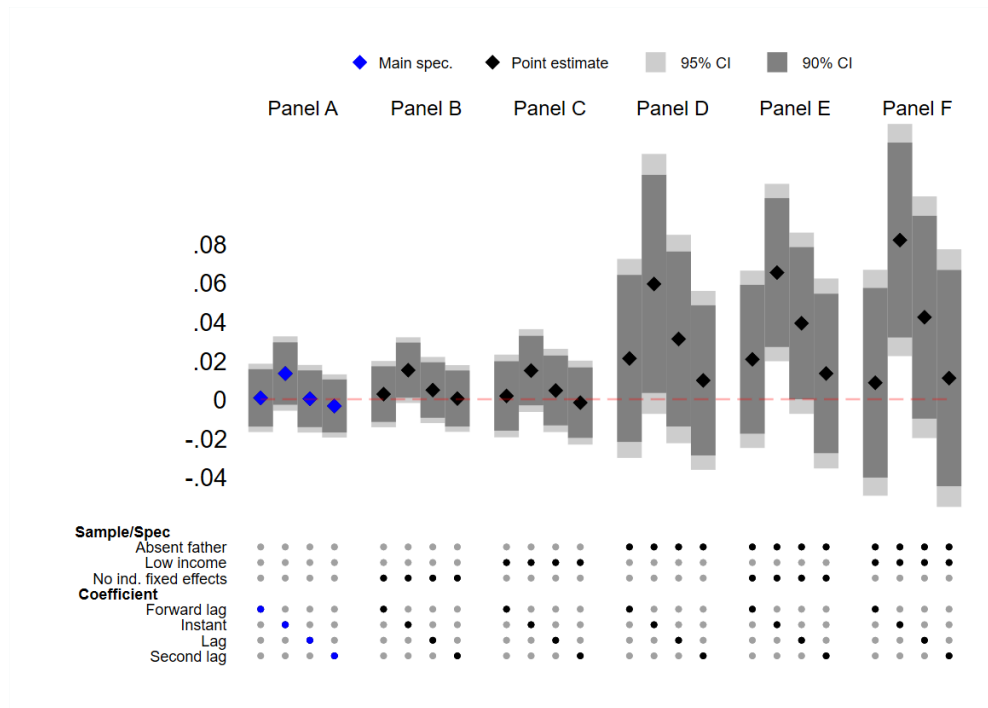
in figure 2.5a. As the theory would predict, we do find a positive effect. In proximity to a job loss of the mother, and conditional on the youth finding a new job, the new job is more likely to be in a lower-ranked occupation. This effect is once again stronger for individuals with absent fathers. Figure 2.5b reports the result for the probability of switching to a higher-ranked occupation. Here the findings are less clear but most results, in particular for those with absent fathers, indicate a negative effect, as theory would predict.

Effect of transfers on labour market outcomes

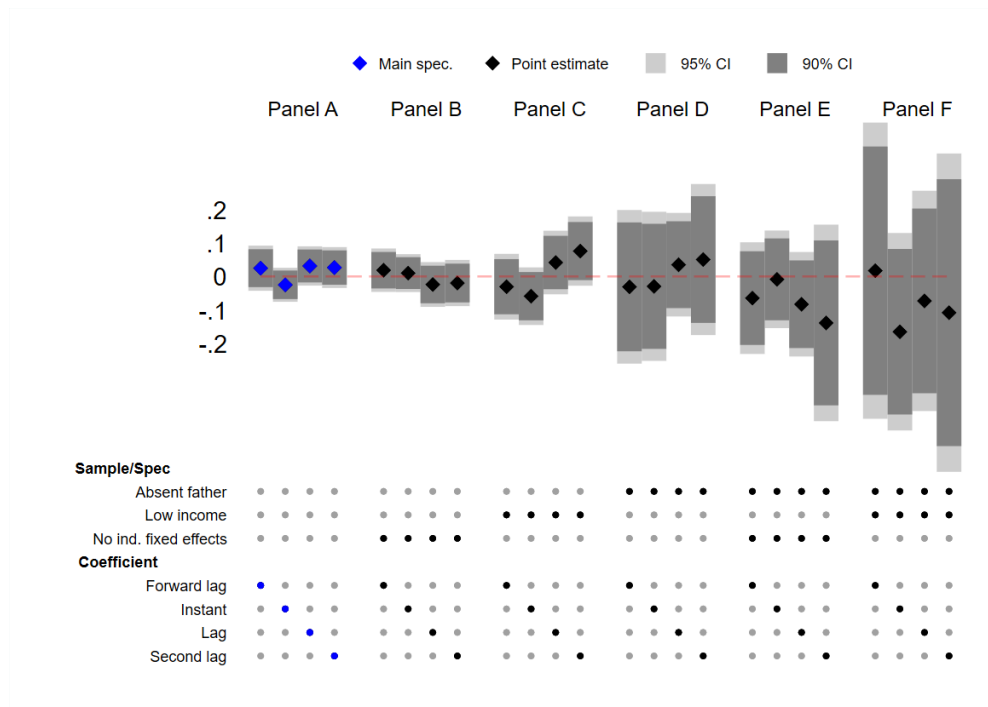
In this section we investigate the impact of transfers from parents to children on the child's job search behaviour. Our goal is to estimate directly the causal effect of inter-vivos transfers on job search behaviour. However, an endogeneity issue makes this measurement difficult: there is likely reverse causality, with those who are struggling to find a job being more likely to receive support from home, which means that estimates are downward biased. We consider two instrumental variables to deal with this endogeneity; lagged transfers and transfers to siblings, but ultimately conclude that the exclusion restriction is unlikely to hold, hence IV estimates will be biased. The reason for believing that the exclusion restriction does not hold is that, although the instruments are highly significant predictors of the endogenous independent variable, the correlation in the first-stage regression is typically small. Furthermore, regressing the outcomes of interest directly on the earlier transfers or sibling transfers provides estimates of similar magnitude to regressions on direct transfers. Taken together this implies that, if the exclusion restriction holds and the only effect of earlier transfers or sibling transfers on the outcome variable is through their effect on current transfer, the effect sizes must be enormous, which is indeed what the IV regression results show.

Figure 2.4: Estimated effect of mother EU transition on child's job finding rate and reemployment wage.

(a) Job finding rate



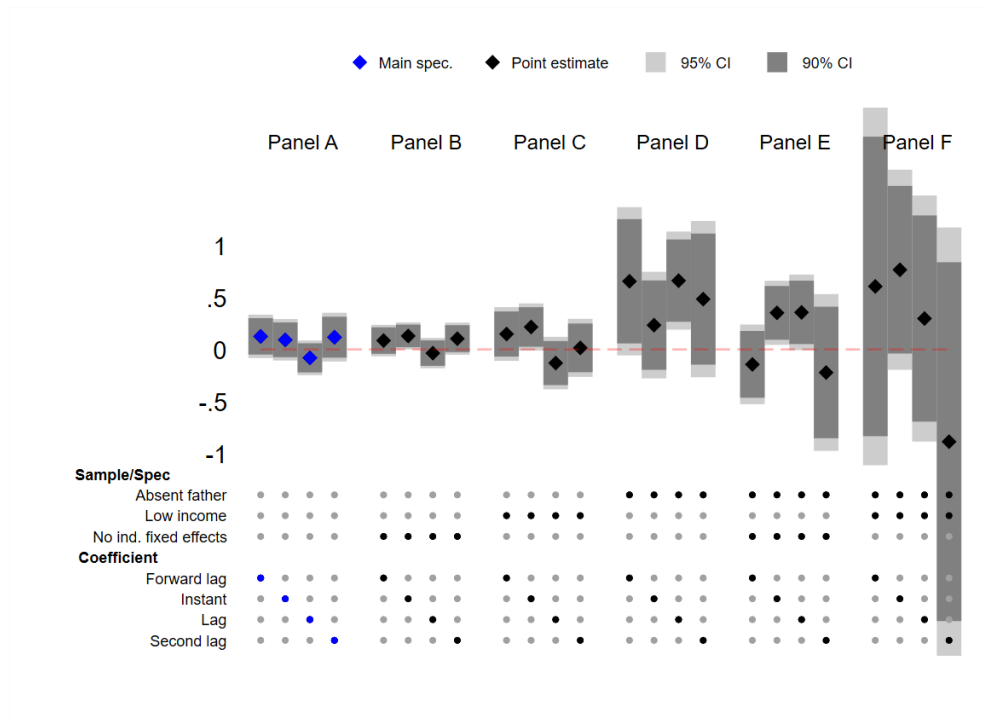
(b) Occupation specific reemployment wage



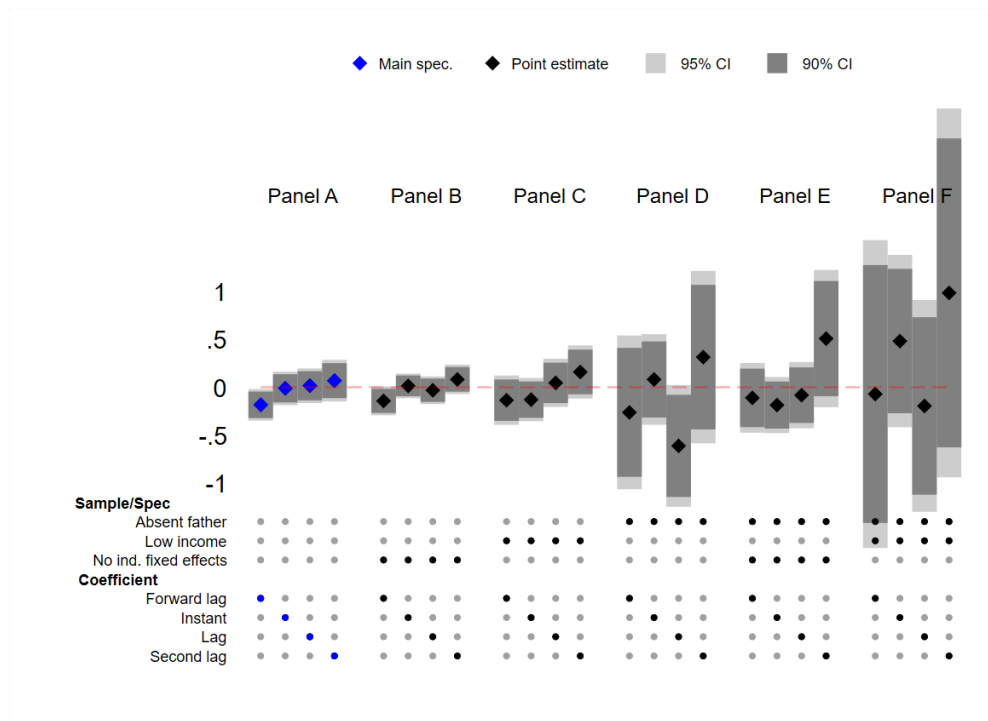
Note:- Data from NLSY79 and CNLSY79. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results with individual fixed effects control for month, age, and mother age fixed effects. Results without individual fixed effects further controls for mother and child education level fixed effects, quadratics in cognitive ability of mother and child, race, and gender. Standard errors are clustered at the individual level.

Figure 2.5: Estimated effect of mother EU transition on child’s job finding rate and reemployment wage.

(a) Prob. of lower ranked occupation



(b) Prob. of higher ranked occupation



Note:- Data from NLSY79 and CNLSY79. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results with individual fixed effects control for month, age, and mother age fixed effects. Results without individual fixed effects further controls for mother and child education level fixed effects, quadratics in cognitive ability of mother and child, race, and gender. Standard errors are clustered at the individual level.

Since we deem the exclusion restriction unlikely to hold we do not report any results from the IV regressions. Instead, table 2.7 shows the results from regressions on the outcome variables (job finding in columns 1-3 and re-employment wage in columns 4-6), using current transfer, previous transfer and sibling transfers as independent variables in turn (along with the standard controls). The results suggest that receiving transfers, in the current period or in a previous one, as well as having a sibling receive transfers, is associated with a lower job finding rate and lower re-employment wages on average.

We offer two potential explanations for this result. First, it may be the case that the reverse causality issue is not only a problem for current transfers, but also for the other independent variables. For earlier transfers, the negative shock that caused the individual to receive a transfer in the past may have lingering effects that lowers their job finding rate and re-employment wages even in later years. For sibling transfers there may be local labour market shocks that had negative effects on job finding and re-employment wages for all siblings, which means that the whole sibship is more likely to receive support from their parents. Second, it may be the case that the ‘moral hazard’ effect of family insurance dominates the liquidity effect: perhaps parents that pay large shares of their children’s living expenses cause a drop in search intensity among their children, which could explain both lower job finding rates and re-employment wages. Trying to disentangle these potential forces is beyond the scope of this paper, but we hope that this result can be a starting point for more research into the effect of family transfers on children’s job search behaviour.

2.4 Conclusion

The results in this paper add to previous findings of the importance of wealth effects in studies of job search behaviour. The analysis of the job search response to the stimulus payments in 2008 confirms the empirical findings from previous literature of a negative response of the job finding rate to an addition in liquidity. The analysis of the heterogeneous response of the liquidity shock also confirm a key theoretical prediction of standard job search models – that the response is stronger for individuals closer to their borrowing constraint, which we proxy by being younger and lower-wage. Whether the effect on job search was due to a shift in the tradeoff between applying

Table 2.7: Estimates of effects of own transfers, previous transfers and sibling transfers on youth's annual average job finding rate and log re-employment wage.

	Job finding rate			Log(Re-employment wage)		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer	-0.0395*** (0.008)			-0.105*** (0.029)		
Earlier transfer		-0.00413 (0.004)			-0.0385** (0.015)	
Sibling transfer			-0.00737** (0.003)			-0.0466*** (0.014)
Individual fixed effects	No	No	No	No	No	No
Age controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	Yes	Yes	Yes	Yes	Yes
N	7974	26667	23040	3310	8527	7174
R^2	0.049	0.040	0.040	0.157	0.146	0.151

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses are robust for heteroskedasticity and clustered at the individual level. Time-invariant controls: quadratics in ability of youth and mother, education of youth and mother (four groups), race and gender of youth. Age fixed effects refer to age of both mother and youth.

for jobs with lower job finding probability but higher match quality, or whether it was due to a fall in search effort is empirically uncertain; our points estimates suggest that those who found new work in proximity to their stimulus transfer did so in higher paying occupations and had longer tenure with their new employer, although these results are not statistically significant.

We also take this finding to a new setting, by thinking about how the effects of wealth on job search and career choice can generalize to *parental* wealth. How to model the impact of parental wealth on the child's job search behaviour is theoretically ambiguous; if wealth is fully dynastic the effect of having wealthier parents should have the same implications as a pure wealth transfer – such as the 2008 stimulus payments – but if wealth transfers from parents to children are not unconditional but rather dependent on the need of the child, the wealth of parents are better analyzed as an insurance policy – such as unemployment insurance – which is known to have distinct theoretical implications on an individual's job search. The empirical findings of the paper shed some light on this ambiguity with two findings: (i) transfers from parents to children are common up to the age of 25, although more than half of these transfers are accounted for by children living at their parent's home, and (ii) the bulk of transfers are independent of the child's employment status, but a significant share of the variation in transfer size does depend on the labour market status and earnings of both the parents and the child in the expected direction; with transfers being negatively correlated to the child's employment status and positively correlated with the parents' income.

Finally, the paper investigates the connection between transfers, wealth and job search behaviour. We document three empirical facts: (i) both the job finding rate and reemployment wages are positively correlated with parental income, even after controlling for a rich set of household characteristics, (ii) following a job loss of the mother, there is an increase in the job finding rate of the child, who is also more likely to find a job in an occupation with a lower wage rank, and this effect is particularly strong for those who either have deceased or absent fathers, and (iii) receiving transfers is negatively correlated with job finding and reemployment wages,

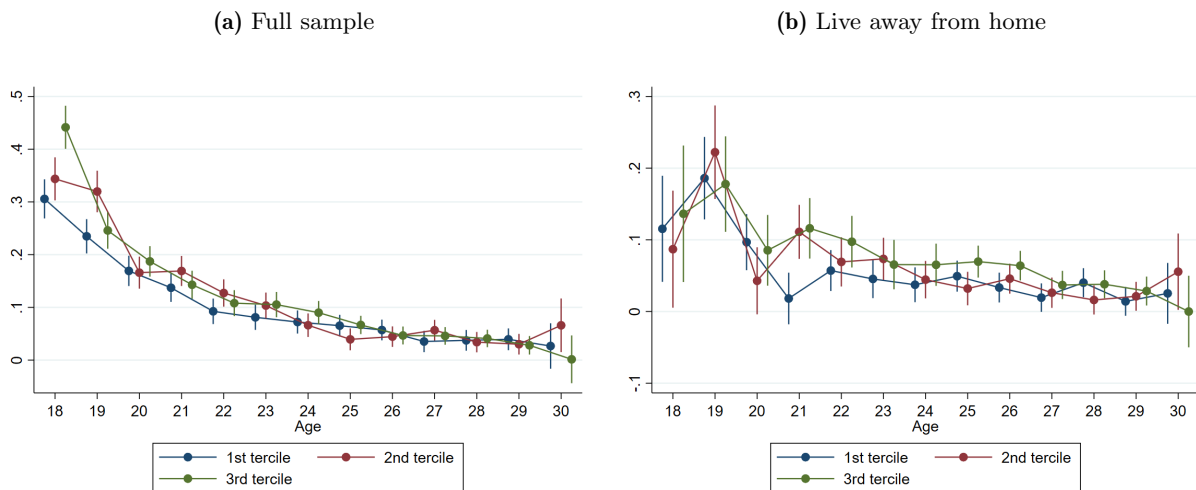
The findings here open up interesting avenues for further research. In particular, they highlight the importance of a study of interactions between parental transfers and common labour market policies. Policies such as unemployment insurance, severance pay, and stimulus payments may affect individuals heterogeneously depending on family wealth, and may also crowd out parental transfers. A model of the labour market that takes into account parental transfers, and matches the empirical findings documented in this paper, should therefore be able to shed light on potential policy improvements in these dimensions.

2.5 Appendix

2.5.1 Effect of family wealth on transfers and job search behaviour

This appendix repeats the analysis of sections 2.3.3 and 2.3.3, but uses the mother's household wealth, rather than income, as a the key independent variable. To measure wealth we use the '*family net wealth*' variable in NLSY79, which is created by summing all asset values and subtracting all debts. Asset information in the NLSY79 is only collected at every second interview, hence this information is only available for every fourth year in the sample; for this reason sample sizes will be smaller, and in particular fixed-effect regressions, will suffer from less identifying variation. Since net wealth can take negative values a log transformation is not possible, hence we instead use the the household's percentile rank in the wealth distribution to reduce the impact of outliers in the data.

Figure 2.A1: Share of living expenses paid by age and tercile of mother's household wealth.



Notes: Data from NLSY79 and CNLSY79. Mother's household wealth terciles refers to the tercile bin of the mother's average household wealth across all waves in the CNLSY79.

Table 2.A1: Regressions of annual employment share of youth and wealth of mother's household on the share of child's living expenses paid for in a year.

	Full Sample			Live away from home		
	(1)	(2)	(3)	(4)	(5)	(6)
Youth employment share	-0.0502*** (0.007)	-0.0389*** (0.009)	-0.0287** (0.012)	-0.00905** (0.004)	-0.0121* (0.007)	-0.00392 (0.009)
Mother's hh wealth percentile	-0.00426 (0.009)	0.0262 (0.024)	0.0249 (0.024)	0.00429 (0.005)	0.0147 (0.017)	0.0317* (0.018)
<i>N</i>	6541	6010	4382	4431	3779	2478
<i>R</i> ²	0.112	0.408	0.573	0.029	0.372	0.540
Individual fixed effects	No	No	Yes	No	No	Yes
Mother fixed effects	No	Yes	No	No	Yes	No
Age & year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	No	No	Yes	No	No

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses are robust for heteroskedasticity and clustered at the individual level. Time-invariant controls: quadratics in ability of youth and mother, education of youth and mother (four groups), race and gender of youth. Age fixed effects refer to age of both mother and youth.

2.5.2 Comparison to the HRS dataset

This appendix compares our results to those of McGarry (2016), who also studies the dynamic aspects of transfers but using data from the Health and Retirement Survey. To do so we replicate as closely as possible the regression that forms table 6 in McGarry (2016). Here the dependent variable is a dummy that takes value one if the child receives a transfer and zero otherwise. The key independent variable is the annual income of the child and a number of additional control variables are included such as the child's age, years of schooling, marital status, home ownership status, number of children, gender, race, and number of siblings. Three estimation strategies are considered: pooled OLS, as well as specifications with family fixed effects, and child fixed effects. The CNLSY data does not include the exact same set of covariates, but does allow for the estimation of a reasonably similar regression, the results of which are reported in table 2.A1. All-in-all results are very similar, with the only significant difference between the estimates being the sign on the gender dummy which is reversed in our estimates – with males receiving larger, rather than smaller, transfers on average.

Table 2.A1: Comparison to results in McGarry (2016), table 6.

	OLS		Family FE		Child FE	
	CNLSY79	McGarry	CNLSY79	McGarry	CNLSY79	McGarry
Child Income (\$10,000s)	-0.0150*** (0.001)	-0.013*** (0.001)	-0.0155*** (0.001)	-0.014*** (0.001)	-0.0127*** (0.002)	-0.009*** (0.001)
Age	-0.0122*** (0.001)	-0.004*** (0.000)	-0.0101*** (0.000)	-0.004*** (0.000)	-0.00926*** (0.001)	-0.007*** (0.004)
Male	0.0110** (0.005)	-0.011*** (0.004)	0.0111 (0.007)	-0.017*** (0.003)		
Nonwhite	-0.0114** (0.005)	-0.018*** (0.005)				
Siblings	-0.0118*** (0.002)	-0.020*** (0.001)				
Mean dependent variable	0.123	0.139	0.123	0.139	0.123	0.139
R^2	0.069	0.089	0.332	0.30	0.482	0.39

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses. McGarry's regression controls for a number of additional covariates, see McGarry (2016) for details.

2.5.3 Comparing mother's household income to other forms of self- or family insurance.

This appendix compares the results on the effect of the mother's household income on job search behaviour to other forms of self-insurance that have been emphasized as important in the literature: credit card debt and spousal income. The CNLSY contains some – albeit limited – information on wealth through questions about the respondent's credit card debt and, in case they own their residence, the house value and mortgage debt. Following the findings of Herkenhoff (2019) of the importance of access to credit card debt we find this dimension particularly interesting, although we cannot observe access to credit, merely the debt level of the individual. Still, we hypothesize that having credit card debt is associated with having low liquid wealth and hence being close to ones borrowing constraint. We also observe spousal income, which has been emphasized as an important insurance vessel in job search, although it has been noted that the correlation seemingly moves differently for men and women, with spousal income being positively correlated with the job finding hazard for men and negatively for women (Lentz and Tranæs 2005b).

Since we want to include non-married individuals and individuals with no credit card debt in the analysis, we choose a non-parametric specification. We construct four bins for each outcome variable. For credit card debt these are 'no debt', '1st debt tercile', '2nd debt tercile' and '3rd debt tercile', where debt terciles are defined within the group with positive debt. Similarly spusal income is sorted into 'unmarried' as well as three terciles, and parental income is sorted into quartiles. Using these as binary dependent variables, along with the standard set of controls, we estimate regressions on the job finding rate and re-employment wages. Since heterogeneous effects by gender has been emphasized as important, especially regarding the effect of spousal income, we estimate model separately for men and women. The results are reported in table 2.A1. Our main result, regarding the job finding rate, is robust for controlling for these alternative insurance mechanisms: for both men and women a higher income quartile of the mother's household tends to be associated with higher job finding rates. However, we cannot distinguish any clear results for the reemployment wages in this setting, which are insignificantly different from zero for both men and women. As for spousal income, we confirm the finding of Lentz and Tranæs (2005b); for men, having a richer spouse is associated with higher job finding rates, whereas the opposite is true for

women. Finally, in terms of credit card debt the evidence is mixed: for men, having credit card debt tends to be associated with both higher job finding rates and reemployment wages, while for women having debt in the first tercile is associated with significantly lower reemployment wage than having no debt at all.

Table 2.A1: Estimated effect of mother's household income, relative to other forms of self- or family insurance.

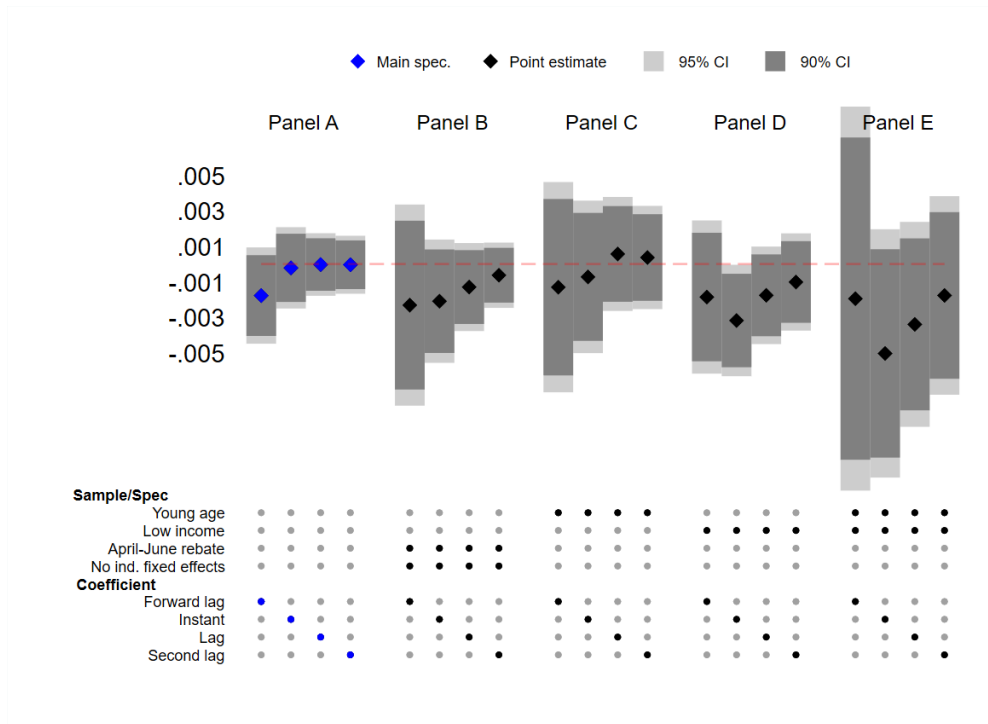
	Men		Women	
	Job find	Log(Reemp. wage)	Job Find	Log(Reemp. wage)
1st debt tercile	0.0644** (0.028)	0.0111 (0.086)	0.0274 (0.020)	-0.131* (0.075)
2nd debt tercile	0.0666** (0.032)	0.164* (0.093)	0.0267 (0.021)	-0.0746 (0.073)
3rd debt tercile	0.0346 (0.040)	0.0778 (0.092)	0.0234 (0.025)	0.0338 (0.084)
2nd mother's income quartile	0.0345* (0.019)	-0.0266 (0.097)	0.0195 (0.016)	-0.0911 (0.101)
3rd mother's income quartile	0.0427* (0.023)	-0.0289 (0.094)	0.0446** (0.019)	-0.104 (0.094)
4th mother's income quartile	0.0418 (0.026)	0.0417 (0.099)	0.0356* (0.020)	0.0596 (0.095)
1st spousal income tercile	0.0181 (0.025)	0.0970 (0.077)	-0.00825 (0.025)	-0.111 (0.090)
2nd spousal income tercile	0.0605* (0.035)	0.0265 (0.089)	-0.0170 (0.023)	-0.0754 (0.093)
3rd spousal income tercile	0.0696* (0.040)	0.216*** (0.071)	-0.0838*** (0.020)	-0.00153 (0.066)
Individual fixed effects	No	No	No	No
Age controls	Yes	Yes	Yes	Yes
Time-invariant controls	Yes	Yes	Yes	Yes
N	1279	432	1476	487
R^2	0.092	0.141	0.055	0.179

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors in parentheses are robust for heteroskedasticity and clustered at the individual level. Omitted category is unmarried individuals from lowest family income quartile with no credit card debt. Time-invariant controls: quadratics in ability of youth and mother, education of youth and mother (four groups), race and gender of youth. Age fixed effects refer to age of both mother and youth.

2.5.4 Additional figures & tables

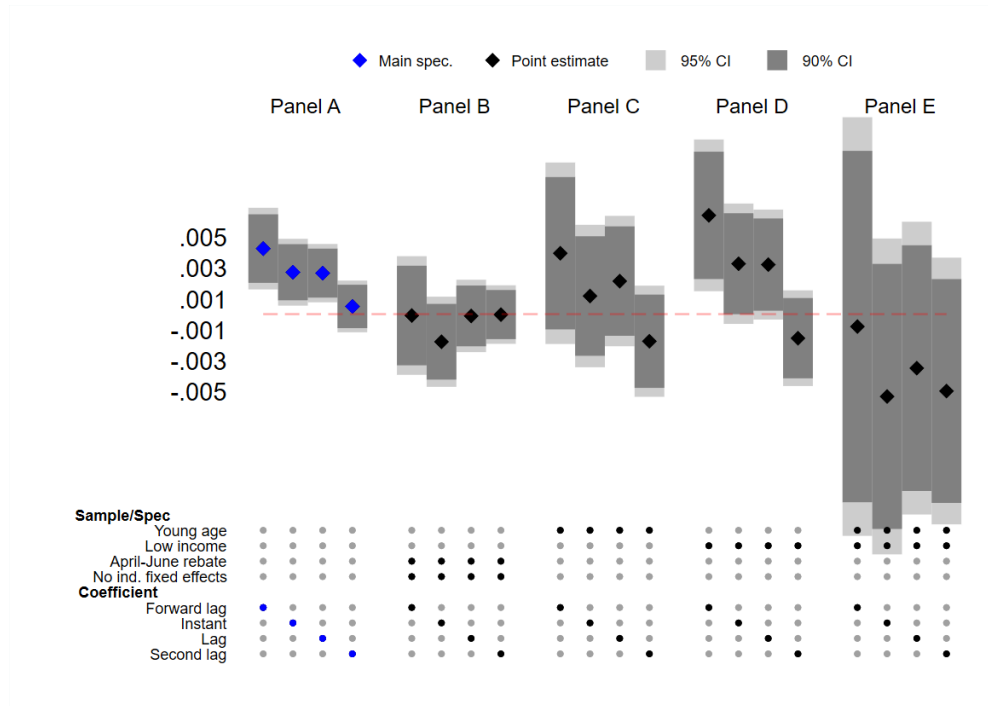
Figure 2.A1: Estimated effect of tax rebate on job-to-job transitions.



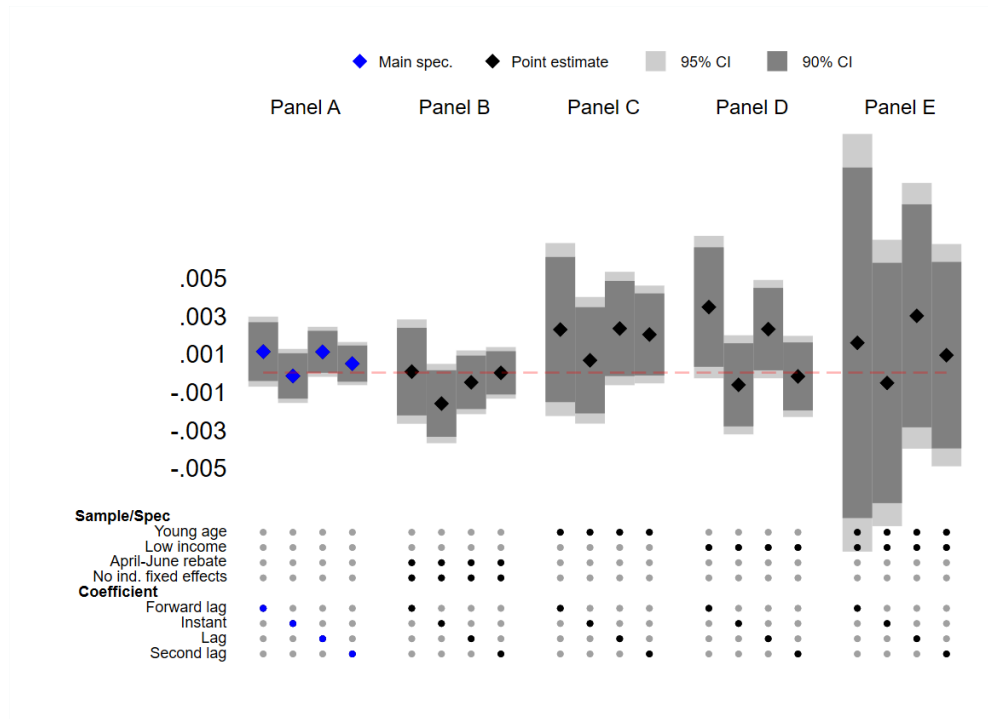
Note:- Data from 2008 SIPP. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results control for month, months from interview and age fixed effects. Standard errors are clustered at the individual level. Regressions are weighted using the SIPP sampling weights.

Figure 2.A2: Estimated effect of tax rebate on job destruction rates.

(a) Job destruction into non- or unemployment



(b) Job destruction into unemployment only



Note:- Data from 2008 SIPP. Each point represent the coefficient corresponding to the indicated variable and sample selection. Results control for month, months from interview and age fixed effects. Standard errors are clustered at the individual level. Regressions are weighted using the SIPP sampling weights.

The age-wage-productivity puzzle: A contribution from professional football

This article was co-authored with Carl Singleton, Rachel Scarfe and Adesola Sunmoni, who have agreed that it can appear as a chapter of this thesis, and that it represents a significant contribution on my part.

3.1 Introduction

There is a positive relationship between age and wages in most labour markets and occupations: *ceteris paribus*, older workers earn more, until a peak is reached around age 50 (Mincer, 1958). This age-wage profile is a key input in many theoretical labour market models, particularly those which feature worker decisions and earnings over the lifecycle. These models typically interpret the age-wage profile as an increase in productivity over time, either through investments in human capital or through returns to experience (e.g. Huggett, Ventura, and Yaron 2011b). However, researchers can rarely observe a worker's life-cycle productivity. They instead often rely on an underlying assumption that individual productivity is at least proportional to contemporaneous wages, implying that age-wage and age-productivity profiles should be similar. Our findings, from a labour market where productivity and wages are directly observable, challenge that assumption.

We use panel data to estimate robust age-wage and age-productivity profiles for professional football players in the United States and Canada. We show that failing to account for selection effects in this labour market and for the unobserved differences in players' average productivity leads to substantial bias in estimates of the age-productivity profile, echoing the results of Castellucci, Padula, and Pica (2011), who studied Formula One racing drivers. But we find stark differences

between age-wage and age-productivity profiles; while the productivity of professional footballers peaks at the age of 26, wages continue to increase throughout most of their careers. We discuss several possible reasons for these career (life-cycle) discrepancies in productivity and wages among footballers, including: the roles of regulation or wage bargaining that are specific to this labour market; the possibility that there are unobserved elements of the level and temporal variance of productivity that are increasing with age; investment in human capital by younger players; and risk aversion of firms (decision makers in football teams, in our setting) leading them to prefer older players. However, none of these appears to explain entirely the seemingly over-generous wages that older talent earns in this market. This leaves us with an unsolved puzzle: why are older professional footballers still paid so handsomely despite rapidly dwindling talent?

As we have panel data for all players throughout the whole of their careers in MLS, we are able to estimate age-productivity and age-wage profiles accounting for both player and firm (football team) fixed effects. In contrast, estimates based on cross-sectional data may be biased due to unobserved individual heterogeneity or selection effects. We find substantial differences in age profiles when we control for player and team fixed effects compared to OLS estimates. In our preferred specification, we find that productivity peaks between 21 and 26 years (depending on the measure we use), compared to 31 years when using OLS estimates. This is unsurprising, since more productive players are likely to remain in the workforce for longer, such that exit from the market is unlikely to be random. Our results provide further evidence that ignoring selection effects can lead to substantially biased estimates of age-productivity profiles.

However, even after controlling for the issues outlined above, we find that the wages of footballers generally peak at age 30, before declining towards the end of their careers. This ‘hump-shaped’ age-wage profile has been extensively studied (e.g., Rupert & Zanella, 2015). The richness of our data though allows us to estimate precisely an age-wage *premium* profile. To do so, we estimate our original age-wage profile, but control for a wide range of other productivity measures as well. We find that the age-wage premium profile increases until a player is in his early 30s. This suggests that older players are paid significantly more than their individual productivity would suggest, and that this difference is increasing until they reach their early 30s. The magnitude of this age-wage premium is significant, our estimates suggest that a 30 year old footballer is paid roughly 40%

more than a 20 year old with the same performance. There is some evidence that this age-wage premium exists in other industries and employee groups. For example, Ilmakunnas and Maliranta (2005) finds an age-wage premium in Finland that is increasing as workers age, and Dostie (2011) finds that a premium exists for older workers in Canada.

There have been a number of explanations for differences between age-productivity and age-wage profiles (see De Hek and van Vuuren (2011) for an overview). In Section 3.6, we discuss those that are most likely to be relevant to our setting. First, we consider the role of salary regulations or collective bargaining, as previous research suggests that wages increase more with seniority in more unionised industries (De Hek & van Vuuren, 2011; Williams, 2009; Zangelidis, 2008). The collective bargaining agreements (CBAs) between the League and the players' union are publicly available. Although these agreements specify minimum salaries and annual increases, these affected very few players. We find the same age-wage profile excluding players more likely to be subject to these regulations. Since the period we study was covered by three different CBAs, we also show that the age-wage profile did not change when the CBA changed. Taken together, these checks suggest that the age-wage premium is not sensitive to institutional factors unique to MLS.

We can also test whether the age-wage premium may be a result of other elements of productivity, not captured in our data. In particular, some talent may be paid more when it is popular and attracts more fans. There is evidence that this mechanism does play a role in setting wages in MLS (Scarfe, Singleton, & Telemo, 2021). Again, our setting provides a useful test for this theory. A number of players in MLS are 'designated players'. These are highly popular players, specifically recruited to increase the popularity of the League, who are subject to different salary regulation (Coates, Frick, & Jewell, 2016). In effect, they are players identified by MLS as being the most popular. We find that dropping these players does not change the shape of the age-wage premium, and thus conclude that this explanation is unlikely.

We next test two theories of human capital that may account for the age-wage premium. First we test whether older players may have accumulated human capital that is not captured by our productivity measures (such as team leadership skills, for example), by comparing the outcomes of teams that chose different age distributions of players on their rosters. To investigate this hypothesis we test whether, conditional on the observed productivity of their players, teams with more older

players perform better. We find that, while observed player productivity predicts team performance, there is no evidence of an effect of age on team performance. Second, we consider whether younger players may accept lower wages in order to play for a team with a reputation for investing in their skills and providing opportunities for younger players. This is similar to the idea that firms offering more on-the-job training may pay lower starting wages (see Barron, Berger, and Black (1999)). However, we find that adding club fixed effects to our models does not change our results, suggesting that younger players do not select into lower paying clubs.¹

Finally, we consider a ‘talent discovery’ theory. This theory states that, if teams are risk averse, they will pay younger players less because their individual productivity is less well known. For example, if a young player has a particularly good season, teams are unable to distinguish whether this is evidence of permanently high productivity, or an idiosyncratic productivity shock. This is not the case for older players, for whom more past performance data is available.² To test this, we regress player’s current productivity on lagged productivity. We find some, limited, evidence that more data on past productivity does indeed help predict future productivity, suggesting that this theory may explain some of the age-wage premium, although further investigation is needed.

There are several advantages to using data from sports labour markets to consider questions in labour economics. Our setting is Major League Soccer (MLS), the premier football league in North America, and our dataset covers approximately the universe of players in MLS between 2008 and 2019. The media and fan interest in professional football ensures that detailed and accurate information on individual productivity over time is freely available. A further advantage of our setting is the structure of the League; MLS is a single-entity with a players’ union that negotiates salary regulations with the League and publishes annual salary data for all the players. We can, therefore, match detailed productivity data with accurate salaries for all players, across their whole careers in MLS. This combination of individual productivity and salary data is unusual. In general, previous studies have either used data from labour markets where individual productivity

1. These conclusions are consistent with previous research which has not found conclusive evidence that employees in other industries bear the cost of on-the-job training through lower wages (Barron et al., 1999; De Hek & van Vuuren, 2011; Parent, 1999).

2. In some sense, this mechanism is the opposite of that described by Lazear (1998), who suggested that firms may actually prefer riskier workers because those who turn out to be more productive can be retained and those who are less productive can be fired.

is measurable, such as sports, to estimate age productivity profiles without comparing these to wage profiles (e.g., Bertoni, Brunello, & Rocco, 2015; Castellucci et al., 2011; Oster & Hamermesh, 1998), or have used firm-level, rather than individual worker-level productivity data (e.g., Cardoso, Guimarães, & Varejão, 2011; Hellerstein, Neumark, & Troske, 1999; Van Ours & Stoeldraijer, 2011). Due to its unique setting with observable wages and performance variables over time MLS has been used previously to test theories of the labour market: for example, Coates et al. (2016) look at the relationship between within-club wage inequality and team performance and Scarfe et al. (2021) use the same data to test whether the productivity based theory of Rosen (1981) or the popularity based theory of Adler (1985) can best describe superstar wages in this setting.

The remainder of the paper proceeds as follows: Section 2 provides an overview of the MLS labour market; Section 3 describes our data sources; Sections 4 and 5 present our estimation for the age-productivity and age-wage profiles of professional footballers; Section 6 discusses possible explanations for the differences between those profiles; and Section 7 concludes.

3.2 Institutional Setting

In this section, we discuss the features of Major League Soccer, why it is an appropriate setting for the robust estimation of both age-productivity and age-wage profiles for individual workers.

3.2.1 Major League Soccer (MLS)

MLS is the top tier football league in North America. Unlike other top leagues in Europe and around the world, it is closed and does not feature promotion or relegation. Changes in the composition of the league can only occur through franchise (team) expansion or dissolution. At the time of writing, in the 2022 season there are 28 teams in MLS (25 in the United States and 3 in Canada) who compete in two parallel leagues: the Eastern and Western Conferences. Each team plays every other team in their conference twice each season (corresponding to a calendar year), and every team in the other conference once. Teams earn 3 points for winning a game and 1 point for drawing (a tie). The top six teams in each conference advance to the MLS playoffs, which is a knockout series to determine the championship winner, known as the MLS Cup.

MLS operates as a single corporate entity and owns a stake in all the franchise teams, which receive some revenues directly, such as ticket sales, all stadium revenue, and local broadcast rights (Peeters, 2015). In addition, the teams receive a portion of the overall League's profits, including national and international broadcast rights, as well as league sponsorship money (Scarfe et al., 2021). A consequence of this structure is the existence of a single players' union, the MLS Players' Association (MLSPA), which negotiates salary regulations with the League. These regulations result in a Collective Bargaining Agreement (CBA) between the MLSPA and MLS, which is renegotiated every five years. As these regulations govern all players in the League, the salary of every single player is published each season by the MLSPA. Unlike other firms or local labour markets, wage data is thus publicly available for the universe of workers in the market.

A major difference between MLS and other top football leagues are the salary regulations. Teams can put together a roster of up to 30 players (as of the 2021 season) who can play for them in each season. There are a number of ways teams can acquire players for their roster, including: directly recruiting players from other leagues; trades with other teams; and a 'draft' of junior players (Major League Soccer, 2021). The total amount each team spends on player salaries, however, must be below a salary cap. Teams can circumnavigate the salary cap by using the 'designated players' rule.³ This rule allows teams to sign one or two players who are not subject to the salary cap, by negotiating with them directly. This rule, introduced in 2007 when an MLS club, LA Galaxy, wished to sign David Beckham from Real Madrid of the Spanish La Liga, was intended to increase the popularity of the League, by enabling teams to sign high quality players from abroad at competitive wages which would be difficult or impossible under the cap (Coates et al., 2016; Major League Soccer, 2013). At the time, David Beckham was one of the highest paid footballers in the world. Teams can now sign up to three designated players. However, there is a fee for teams who sign a third designated player. This amount is then shared to lower performing teams who have fewer than three designated players on their roster. In principle, this money, as well as other

3. There are other ways teams can circumvent the salary cap such as trading players or their international roster allowance with other teams.

“allocation money” from the league, helps to maintain a competitive balance in MLS, by allowing younger and lower performing teams to sign high quality players by spending amounts over the salary cap (Scarfe et al., 2021). As a result, despite the salary cap and other salary regulations, there is considerable variation in player salaries, as we show in Section 3.3.

There are further, lengthy, regulations regarding which players a team can sign, including limits on the number of international players.⁴ There is also a quota for the number of younger players (aged under 24) that a team must include on its roster and a ‘draft’ system where teams can pick young players new to MLS in reverse order of the team’s finishing position in the league in the previous year. Consequently, in our data we observe players at all points in their career.

MLS argues that these institutional structures and regulations ensure the league remains competitive. This appears to have been successful, as the MLS Cup was won by 12 different teams in the 13 seasons between 2007 and 2018, compared to say the Italian Serie A, which was won by only three teams in the same period.⁵ This is an advantage from our perspective: team managers can theoretically improve their team’s performance dramatically through their roster choices, and should thus be aiming to secure the most productive players at the lowest possible salaries.

3.3 Data and Summary Statistics

We use data on player wages, ages and productivity from two main sources: the official MLS website and the MLS Players Association (MLSPA). The data covers the universe of players and teams in the MLS between 2007 and 2019. We also use player ratings from WhoScored.com as a further source of productivity data, as well as data on page views from Wikipedia, which we use to proxy for a player’s popularity.

4. See, for example, (Major League Soccer, 2020), and further discussion in Section 3.6 for more detail.

5. Inter Milan won 4 times, A.C. Milan once and Juventus F.C. 6 times.

3.3.1 Wage and Productivity data

To estimate the age-wage profile of players, we obtain data on wages and team affiliations from the MLSPA. This captures the mid-season of the MLS in August, after the secondary transfer window when players can be signed from other leagues, and covers the 2007–2019 seasons. The measure of wages we use is the guaranteed annualised compensation or salary, henceforth referred to as wages. This is the player’s total base salary over the years covered by their contract, plus payments for signing with a team or related to marketing, divided by the number of years covered by the contract. It does not include performance related payments. However, the league’s salary regulations require that any “readily achievable” individual bonuses are reflected in the guaranteed annualised compensation published by the MLSPA, so that they can be included in the salary cap. This salary measure is less affected if a player has a particularly good or bad year and therefore receives performance bonuses that are much higher or lower than expected. To account for increases in wages over time, both due to inflation and to changes in the CBA that pushed wages for all players up, we detrend wages by season.

Our key productivity measures are average minutes played per season and average ratings data from WhoScored.com. Minutes played is a suitable proxy for players’ on-pitch productivity, as better players will play more minutes over a season, assuming that football managers are only aiming to win football matches. There has been some debate though about whether this is the case, or whether clubs and managers have other objectives, such as maximising revenue and profits.⁶ It is possible that managers want players who are more popular with fans to play more.⁷ Other readily available productivity measures for all the players and years in our dataset, such as goals, shots or assists per game, are more applicable to forwards and mid-fielders than defenders and goal keepers. As the roster sizes and the numbers of games within seasons changed over the period we consider, our estimations focus on minutes played per game within a season, which we detrend so that the overall average values over players in each season stay constant over time.

6. Késenne (2006) provides a more detailed discussion of this topic.

7. We discuss the effect this could have on our estimation of age-wage and age-productivity profiles in Section 3.6.

We obtained player ratings from WhoScored.com. The website constructs these ratings using statistics for the matches in top football competitions around the world from Opta, a market-leading British sports analytics company that provides raw data for 30 different sports in 70 countries. To generate ratings on a scale of 1–10 for every player live during a football match and over its duration, WhoScored.com uses a unique, comprehensive statistical algorithm. Over 200 raw statistics are included in the computation of a player’s rating, weighted by their influence within the game. All events of importance are taken into consideration, with a positive or negative effect on ratings weighted in relation to the area on the football pitch and the outcome. For example, an attempted dribble in the opposing team’s final third that is successful will have a positive effect on a player’s rating. According to WhoScored.com, ratings less than 5.9 are “poor”, ratings of 6.0 – 6.9 are “average”, 7.0 – 7.9 are “good”, 8.0 - 8.9 are “very good” and 9.0 - 10 are “excellent”⁸. We use ratings data from the 2013-2019 seasons of MLS, which we merge with the data sources described above, as well from as the top division of German professional football (Bundesliga) over the same period for a later robustness check. The player ratings provide an alternative measure of player productivity that captures a player’s overall performance and is relevant and comparable for all playing positions (forwards, midfielders, defenders and goalkeepers). These ratings are widely used by football clubs, media and bookmakers. As we are interested in the relative ratings between players, we detrend the ratings by season and position-specific means, to account for any changes in the algorithm used by WhoScored.com.

We obtain data on players ages, number of games started per season, minutes played per season and designated player status from the MLS official website. As in Scarfe et al. (2021), we merge the three sources of data using player names and seasons, creating a dataset with 6,135 player-season observations of 1,885 individual players contracted to the MLS during the 2007–2019 seasons. We drop a tiny number of observations due to missing age or other season performance indicators, or because they could not be matched with our other data sources.

8. See whoscored.com/Explanations for a more detailed description of how these ratings are calculated.

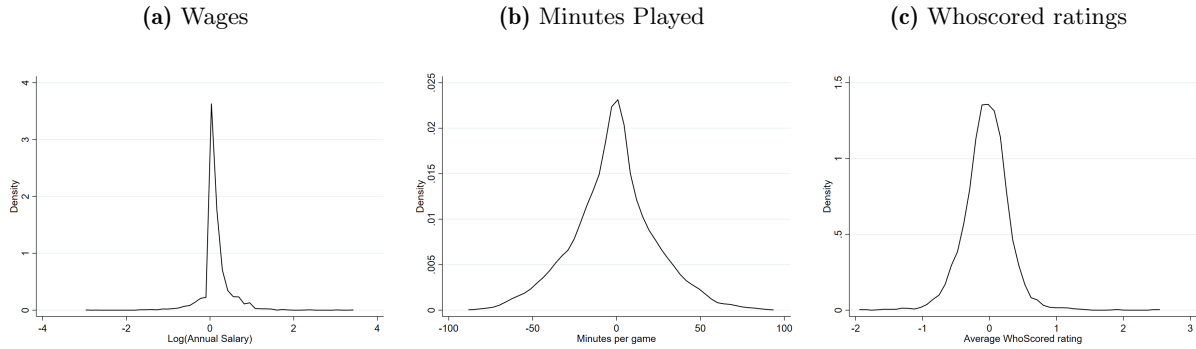
Table 3.1 presents some descriptive statistics. The average age was 25.9, with a standard deviation of 4.0 (we exclude players younger than 19 or older than 35, as we do not have enough observations outside this range to robustly estimate age profiles). Minutes played per game within a season ranged from zero (for the 11% of players who acted as reserves for the whole season, or who were injured) and 90 (for the 1% of players who played every single game), with an average of 34.5. Since we will later use the panel structure of the dataset, we also show descriptive statistics in Table 3.1 for players who spent at least 2 seasons in MLS.

Table 3.1: Summary Statistics over player-season observations, Major League Soccer, 2007-2019

Variable	Mean	St. dev.	Min.	Median	Max.	<i>N</i>
<i>All Players</i>						
Log(Guaranteed Salary)	11.658	1.024	9.465	11.535	15.973	6135
Mins played per game	34.494	28.186	0.000	31.015	90.000	5516
WhoScored ratings	6.753	0.346	4.684	6.767	8.941	2928
Age	25.928	4.004	19.000	25.000	35.000	6135
Tenure	2.887	2.255	1.000	2.000	13.000	6135
<i>Players with at least 2 seasons in the MLS</i>						
Log(Guaranteed Salary)	11.915	0.876	9.908	11.824	15.973	2599
Mins played per game	41.789	27.700	0.000	42.900	90.000	2337
WhoScored ratings	6.756	0.327	4.684	6.767	8.368	1576
Age	27.227	3.780	19.000	27.000	35.000	2599
Tenure	4.944	2.084	3.000	4.000	13.000	2599

Notes.- Data on WhoScored ratings are from WhoScored.com, data on guaranteed salaries are from the MLS Players Association and all other data are from the the official MLS website.

Figure 3.1 displays the year to year change in our wage and two productivity variables. This is relevant as we use fixed effects to account for the selection of players in and out of MLS. Panels A-C show that there is considerable within-player variation across seasons in these variables. There is however, a mass point in Panel A at zero (i.e. players whose wage did not change). This is due to our wage measure, which is the annualised guaranteed wage over the length of a player's contract with their team.

Figure 3.1: Kernel density estimates of year to year change in wage and productivity variables

Notes.- Kernel densities are estimated using an Epanechnikov kernel with Stata's default bandwidth choice.

3.4 Age-productivity profiles

3.4.1 Empirical strategy

We use ordinary least squares to estimate the age-productivity profile in our sample under a range of model specifications. As dependent variables we use two measures of productivity; average minutes played per game over a season, and average WhoScored rating over a season. We estimate the profiles both using a non-parametric model, with dummy variables for each year of age, and using a parametric model, where the age-productivity relationship is captured by a third-degree polynomial.

In our main estimation, we control for selection using a player fixed effects specification, where the estimated intercepts are allowed to vary at the player level. We also investigate how allowing for team and player-team match fixed effects affects the results. The models we estimate are:

$$y_{i,t} = \alpha + \beta \mathbf{Age}_{i,t} + \epsilon_{i,t} \quad (\text{OLS}) \quad (3.1)$$

$$y_{i,t} = \alpha_i + \beta \mathbf{Age}_{i,t} + \epsilon_{i,t} \quad (\text{Player FE}) \quad (3.2)$$

$$y_{i,t} = \alpha_i + \gamma_{J(i,t)} + \beta \mathbf{Age}_{i,t} + \epsilon_{i,t} \quad (\text{Player and team FE}) \quad (3.3)$$

$$y_{i,t} = \alpha_{i,J(i,t)} + \beta \mathbf{Age}_{i,t} + \epsilon_{i,t} \quad (\text{Match FE}) \quad (3.4)$$

Subscript i denotes an individual player, $j = J(i, t)$ a team and t a season. In the parametric model, $\boldsymbol{\beta}$ is the vector $[\beta_1 \beta_2 \beta_3]$ and $\mathbf{Age}_{i,t}$ denotes the vector $[Age_{i,t} \ Age_{i,t}^2 \ Age_{i,t}^3]'$, whereas for the non-parametric model $\boldsymbol{\beta} = [\beta_{19} \beta_{20} \dots \beta_{35}]$ and $\mathbf{Age}_{i,t} = [\mathbb{1}\{Age_{i,t} = 19\} \ \mathbb{1}\{Age_{i,t} = 20\} \ \dots \ \mathbb{1}\{Age_{i,t} = 35\}]'$. As explained in Section 3.3, we account for the possibility that the WhoScored.com rating system has changed over the years by normalising the scores by year and position specific means. We also de-trend the minutes per game variable by year, since year-specific changes in squad size regulations could affect this variable.

3.4.2 Results

Our first set of results regard the importance of accounting for selection into and out of the MLS by comparing the various econometric models considered. Figure 3.2 shows that the ‘naive’ OLS regression estimates both the peak of a footballer in terms of minutes played and WhoScored ratings at age 31. Accounting for individual fixed effects lowers these estimates to 26 and 21 years of age, respectively. One likely explanation for this is that weaker players tend to drop out as they age, while another possibility is that it is due to MLS’s history of purchasing older ‘superstar’ players from Europe, who, unless accounted for in a fixed effects model, will skew the productivity age-profiles upwards for older players.

We also consider whether teams of different quality pursue different recruitment strategies with respect to the age distribution of players on their roster. However, since MLS teams are likely closer to each other in overall productivity than those in other football leagues, we would anticipate that adding team or player-team match fixed effects to the models would not be of great importance. Indeed, the player and team fixed effects and match fixed effects models (Figure 3.A1) do not seem to alter the results in any meaningful way, with peak ages remaining within one year of the fixed effects specification, and productivity curves remaining similar over the the life-cycle. This may appear surprising. However, average minutes per game for a player is bounded above by 90 minutes and below by zero minutes, and so is unlikely to differ greatly between teams. As we discuss in Section 3.2, MLS has very stringent salary regulations, including a salary cap, that are aimed at

Table 3.2: Estimated parametric age-productivity profiles of MLS players

	(1)	(2)
	Minutes per game	WhoScored Rating
Age (β_1)	20.59* (11.466)	0.347 (0.295)
Age ² (β_2)	-0.492 (0.434)	-0.0121 (0.011)
Age ³ ($\beta_3 \times 100$)	0.00233 (0.005)	0.000123 (0.000)
Estimated peak age	25.59	21.15
95% confidence interval	[24.78, 26.40]	[17.23, 25.08]
Player fixed effects	Yes	Yes
N	4,703	2,481
Within R^2	0.038	0.051

Standard errors in parentheses, as well as the 95% confidence interval of age peak calculated using bootstrapping.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

maintaining a competitive league. As a result, the distribution of talent across teams is likely to be more even than in other football leagues, so that the team a player joins is less likely to affect his productivity. For this reason, we use the more parsimonious player fixed effect model as our preferred specification.

For the parametric specification with player fixed effects (Equation 3.2), we report the detailed estimation results in Table 3.2. We solve for the estimated peak productivity analytically by finding the roots of the first-order condition, and use bootstrapping to estimate a 95% confidence interval for the peak age.

We also investigate whether age-productivity profiles differ depending on a player's position. We estimate our player fixed effects model separately depending on the player's main position (goalkeeper, defender, midfielder or forward). Figures 3.A2 and 3.A3 display the results. Using minutes played as the dependent variable we estimate that goalkeepers peak at age 31, whereas all other positions have estimated peaks at age 25. In the WhoScored data we cannot estimate any significant age-productivity effect for goalkeepers, although the point estimate suggests a local

peak at age 29. For defenders we estimate a peak at age 20, for midfielders at 22 and for forwards at age 23. The finding that defenders peak earlier than midfielders and forwards is surprising, although we note that this difference is not statistically significant so should be interpreted with care.

To test whether conclusions drawn from MLS are likely to be valid in other football leagues, we also estimate age-productivity profiles in the German top division Bundesliga, for which we have data on WhoScored ratings and age, but not on salaries or minutes played. Figure 3.A4 displays the results, which for the player fixed-effects specification are similar in Bundesliga and MLS, with the estimated peak age in the Bundesliga of 21 years being the same as in the MLS. The shape of the age-productivity profile is also similar, although it appears that Bundesliga players experience a smaller productivity drop at older ages, with 35-year-olds only estimated to have dropped 0.2 WhoScored units relative to their peak, compared to a drop of 0.5 units in MLS. Selection in and out of the Bundesliga seems to bias the estimates in the same direction as in MLS, with the OLS model suggesting an older age peak than the player fixed effects model, although not to the same extent as in the MLS. This is as we expect, since the Bundesliga is a higher profile league, without the need to recruit older, popular, players to boost its audience.

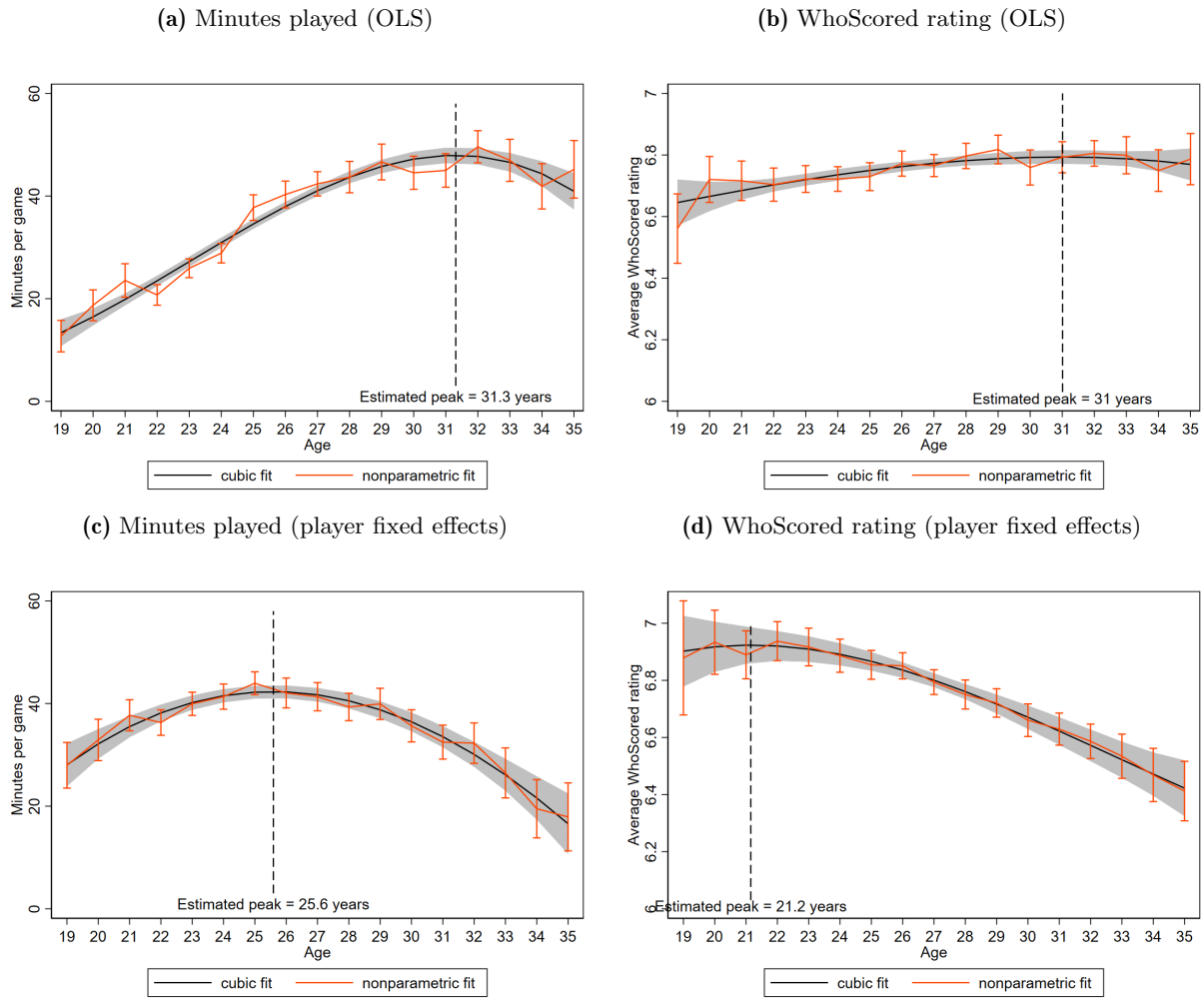
3.5 Wage-age profiles

3.5.1 Empirical strategy

As we have salary data for all players in MLS, we can also estimate players' average age-wage profiles. We are especially interested in whether productivity and earnings peak at the same age. Here we display results from two separate regressions. We first estimate an age-wage profile using a player fixed effects model to account for selection effects, as in Section 3.4:

$$\text{Log}(w_{i,t}) = \alpha_i + \beta \text{Age}_{i,t} + \epsilon_{i,t}. \quad (\text{Wage-age profile}) \quad (3.5)$$

Figure 3.2: Estimated age-productivity profiles using OLS and player-level fixed effects



Notes.- Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

We estimate equation 3.5 for two separate samples, one including designated players (DPs) and one without, as DPs wages are not subject to the same regulation and hence may follow a different age profile.

We also look specifically at how players' age-wage and age-productivity profiles differ. To this end we estimate an age-wage *premium* profile, adding performance variables as regressors in the model given by Equation (3.5). This should account for the part of a player's salary that can be explained by their on-pitch performance. Since wages are determined at the beginning of the season we use lagged performance variables, including the productivity measures from Section 3.4:

WhoScored rating and minutes played; as well as goals scored, shots on/off goal, assists, fouls committed/conceded and yellow/red cards for outfield players, and saves for goalkeepers, where all variables are normalised per 90 minutes played, and included as cubic polynomials to ensure the best possible fit of their effect on wages. We write this model as follows:

$$\text{Log}(w_{i,t}) = \alpha_i + \beta \text{Age}_{i,t} + \delta \mathbf{x}_{i,t-1} + \epsilon_{i,t}. \quad (\text{Wage premium-age profile}) \quad (3.6)$$

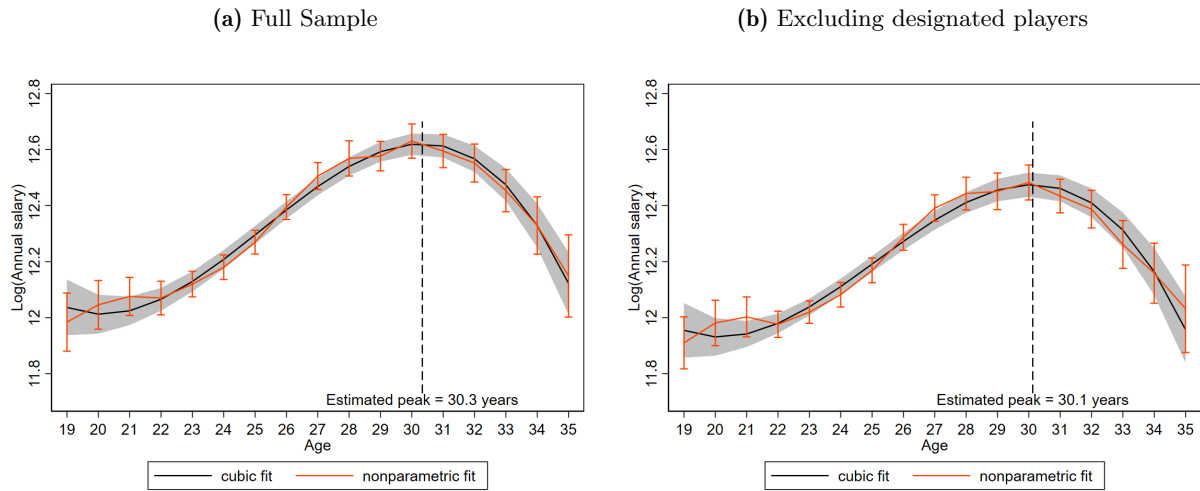
where $\mathbf{x}_{i,t}$ denotes the vector of player- and time-specific performance variables. Since the vector of regressors differ for outfield players and goalkeepers, we estimate equation 3.6 separately for these two groups.

3.5.2 Results

Figures 3.3 and 3.4 display the results from the models presented above. Players' wages are estimated to peak at age 30, and the regression output in Table 3.3 shows that this is significantly higher than their estimated productivity peak. Players do experience a sharp drop-off in their salaries from this point and at age 35 the average wage is almost back to its initial level, which is 0.4 log points lower than the peak. Excluding designated players does not alter the results significantly, so the late peak age does not appear to be driven by designated players.

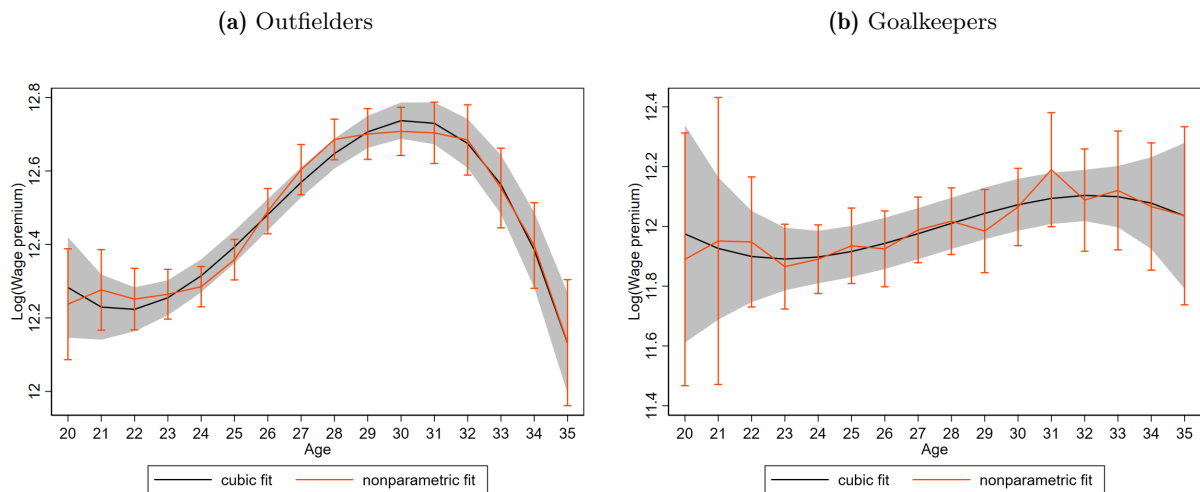
A surprising result from the estimation of equation 3.5 is that the timing of the drop-off in wages does not correspond to the estimated drop in productivity, which in section 3.4 was estimated to start already at age 21 or 25, depending on the performance measure used. Indeed, even after controlling for other observable productivity variables according to equation 3.6, we estimate that the *age-wage premium*, i.e., the excess wage not accounted for by measurable performance, increases throughout most of their career, until it reaches a maximum in the early 30s. The fact that the age-wage premium is increasing in age poses a puzzle, since we might expect teams to compete for a player by offering higher wages up until the point where the salary equals the value of their on-pitch contribution to the team, implying that wages and productivity should peak at the same age. In Section 3.6 we discuss and evaluate some possible explanations for this discrepancy.

Figure 3.3: Age-wage profile



Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Figure 3.4: Age-wage premium profiles



Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

3.6 Discussion

The results we present above suggest that, although footballers peak in productivity between the ages of 21 and 26 (depending on the measure of productivity), their wages continue to increase through the most part of their career. This is a puzzle: if wages are paid primarily in respect of a footballer’s productivity, then we would expect them to follow the same profile.

Table 3.3: Estimated parametric age-productivity profiles of MLS players. Dependent variable is Log(Wage).

	(1) Full Sample	(2) No Designated Players
Age	-2.103*** (0.251)	-2.002*** (0.248)
Age ²	0.0869*** (0.009)	0.0829*** (0.009)
Age ³	-0.00115*** (0.000)	-0.00110*** (0.000)
Estimated peak age	30.34	30.13
95% confidence interval	[30.00, 30.67]	[29.80, 30.45]
Player fixed effects	Yes	Yes
<i>N</i>	5,245	4,925
<i>R</i> ²	0.139	0.128

Standard errors in parentheses, as well as 95% confidence interval of age peak calculated using bootstrapping.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In this section, we discuss five potential explanations for the discrepancy between age-productivity and age-wage profiles. The first two explanations we consider may be specific to this particular type of labour market: (1) regulations and institutional effects in MLS which force teams to pay older players more; and (2) “superstar” effects, where older players are paid more because they are more popular (despite not being more talented) and attract greater audiences. We note that this explanation could hold in other industries, such as the media.

We then consider three more general explanations: (3) the existence of some aspect of productivity or human capital that is not reflected in our measures of productivity, but is related to age (leadership qualities, for example); (4) a human capital investment channel, where younger players pay a wage-penalty to play in teams with better on-the-job training; and (5) a “talent discovery” effect, where older players earn more because their level of talent is well known and they are less of a risky investment.

3.6.1 Regulation

MLS is a single-entity that owns a stake in all teams in the League. Unlike elsewhere in professional football, players sign a contract with the league, rather than with the individual team that they play for. This contract is known as a Standard Player Agreement (SPA), and specifies an initial guaranteed period, during which the contract cannot be terminated by MLS due to poor performances or injury. This is followed by up to three option years, when MLS has the right to extend the SPA without renegotiating salary. The SPAs are governed by a Collective Bargaining Agreement (CBA) between the MLSPA and the league. The CBA is renegotiated every five years. In addition, each team is subject to a salary cap, which limits the total amount they can pay to all the players on their roster (see Coates et al., 2016; Kuethe & Motamed, 2010; Scarfe et al., 2021 for further detail on the structure of MLS.)

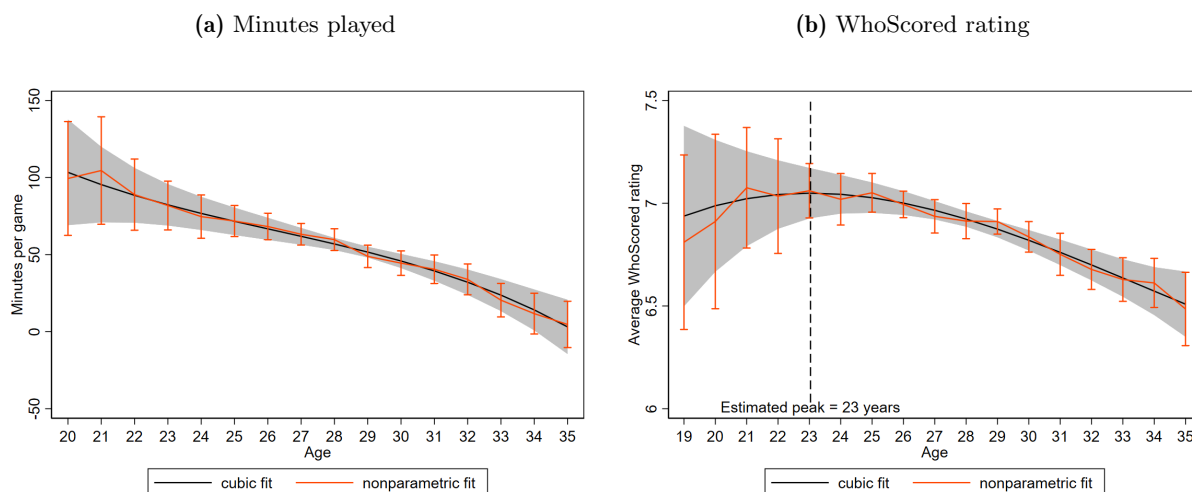
There are a number of clauses in the CBA limiting the salary that a player can earn. Regulations surrounding salary increases are potentially relevant to the age-wage premium estimated in the previous section. The 2015 to 2018 CBA specified that players earning less than \$150,000 must receive an increase of 5% per year in each year of their SPA. Between 2005 and 2009, this clause applied to all players earning less than \$60,000.⁹ This means that, for some players at least, salaries increase every year, regardless of their productivity.

In addition, the CBA specifies a minimum salary for each season. The minimum salary for a player aged under 24 on a team's reserve roster is lower than for an older player on the main roster. For example in 2018, the minimum salary was \$54,500 for players under 24 and \$67,500 for older players. However, most players earn over the minimum. All but 26 out of 537 players older than 24 were paid more than \$67,500 for the 2018 season. We also note that most players received annual salary increases that were far greater than the minimum; the median salary increase was 9.5% and the annual change in salary was greater than 5% for 79% of player-year observations in our estimation samples.

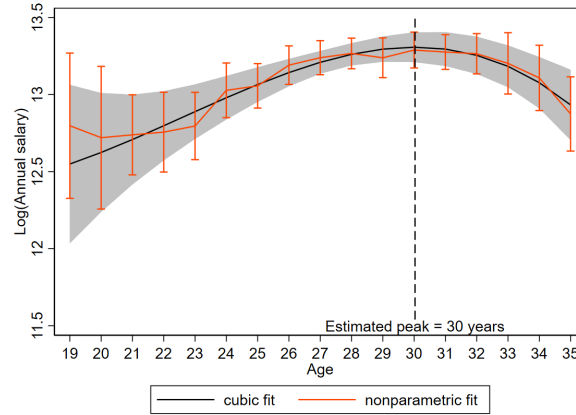
9. Unfortunately the CBA for the year 2010 to 2014 is not publicly available.

To investigate whether the differences in age-productivity and age-wage profiles is determined by salary regulations, we perform two further robustness checks. First, we repeat our estimation of the age-productivity profile using Equation 3.2 and the age-wage profile, using Equation 3.5, restricting our sample to those players who earned more than \$150,000 and to the years 2015 and 2019. This gives us a smaller sample of 565 players that we can be confident did not receive an annual salary increase that was purely the result of salary regulations. Using WhoScored ratings as our dependent variable, we find a somewhat similar age-productivity profile. Using minutes played as the dependent variable, the fall in productivity over these players' careers was even greater than in the full sample: minutes played fell monotonically with no peak at age 26 (as observed in the full sample). This suggests that these players do not differ markedly in terms of productivity over their careers compared to the full sample; their productivity was also decreasing as they aged. However, once again the age-wage profiles show that wages increase over a player's career. If the increase in wages over players' careers that we observe in the full sample was a result of salary regulations forcing teams to pay older players more, then we would not expect to see this increase in a restricted sample of players that are not subject to such regulations.

Figure 3.5: Age-productivity profile of players with earnings $>$ \$150,000 in years 2015-2019



Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Figure 3.6: Age-wage profile of players with earnings > \$150,000 in years 2015-2019

Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Second, we repeat our estimation of the age-wage profile, including a dummy variable for each period covered by the three CBAs, i.e., one dummy variable for the years 2007 to 2009, one for the years 2010 to 2014, and one for the years 2015 to 2019. We also include the interaction between age and CBA period, so that we estimate the following model:

$$\text{Log}(w_{i,t}) = \alpha_i + \beta \text{Age}_{i,t} + \eta \text{CBA}_t + (\phi \text{Age}_{i,t})' \text{CBA}_t + \epsilon_{i,t} \quad (3.7)$$

β , Age are as in the non-parametric version of Equation (3.2) (with a dummy for each age group). CBA_t is a column vector of dummy variables for each CBA period and η is a column vector of coefficients. ϕ is a 3x16 matrix of age and CBA period specific interaction coefficients. If regulations governed by the different CBAs had an effect on the age-wage profile then we would expect that the interaction coefficients in ϕ are significantly different from zero. This is not the case. In other words, changes in regulations did not result in changes in the age-wage profile. This provides further evidence that regulations did not affect the wages of players of different ages, and are not driving the difference between the age-productivity and age-wage profiles.

3.6.2 Superstar effects

A football player's productivity cannot only be measured by their ability to win football games. Since a football teams' revenue ultimately come from fans we might expect other factors, such as the charisma and popularity of its players, to affect the profitability of a team. There is evidence that 'superstar effects' (the popularity of a player) affect fans' willingness to pay for tickets (S. M. Kaplan, 2022) as well as the wages of players (Scarfe et al., 2021). It is therefore possible that superstar effects are biasing our productivity measures, insofar as the level of superstardom is correlated with age in a way that cannot be explained by on-pitch performances. Indeed, such an age effect may be plausible if we assume that part of a player's popularity comes from building up a reputation, or a fan base, over time.

To test whether superstar effects are a possible explanation, we use Wikipedia page views as a proxy for popularity. We collect data on Wikipedia page views for each player in the years 2016-2018, and regress the logarithm of page views on a linear age trend under a number of different specifications. In these regressions we control both for observed productivity (using the same controls as in the wage premium profiles in Section 3.5) and for player fixed effects. Table 3.4 reports the regression output. The estimates suggest that, controlling for observed productivity, each additional year of age is associated with 6.3% more Wikipedia page views; however, much of this effect seems to be driven by selection, since adding player fixed effects to the model reverses the sign of this relationship. Using only within player variation, we find that one extra year of age is associated with a 5.8% *reduction* in Wikipedia page views. As a robustness check we also estimate a separate regression where we drop designated players from the sample, in order to make sure that our results are not driven by the first-year buzz that comes with the purchase of designated superstar players, which has been shown to fade with time (Jewell, 2017). The results without designated players are reported in columns 5 and 6 of Table 3.4. We find that dropping designated players does not alter the conclusion significantly. These results suggest that the superstar effect does have a role in explaining why older MLS players are over-paid in the cross-section, which is not surprising given MLS's strategy of purchasing aging superstars. However, it does not appear that increasing popularity with age explains our finding that the age-wage premium is increasing for a given player as they age.

Table 3.4: Results from regression of age on log wikipedia page views under different specifications

	OLS		Player Fixed Effects			
					No designated players	
Age	0.050*** (0.010)	0.063*** (0.014)	-0.110*** (0.029)	-0.057* (0.029)	-0.100*** (0.024)	-0.053** (0.025)
Observed productivity controls	No	Yes	No	Yes	No	Yes
Player fixed effects	No	No	Yes	Yes	Yes	Yes
N	1,458	851	1,458	851	1,318	759
R^2	0.043	0.117	0.030	0.042	0.013	0.010

***, **, * indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors are robust to heteroskedasticity and, for the fixed effects specification, calculated using bootstrapping. In specifications with controls for observed productivity only outfield players are kept in sample.

3.6.3 Unobserved productivity or human capital

It is possible that during their career, football players accumulate human capital that is not reflected in our data. Our productivity measures – minutes played and WhoScored rating – should do a good job at picking up players’ on-the-pitch performance; the WhoScored ratings are based on measurable performance indicators, such as completed passes, goals scored, interceptions etc. and minutes played should also account for on-the-pitch leadership qualities that the manager observes but the WhoScored rating fails to acknowledge. However, it is still possible that older players contribute more to the performance of the team with *off-the-pitch* qualities, such as responsibilities during training or in the dressing room. This could explain why they seem to be overpaid relative to their ability. We test this hypothesis by looking at whether the age of the players can predict a team’s performance, in a way that their observed on-the-pitch performance cannot. Specifically, we collect the average points per game of a team during a season¹⁰ and regress this measure on a linear trend in the average age of the roster, as well as the average WhoScored ratings and other performance metrics of the team’s players (as listed in Section 3.5). We weight the performance metrics by each player’s minutes played over the season, so as to capture the team’s average observed performance, but we do not weight the age variable, since our null hypothesis is that age affects performance in an off-the-pitch fashion. We also include team fixed effects and season fixed effects in the model, to control for potential other season/team specific variation which is correlated with age. Table 3.5 reports the results: the first column includes no controls, the second

10. This is calculated as in MLS’s league table, with three points for a win and one point for a draw.

controls for WhoScored rating and the third controls for WhoScored rating as well as other observed productivity variables. We find that, while WhoScored rating is a strongly significant predictor of team performance, there is no evidence of an effect of age on team performance. If anything our point estimates suggest that, after controlling for individual on-the-pitch performance, age has a negative effect on team success, although this result is not statistically significant. Together we interpret these results as suggesting that older players do not positively affect the team performance through off-the-pitch behaviour, which suggests that the explanation for the age-wage premium must lie elsewhere.

Table 3.5: Results from regression of average roster age on points per game under different specifications

	(I)	(II)	(III)
Average Roster Age	-0.011 (0.039)	-0.025 (0.033)	-0.036 (0.028)
WhoScored rating		66.31*** (8.91)	50.68*** (8.06)
WhoScored rating squared		-1792.8*** (534.8)	-1031.2*** (370.5)
Observed productivity controls	No	No	Yes
team fixed effects	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes
N	217	122	122
R^2	0.22	0.72	0.76

***, **, * indicate significance from zero at 1%, 5% and 10% levels, respectively, two-sided tests. Standard errors are robust to heteroskedasticity. In specifications with controls for observed productivity, only outfield players are kept in sample.

3.6.4 Human capital investment

Another potential explanation for the increasing wage-age premium relates to the Ben-Porath (1967) model of human capital investment, which postulates that workers face a tradeoff between human capital investment and paid work. In the market for footballers, younger players may be willing to sacrifice some of their wages in return for playing in a team with a good reputation for developing playing skills. If developing skills is a costly investment for the team, then the lower wages of younger players could be interpreted as a payment from player to team for skills improvement services. This is similar to the idea that firms may pay workers who receive on-the-job training lower starting wages, although little empirical support has been found for this

(Barron et al., 1999; Parent, 1999). Our statistical framework provides a good way to test for this hypothesis, at least insofar as it is only through team selection that players choose the mix of investment and earnings, which would mean that variation in skill investment can be seen in variation *between* teams rather than in variation *within* teams. As a test we simply add team fixed effects to our wage premium regression in Section 3.5. If the Ben-Porath framework is accurate, and some firms specialise in developing players' skills at the expense of wages, we would expect that these teams systematically underpay workers relative to their performance, i.e., they have negative team-specific coefficients in a regression of productivity on wage. Contrary to the hypothesis, we find that adding team fixed effects into the model in equation (3.6) has a minuscule effect on the estimates, suggesting that younger players do not select into lower-paying teams in a way that can explain the observed wage premium age-profile. As a further check, we also estimate the team fixed wage effects without adding age in the regression, which we then use as the dependent variable in a regression with respect to a linear age trend. We find a positive but insignificant relationship, with one extra year of age on average being correlated with playing at a team with an estimated fixed effect that is 0.003 log points higher, which suggests that some sorting of this kind may be occurring, although it is quantitatively too small to explain a significant part of the age-wage premium.

3.6.5 Talent discovery and risk aversion

A fourth potential explanation for the puzzle is that football teams are *risk-averse*, which causes older players to earn a risk premium if they are considered 'safer bets' than younger talent. There is evidence from sports labour markets that firms pay more consistent performers more (Deutscher, Gürtler, Prinz, & Weimar, 2017; Özdemir, Dietl, Rossi, & Simmons, 2022). In other labour markets, Kuhnen and Oyer (2016) find that firms are more likely to hire MBA graduates who have previously worked in the same industry. If a player's productivity over time has a large component of idiosyncratic variance, then perhaps teams will pay players with more available past performance data, i.e. older players, more. For younger players, however, an especially strong season provides less proof of high permanent ability, and they are more likely to be a 'one-season wonder' (a term that gets a lot of attention in the media). This is, in a sense, the opposite of Lazear (1998)'s

theory, which suggests that firms value riskier workers more, since those who perform better than their expected productivity can be retained, and those who perform worse can be fired. This theory has found some empirical support. For example, Bollinger and Hotchkiss (2003) find that baseball players with more variable performance are paid more.

One way to test this ‘talent discovery’ hypothesis using our data is to regress our productivity measures on their lagged values: if idiosyncratic variance is important, adding more lags should add significantly more predictive power to the model compared to just using one lag. Limiting our sample to players who have had at least a 4-season long stint MLS with non-missing performance observations, which gives us 509 unique players for minutes played and 262 for WhoScored rating, we run these regressions for our two productivity measures. Table 3.6 displays the results. For minutes played we find that, although lags from more than one season ago are occasionally significant they are much worse predictors of performance than the most recent season, and indeed adding more lags does not increase the R-squared of the regression much. One interpretation of this result is that the persistent component in a player’s performance process, as measured by minutes played, is much larger than the idiosyncratic one, so that performance data from more than one season ago does not do much to predict the player’s future performance. Perhaps this result is not too surprising, since that the season level data we have access to is aggregated over many matches.

Interestingly, using WhoScored ratings as our dependent variable paints a different picture: here lagged performances are significant and large up until and including the third lag, and including three lags increases the R-squared by 34% relative to just including one lag. This suggest that players’ performance on-the pitch, as measured by their WhoScored rating, does have a significant year-to-year idiosyncratic component. In this case, risk-averse firms may be hesitant to sign young players as they cannot infer how good the players are from the limited data available to them. We believe that it provides the most plausible explanation to the puzzle that we have considered so far, although this evidence is far from conclusive. For example, we have not yet shown whether or not teams in MLS are indeed risk averse, which is required for this theory to hold.

Table 3.6: Results from autoregressions on performance variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Minutes per game			WhoScored rating		
First lag	0.599*** (0.021)	0.540*** (0.027)	0.532*** (0.027)	0.435*** (0.044)	0.325*** (0.050)	0.288*** (0.053)
Second lag		0.0983*** (0.028)	0.0454 (0.032)		0.256*** (0.061)	0.180*** (0.060)
Third lag			0.0967*** (0.026)			0.166*** (0.047)
Constant	14.43*** (1.183)	12.39*** (1.321)	11.03*** (1.332)	3.802*** (0.297)	2.800*** (0.347)	2.435*** (0.379)
N	1523	1523	1523	592	592	592
R^2	0.332	0.338	0.344	0.181	0.224	0.243

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While the model in Table 3.6 tests the hypothesis that figuring out the ‘true’ ability of a player requires several seasons worth of data, there is an alternative mechanism through which risk aversion could explain the increasing wage premium: if older players are *on average* more consistent performers than younger players, for example through the additional experience they have acquired, firms may be willing to pay older players a risk premium. We test this hypothesis by directly estimating season-specific variance of performance as a function of age, using a two-step procedure: first we estimate the age-productivity profile, including player fixed effects as in section 3.4, and collect the residuals; then we regress the absolute value of the residuals on age, again including player fixed effects to account for the possibility that some players are inherently more consistent performers than others. Table 3.7 displays the results from the second step regression. We do not find evidence for an age trend in the variability of performance, if anything the variance seems to be *increasing* with age, although this effect is small and not statistically significant. Hence, we do not believe that older players being on average more consistent can explain the puzzle. We thus consider that this hypothesis is worthy of further investigation. In particular, future work should consider the extent of risk aversion amongst football teams, which is required for this theory to hold.

Table 3.7: Results from regression of productivity residuals on age

	(1)	(2)
	Minutes residuals	WhoScored residuals
Age	0.0907 (0.094)	0.000614 (0.004)
Constant	23.04*** (2.442)	0.286*** (0.106)
Player fixed effects	Yes	Yes
N	5516	1701
R^2	0.000	0.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.7 Conclusion

There are a number of reasons why it is difficult for researchers to robustly estimate the effect that a worker's age has on their wage and productivity. In this paper, we use data from Major League Soccer in the United States to estimate professional football players' age-productivity and age-wage profiles. Our data provides us with both observable productivity and salary measures, a combination that is not often available. We also observe a player's performance and salary for his whole career in MLS, allowing us to estimate age-productivity and age-wage profiles controlling for unobserved heterogeneity and selection effects. We find that age-productivity profiles peak significantly earlier than age-wage profiles, so that younger players earn less than their contemporaneous observed productivity would suggest, whilst older players earn more. This result has been observed in other industries and settings (Dostie, 2011; Ilmakunnas & Maliranta, 2005), and is not unique to professional football. However, there has not been any definitive explanation as to why older workers appear to be overpaid.

In the remainder of this paper we investigate a number of plausible reasons for the difference between the two age profiles: the role of regulation or wage bargaining that are specific to this labour market; the possibility that there are unobserved elements of productivity that are increasing with age; investment in human capital by younger players; and risk aversion of firms causing them to prefer older players. We do not find convincing evidence that any of these can explain the wage

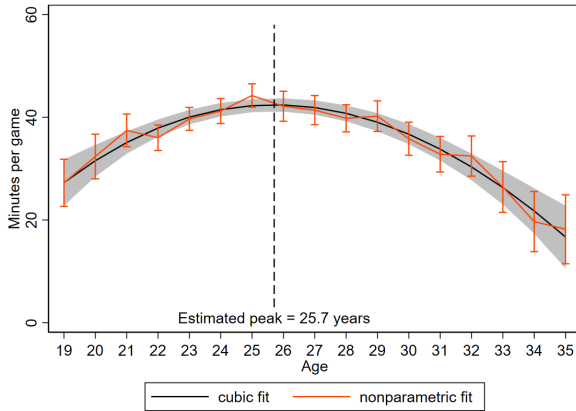
premium that older players earn. However, we do find some evidence that more available data on past productivity is useful in predicting future productivity. This suggests that the productivity of older players may be better known, making them a less risky investment for teams. Despite this, more investigation is required. In particular, for this theory to hold, it must be the case that teams are indeed risk averse, a question which we have not yet considered. There may be other explanations which we have not yet considered. For now, though, the puzzle remains.

There are several caveats that apply to our analysis. We consider a specific labour market with distinctive features, so our conclusions may not be applicable more generally. For example, careers in professional sport are much shorter than in other industries, and mobility between firms (teams) is greater. There are also salary regulations that are unique to MLS, even compared to other football leagues. However, the shapes of our estimated age-wage and age-productivity profiles is similar to those found in other sports and industries, providing some confidence that our results may extend to other labour markets.

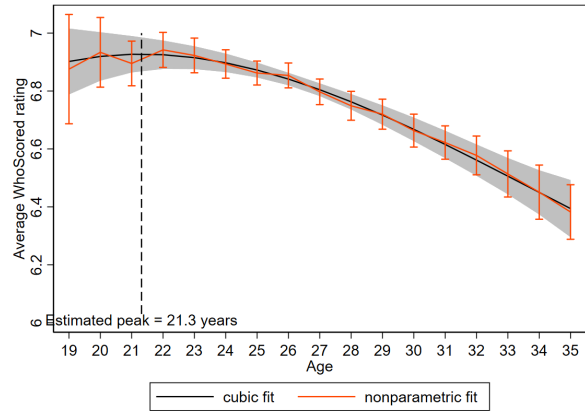
3.8 Appendix

Figure 3.A1: Estimated productivity profiles under the player and club fixed effects and match fixed effects specifications.

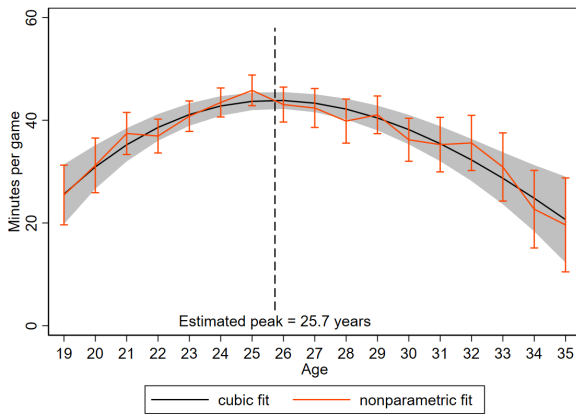
(a) Minutes played (player and club fixed effects)



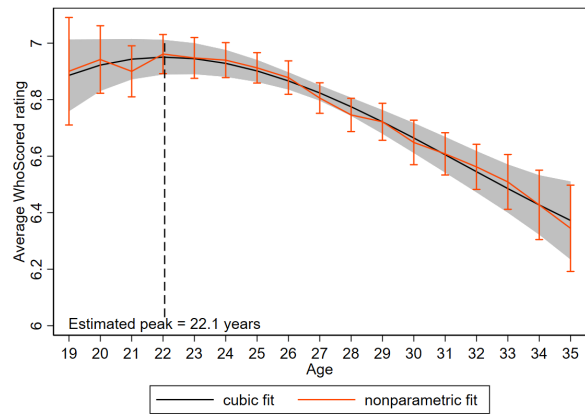
(b) WhoScored rating (player and club fixed effects)



(c) Minutes played (match specific fixed effects)

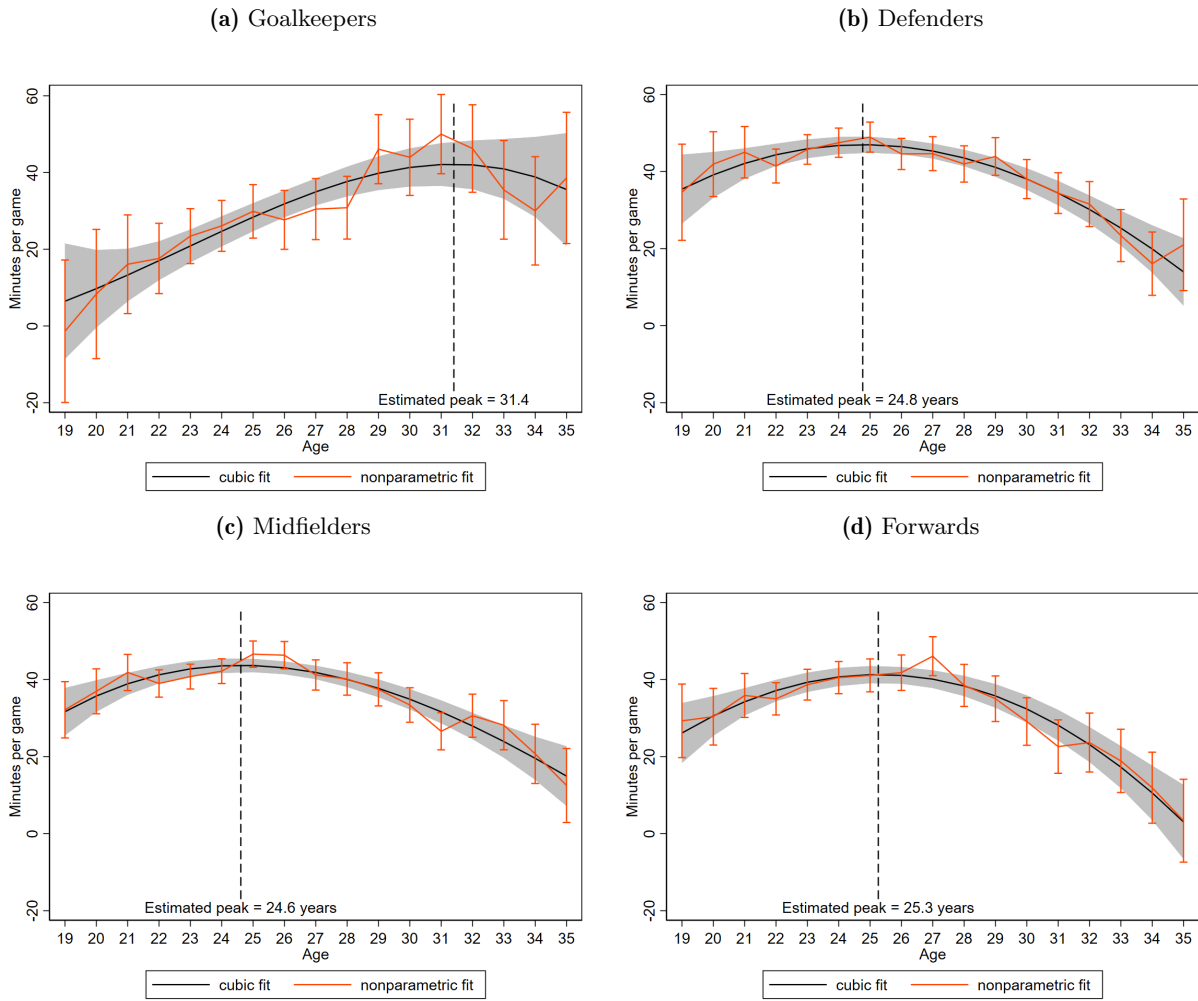


(d) WhoScored rating (match specific fixed effects)



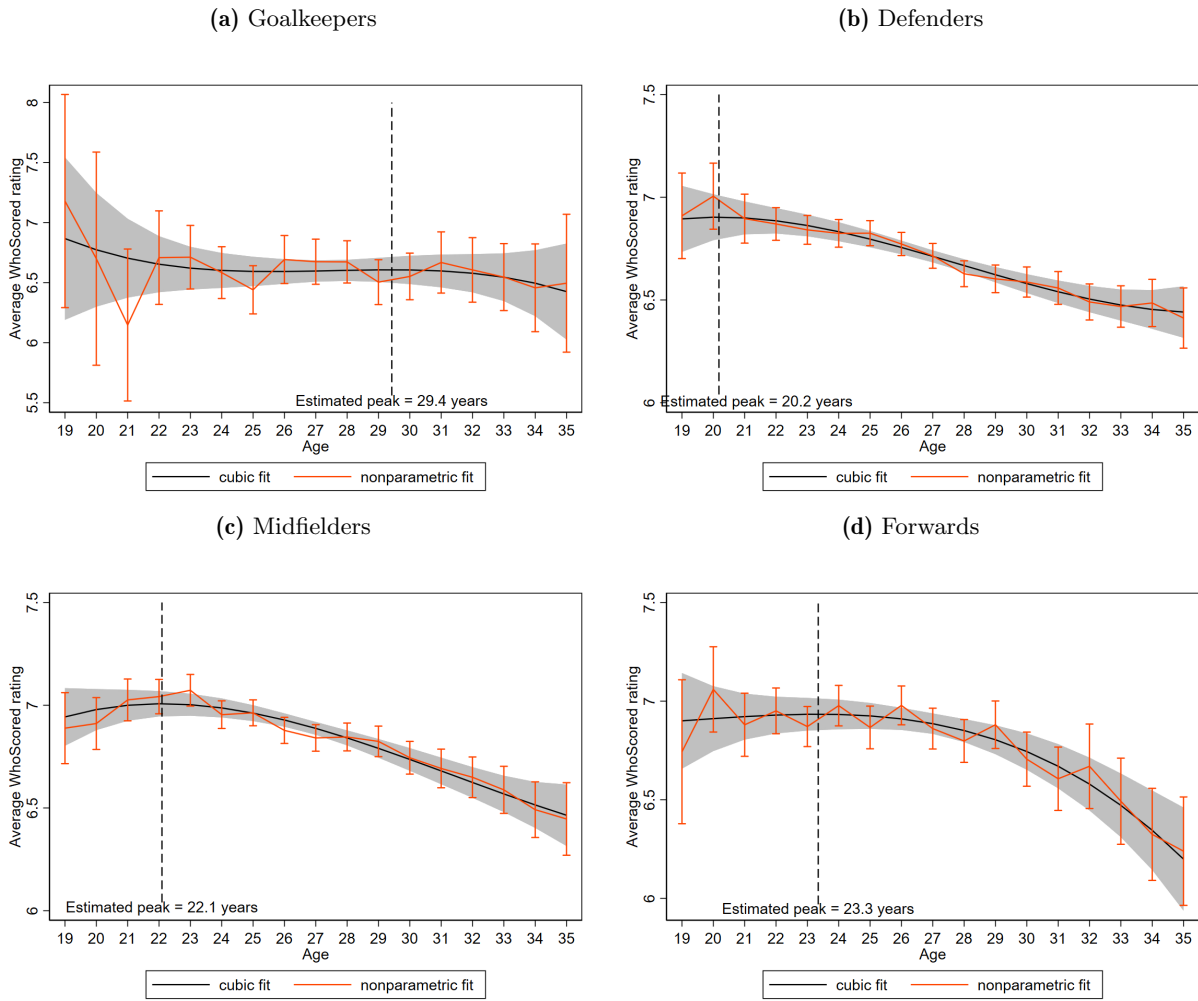
Notes.- Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Figure 3.A2: Minutes per game age profiles by position



Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Figure 3.A3: WhoScored age profile rating by position

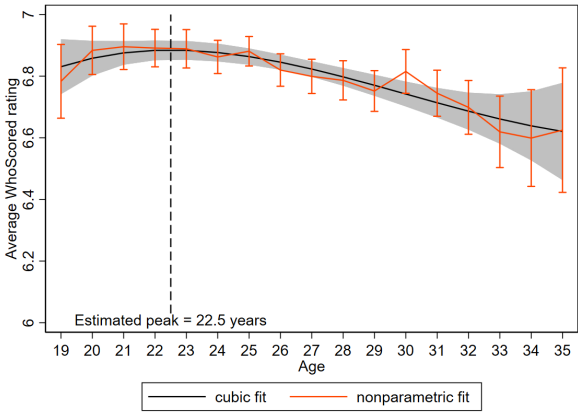
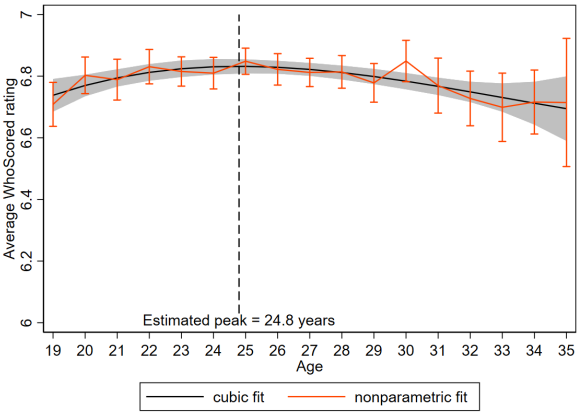


Notes.- Estimates control for fixed effects at the player level. Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

Figure 3.A4: WhoScored rating age profile in Bundesliga

(a) OLS

(b) Player fixed effects



Notes.- Shaded area and orange bars represent 95% confidence intervals calculated using bootstrapping.

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