Parental Wealth and Early Labor Market Outcomes

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Abstract

We use matched employer-employee data together with detailed wealth records for the entire Swedish population to examine the relationship between parental wealth and early-career labor market outcomes of children. We find that young adults at the bottom of family wealth distribution tend to have lower earnings, higher income volatility, and less stable jobs. However, we also find that controlling for a comprehensive set of observable characteristics —including educational major and parents' earnings —renders this relationship non-monotone with the wealthiest 10% having lower earnings relative to the middle part of the distribution. Our analysis reveals that the positive correlation between initial wealth and early-career earnings is primarily driven by between-firm differences, suggesting an important role for the allocation of workers across employers. To better understand these results, we develop a parsimonious model with on-the-job search, savings, stochastic disutility of work, and heterogeneity in job destruction rates. The model successfully replicates the observed patterns, including the within- and between-firm earnings dynamics across the wealth spectrum. Policy simulations suggest that providing greater unemployment benefits to workers upon labor market entry - financed through labor income taxes - can substantially increase wages and overall welfare.

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1 Introduction

Why do some young adults thrive in the labor market while others struggle, even when they share similar educational backgrounds and skills? The answer may lie in an often-overlooked factor: parental wealth. This paper explores how the financial safety net provided by parents can significantly influence early career outcomes, offering a form of insurance that shapes the trajectory of young workers' lives.

Parental wealth is an important determinant of children's labor market outcomes and consequently is a key driver of social mobility and intergenerational inequality. Previous literature has explored various channels for the link between individual earnings and parental income (or wealth), including genetics (e.g., Bjorklund et al., 2005; Liu and Zeng, 2009), parental time and educational investment (e.g., Restuccia and Urrutia, 2004; Cunha and Heckman, 2008; Del Boca et al., 2014; Lee and Seshadri, 2019), higher education levels (e.g., Keane and Wolpin, 1997; Carneiro and Heckman, 2002; Lochner and Monge-Naranjo, 2011), and connections (e.g., Staiger, 2021; San, 2022). Our focus in this paper is to examine the role of family wealth through the lens of labor market dynamics, conditional on having similar education and other observable characteristics. Following the literature on the role of parental insurance (e.g., Rosenzweig and Wolpin, 1993; Kaplan, 2012), we concentrate on young adults who, arguably, are at a stage where parental wealth has the greatest potential to influence their labor market outcomes.

For our empirical analysis, we use a matched employer-employee dataset containing annual information on individual labor market outcomes, and demographic and socioeconomic variables for the entire Swedish working-age population over the years 1990–2019, matched with information on individual wealth for the period 1999–2007, as well as the intergenerational register, which links children to their biological or adoptive parents.

We begin our analysis by examining the link between parental wealth and children's earnings during the initial five years after the labor market entry. We do so in three steps. First, we document substantial differences in average labor earnings across family wealth deciles: workers in the top wealth decile earn about 25% more than those from the lowest two deciles. About half of this gap can be attributed to differences in education; however, even after controlling for a wide range of observable characteristics – including the length of study, the educational major, the region of residence, and earnings of parents – a residual income gap remains. More importantly, the residualized schedule reveals an inverse U-shape relationship —workers from the lowest two wealth deciles earn 4% less than the median, whilst those from the top decile earn 2% less than the median. The same non-monotonic relationship holds at the extensive margin after controlling for observables: the employment rates are higher in the middle of the wealth distribution than at the tails.

Second, we examine how parental wealth affects job mobility of young adults. Most striking differences by wealth deciles are observed for employment to non-employment transitions: the least wealthy young adults are over 50 (70) percent more likely to separate from their jobs than those in the middle (top) of the distribution. Again, controlling for demographic characteristics produces a non-monotone relationship, where both the bottom 30% of individuals and the top 10% in wealth distribution have a higher probability of exiting employment than median workers. Overall, we find that low-wealth individuals have significantly less stable jobs and more volatile earnings, even after controlling for a comprehensive set of observable characteristics.

Third, to understand the role that firms play in explaining the facts above, we decompose the variation in earnings into within- and between-firm components. We find a clear pattern of sorting on wealth across firms: wealthier individuals tend to work in higher-paying firms. This positive relationship holds even after we control for observables, and across the whole spectrum of wealth. In contrast, the within-firm component is relatively flat across wealth deciles, with a prominent drop for the top 10%. This analysis helps us better understand the observed inverse U-shape relationship between family wealth and earnings, suggesting that most of the growth in (residualized) labor earnings for all but the top decile of wealth distribution can be accounted for by sorting into higher-paying firms. In contrast, the dip in earnings among the wealthiest 10% is driven by the within-firm component, possibly reflecting differences in preferences, unobserved ability, or labor supply. Notably, after replicating this analysis by 3-digit occupations, we do not find systematic sorting by wealth across occupations further highlighting the importance of firms. Finally, we show that low wealth workers are exposed to higher unemployment risk in that they tend to work in firms with higher average job separation rates.

To better understand the observed patterns, we build a partial equilibrium job search model with savings. We follow closely Lise (2013) and add two new elements. First, firms are heterogeneous in the wage they offer, and the security of the job depends on the wage level of the firm. The assumption that the job destruction rate is higher in low-wage jobs allows us to fit the negative gradient between job separations and wealth for the bottom part of the distribution. Second, similar to Clymo et al. (2022), our model includes a non-pecuniary cost of working, which is key to replicating a higher job separation rate among the wealthiest individuals.

The main mechanism through which parental wealth induces sorting into higher-paying jobs across observationally equivalent workers is by providing a financial safety net for unemployed children. By having access to additional consumption while unemployed, young workers can afford to search longer for higher paying and more stable jobs.[1] We provide supporting evidence for this channel by showing that wealth-earnings profiles become steeper when non-employment rates are higher and jobs are scarce. Moreover, in line with the model,

[1]In general, previous literature found empirical support for this mechanism in the form of the extension of unemployment benefits eligibility and other cash transfers. Card et al. (2007), for example, show that severance payments reduce job finding rates from unemployment in Austria (see Chetty, 2008, for qualitatively similar results for the US). In addition to an increase in unemployment duration, Nekoei and Weber (2017) find that higher UI raises wages by improving reemployment firm quality and attenuating wage drops due to longer joblessness. Herkenhoff et al. (2023) shows that increasing credit limits also prolongs job search in unemployment.

we also observe a gradual convergence in labor earnings between low- and high-parental wealth individuals over time, as individuals start accumulating their own assets.

We calibrate the model and show that it can replicate the observed relationships between labor market outcomes and initial wealth, including the between- and within-firm decomposition. Furthermore, the model allows us to consider the welfare implications driven by differential access to wealth upon labor market entry. In particular, we simulate a counterfactual policy of increasing unemployment benefits for young adults at the point of entry and assess its effect on average wages by wealth decile, and the overall welfare.

Our paper contributes to several strands of literature. Most related is the literature concerned with understanding the insurance that parents, or families more broadly, provide to their children. For example, Rosenzweig and Wolpin (1993) find that parental assistance, in the form of both financial transfers and cohabitation, is as important as government transfers for consumption smoothing of young adults. Kaplan (2012) demonstrates similar benefits from parental assistance, where the option to move in and out of the parental home allows youths to search for jobs with high earnings growth potential. Angelucci et al. (2018) shows that family networks can pool resources to facilitate investment in non-collateralizable assets, like human capital, where credit market imperfections are most binding. Our paper extends this body of work by exploring whether the ability of parents to provide financial transfers affects early career labor market outcomes of their children.

Second, our paper relates to empirical work on intergenerational income mobility that measures the extent to which socioeconomic status persists across generations (see Solon, 1992; Zimmerman, 1992; Björklund and Jäntti, 1997; Chetty et al., 2014, 2020, among others). While most of this literature uses data on earnings (or occupations) for both children and their parents, we argue that studying social mobility using family wealth is beneficial as it serves as a natural stock measure of socioeconomic status and is more likely to be correlated with permanent rather than current income.

Third, our research is connected to the large literature assessing empirically the relationship between own wealth and labor market outcomes (e.g., Rendon, 2006; Card et al., 2007; Chetty, 2008; Lentz, 2009; Herkenhoff et al., 2023, among many others), as well as theoretical work that incorporates search frictions into models with savings and incomplete markets (e.g., Bewley, 1979; Huggett, 1993; Aiyagari, 1994), that has recently accelerated (see Rendon, 2006; Lentz, 2009; Krusell et al., 2010; Lise, 2013; Griffy, 2021; Chaumont and Shi, 2022; Huang and Qiu, 2022; Clymo et al., 2022; Sepahsalari and Eeckhout, 2023, to name a few). While wealth is generally accumulated over the working life (see Cagetti, 2003; Jakobsen et al., 2020), we show that the same forces can also apply at the start of young workers' careers if they have access to (some of) their parental wealth.

Finally, our paper relates to a large recent literature documenting the dynamics and variance of income using large panel data sets (e.g., Bingley et al., 2013; Blundell et al., 2015; Song et al., 2019; Friedrich et al., 2019; Guvenen et al., 2021; Juraj et al., 2022; Haltiwanger et al., 2022; Gustafsson and Holmberg, 2023; Engbom et al., 2023, to name a few). For example, Song et al. (2019) found that the rise in earnings inequality between 1981–2013 in the U.S. was mainly driven by between-firm differences. Our contribution to this literature is to study how wealth affects the allocation of workers across firms.

This paper is organized as follows. Section 2 describes the data used in the analysis. Section 3 outlines the differences in early career labor market outcomes by parental wealth, focusing on annual earnings and labor market transitions. Using matched employer-employee data, we then explore the role of firms in explaining our main empirical facts Section 4. Section 5 introduces the model, and provides additional empirical evidence to support the model's predictions. Our calibration strategy, the fit of the model, and the results of policy experiments are presented in Section 6. Finally, Section 7 concludes.

2 Data

For our empirical analysis, we use a matched employer-employee dataset that combines information from three different registers compiled by Statistics Sweden. The first is the Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier (LISA) containing annual information on individual labor market outcomes, firm characteristics, demographic and socioeconomic variables for the entire Swedish working-age population over the years 1990–2019. We use information on wage earnings, education (length and major), workplace identifier, municipality of residence, three-digit occupation codes, age, and gender from LISA.

The second data set is the Wealth Register, which contains information on individual wealth gathered from tax records and primarily based on third-party reports, i.e. bank reports, for the Swedish population over the period 1999–2007. The main content of this register is wealth information in terms of the type and current market value of real and financial assets and debt. Some inconsistencies in wealth data were identified for the inaugural year of data collection (Lundberg and Waldenström, 2018); consequently, our analysis includes data only from 2000 to 2007.

In our main analysis, we define wealth as "*liquid wealth*," which is the aggregate of financial wealth and positive housing equity. This decision stems from the fact that we consider wealth as a protective buffer against labor market shocks. Financial wealth, encompassing bank account balances, trust funds, and investments in publicly traded stocks and bonds, can be easily converted into cash to support consumption. We also factor in positive housing equity, which can serve as collateral for loans (or directly serve as the place of co-residence for children). This measure includes the net market value of residential properties —houses, apartments, and vacation homes —after deducting total debt. However, we exclude negative housing equity from our analysis, as it does not directly affect the ability to use financial wealth for consumption. We have also conducted the analysis considering financial wealth alone, yielding similar results.[2]

[2]The wealth register exclude information on non-listed business equity holdings, which Waldenström (2016) estimated to account for approximately five percent of the total household wealth. Given that these

This reporting structure resulted in the exclusion of low or non-interest-bearing account holdings, such as checking or salary accounts, from the data for the majority of our sample period.[3] This led to a concentration of zero liquid wealth for about 14% of the population. To address this, we aggregated the bottom two deciles in our primary analysis.

The third data set is the intergenerational register linking children to their biological or adoptive parents. One of our main variables of interest is family liquid wealth. We define this as the sum of the liquid wealth held by a child and his or her guardians. To facilitate comparisons between individuals at comparable life stages and to minimize the influence of the children's personal labor market outcomes, we assess family wealth when the child reaches the age of 18.

Sample construction

We aim to determine the relationship between parental liquid wealth and early career labor market outcomes. To do so, we include all individuals who turned 18 at some point during the period 2000–2007, i.e., cohorts born 1982–1989.[4] This allows us to calculate family wealth before the child's labor market entry. Because labor market entry is endogenous and depends on education, we rank all individuals by family wealth at age 18. To prevent sample attrition among higher-educated individuals in the younger cohorts, we define labor market entry as the year when a young adult reaches their maximum level of education and focus on the first five years after entry in our main analysis. Arguably, the start of a worker's career is when family background and household wealth are likely to have the largest impact. Individuals without a record of education are excluded from our analysis.

When analyzing employment rates and labor market transitions, we consider all employed individuals, including wage employees and self-employed. However, when analyzing labor earnings, we focus on employees and their annual wage income. Since we do not observe hours worked in the data, we cannot construct hourly wages. Finally, as the primary focus of our analysis is economically active individuals, we restrict our sample to workers who earned at least SEK 1,000 (approximately, USD 100) per month, or equivalently SEK 12,000 (USD 1,200) annually, in least one year after labor market entry.

Table 1 shows descriptive statistics related to family liquid wealth at age 18 and completed education by wealth deciles. As expected, the average length of education (and correspondingly, the average age at labor market entry) and the share of workers with a college degree increases across wealth groups. The table also highlights the large dispersion in liquid wealth. Individuals belonging to the top decile have an average financial wealth more than five times as large as the average of the ninth decile, while the top 1 percent of households own 5.7 times the average financial wealth of the top decile. Even within the top

assets are not easily liquidated, their exclusion from the data is unlikely to significantly impact our analysis.

[3] Prior to 2006, only bank account deposits accruing an annual interest of 100 SEK (approximately 10 USD) were required to be reported. From 2006 to 2007, the reporting requirement was expanded to include all bank accounts with balances exceeding 10,000 SEK.

[4] We carried out the analysis separately for men and women with similar results.

Table 1: Summary statistics by wealth decile.

	Family wealth at age 18, deciles									%ile
	1–2	3	4	5	6	7	8	9	10	100
Median wealth	0	7.4	31.8	91.0	164.3	193.1	250.3	441.1	1,359.0	7,129.2
Mean wealth	0.6	12.2	39.4	91.3	170.1	238.4	378.7	591.1	3,414.1	12,780.1
Std. dev. wealth	2.6	12.4	27.9	54.5	121.0	217.5	384.2	548.3	8,558.8	17,896.6
Education years	12.4	12.8	13.1	13.3	13.4	13.5	13.7	14.0	14.3	14.6
Bachelor (%)	20.3	25.0	29.9	33.8	36.4	38.4	42.3	47.6	55.8	61.3
Age at graduation	22.6	22.7	23.0	23.2	23.3	23.4	23.6	24.0	24.4	24.7
Empl. rate (%)	83.9	87.9	89.9	91.0	91.3	91.5	92.4	93.0	93.3	92.2
Self-employment(%)	0.7	0.7	0.8	0.9	1.0	1.0	1.0	1.2	1.8	2.8
Obs.	156,093	80,899	82,413	82,477	82,513	82,708	82,964	83,207	82,932	8,159

Note: Wealth is measured as liquid wealth owned by children and their parents when the child is 18 years old, in thousands of Swedish krona at 2010 prices. Bachelor (%) is the share graduating with at least a bachelors degree. Employment and self-employment are measured at the year of labor market entry.

percentile, the mean is almost three times larger than the median, indicating strong positive skewness.

3 Early career labor market outcomes

In this section, we utilize the richness of Swedish data to better understand the role of parental wealth for labor market outcomes, before and after controlling for observables. We focus on labor market outcomes during the first five years after entry, where entry is defined as the year when the highest observed education level is achieved. Throughout, we show outcomes of interest while controlling for an increasing number of observable characteristics. We will describe some outcomes as "Raw" when we control only for age and birth-year cohort. Controlling for age accounts for the fact that older individuals earn more, and controlling for age and cohort together removes common macroeconomic effects. Next, we present outcomes where we sequentially add years of education ("Edu"), degree major ("Major"), and municipality of residence together with a third-order polynomial in average parental earnings ("Residualized").[5]

Formally, we residualize the outcomes by running regressions of the following form:

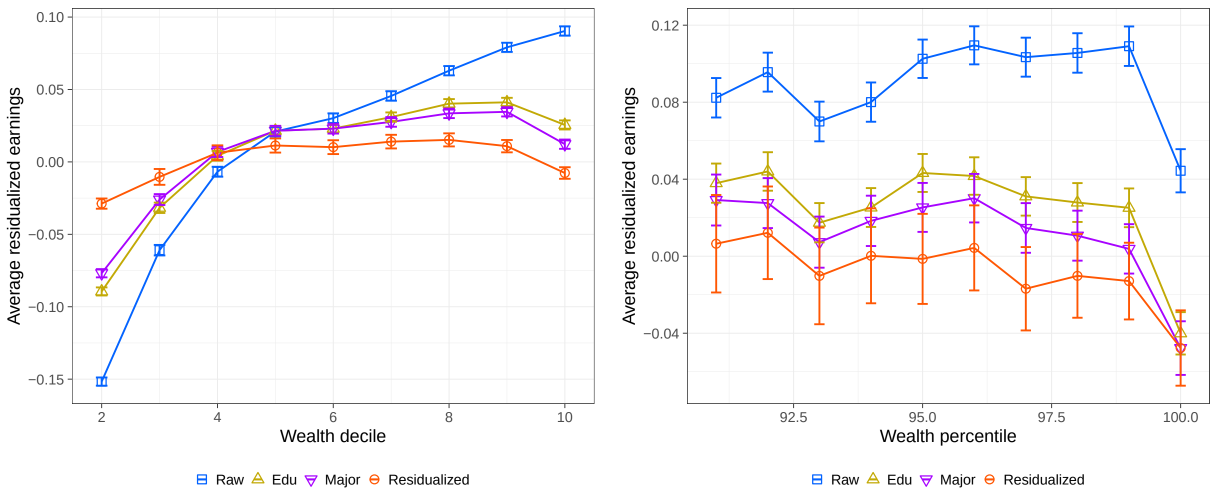
$$y_{ixt} = \phi_{xt} + f(earn_p) + \epsilon_{it}, \tag{1}$$

where y_{ixt} is, for example, the natural logarithm of worker i's annual earnings, belonging to group x, in year t. ϕ_{xt} represents the interacted fixed effect for group x in year t.[6] For the "Residualized" outcomes, we also control for a polynomial in parental earnings, $f(earn_p)$. Then, the mean-zero error term, ϵ_{it}, gives the distribution of relative earnings conditional

[5] Studies have found that cognitive and non-cognitive ability is positively correlated across generations (e.g., Björklund et al., 2010; Anger and Heineck, 2010; Grönqvist et al., 2017). Hence, controlling for average parental earnings partially addresses the issue of unobserved ability. Parental earnings were deflated using the CPI with 2010 as the base year and averaged over the years when the child was 13 to 19 years old.

[6] We get 288 birth-year and age groups. When adding years of education, we get 2,441 unique combinations. Adding major results in 139,213 groups. Finally, adding the municipality of residence results in 1,538,825 unique groups. Our sample has over 3.4 million observations.

Figure 1: Average log earnings, by family wealth decile.



Note: We use earnings wage among employees observed for the first five years after labor market entry. We control for interacted cohort and calendar year fixed effects ("Raw" series), and progressively add interactions with years of schooling ("Edu"), educational major ("Major"), municipality of residence, and a third-order polynomial in parental earnings ("Residualized"). The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

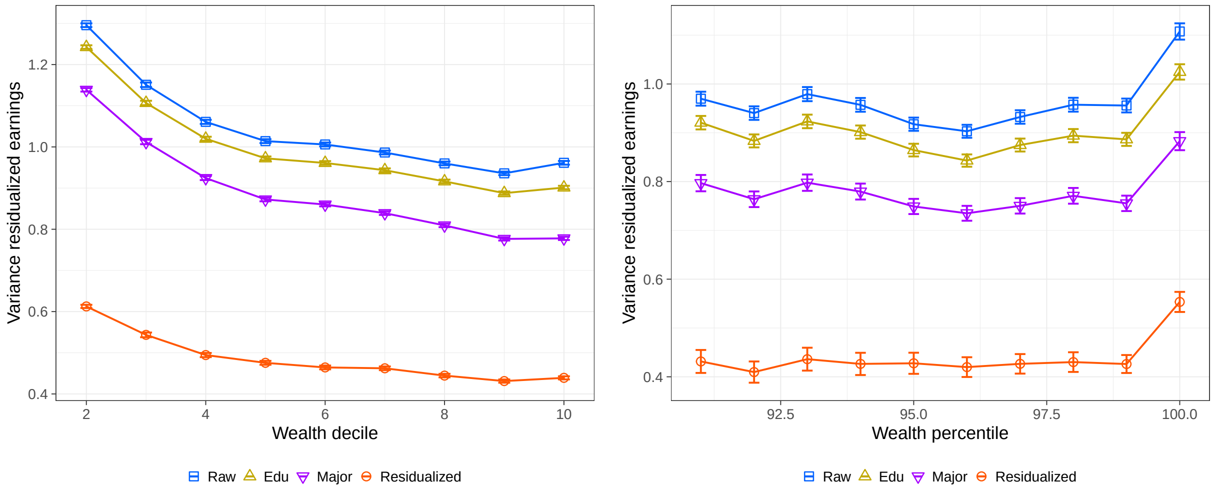
on the group characteristics. We then take the average of these residuals by family wealth decile, or in some cases percentile, and plot them in the graphs below.

Labor earnings

Figure 1 shows the average log earnings over the first five years after labor market entry by household financial wealth. The left panel displays earnings across household wealth deciles, while the right panel focuses on percentiles within the top decile. There is a substantial variation in raw earnings across the wealth spectrum: individuals from the bottom 20% of the wealth distribution earn approximately 14% less than the average worker, whereas those in the top 30% earn about 8% more. Notably, the opposite pattern emerges within the top decile: young adults from households in the top 1% earn 7% less, on average, than those at the 99th percentile.

After controlling for years of education ("Edu" line), individuals in the bottom two household wealth deciles earn approximately 10% less than the average worker, while those in the top decile earn about 2% more. The inclusion of fixed effects for educational majors yields only a marginal change beyond the effect of years of education alone. Adjusting for municipality of residence and a third-order polynomial in parental earnings reduces the gap further to -3% for the bottom two deciles. However, the earnings gap for the top decile of wealth distribution reverses its sign, with wealthiest individuals now earnings about 1% less than the average worker with similar characteristics. This highlights a clear non-monotonic pattern in fully residualized earnings: individuals in the middle of the wealth distribution tend to earn more than those at either end. Moreover, the right panel of Figure 1 shows that the decline at the top is primarily driven by individuals in the wealthiest one percent.

Figure 2: Variance of log earnings, by family wealth deciles.



Note: We use earnings among wage employees observed for the first five years after labor market entry. We control for interacted cohort and calendar year fixed effects ("Raw" series), and progressively add interactions with years of schooling ("Edu"), educational major ("Major"), municipality of residence, and a third-order polynomial in parental earnings ("Residualized"). The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

Next, we examine the variance of annual log earnings over the first five years in the labor market. Figure 2 shows that within-group earnings inequality tends to be higher among children from poorer households, and this relationship remains stable even after controlling for a wide range of observables. Again, a notable exception emerges at the very top of the distribution: the variance of log earnings within the top 1% exceeds that observed at any point between the 90th and 99th percentiles. We find similar patterns for the variance of income growth: growth volatility decreases steadily with household wealth, with a slight increase at the very top.

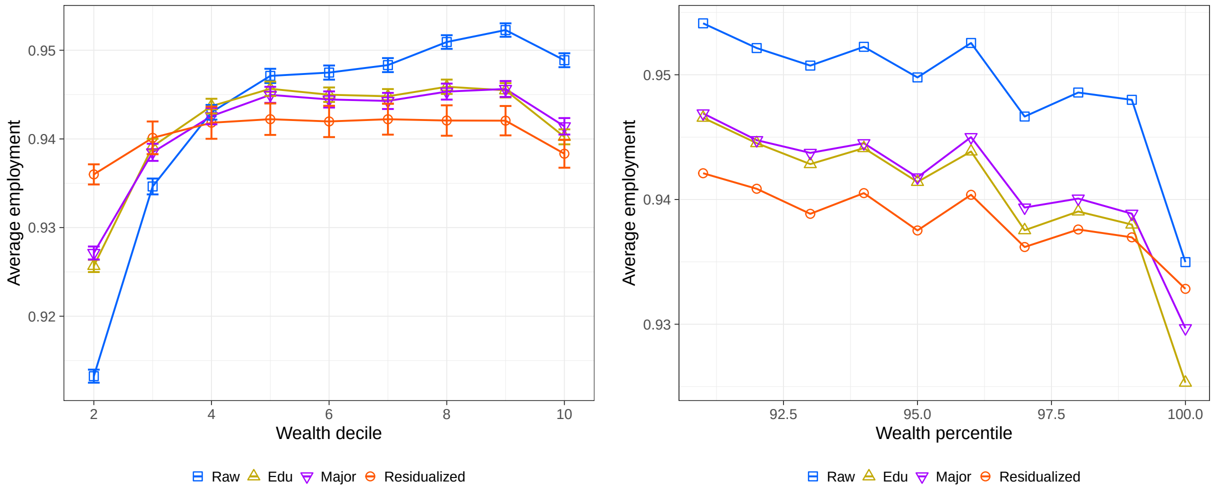
Employment rate and labor market transitions

One reason why children from poorer families experience more volatile earnings might be due to differential labor market transitions. Figure 3 shows the relationship between family wealth and employment (as opposed to non-employment).[7] Young adults at the bottom of the wealth distribution have about 5 percentage points lower probability of being employed compared to those with above-median family wealth. Similarly to labor earnings, the employment rate falls at the top of the wealth distribution after we control for observables. The most prominent fall is observed for individuals from the top 1 percent.

To better understand what determines the employment rate at each wealth decile, we

[7]Note that we do not have a good measure of unemployment. While we can observe whether a worker is registered as unemployed, the registration rate is far from perfect. In Sweden, to receive unemployment insurance (UI) benefits a worker needs to be a member of an unemployment insurance fund for the past 12 months. If not a member of an UI fund, they can still receive basic benefits after working for 6 months. Given that we are considering young adults at the start of their careers, their take-up rate of benefits is likely to be lower than that of an average worker. For this reason, we consider two states only – employment and non-employment.

Figure 3: Average employment rate, by wealth decile.



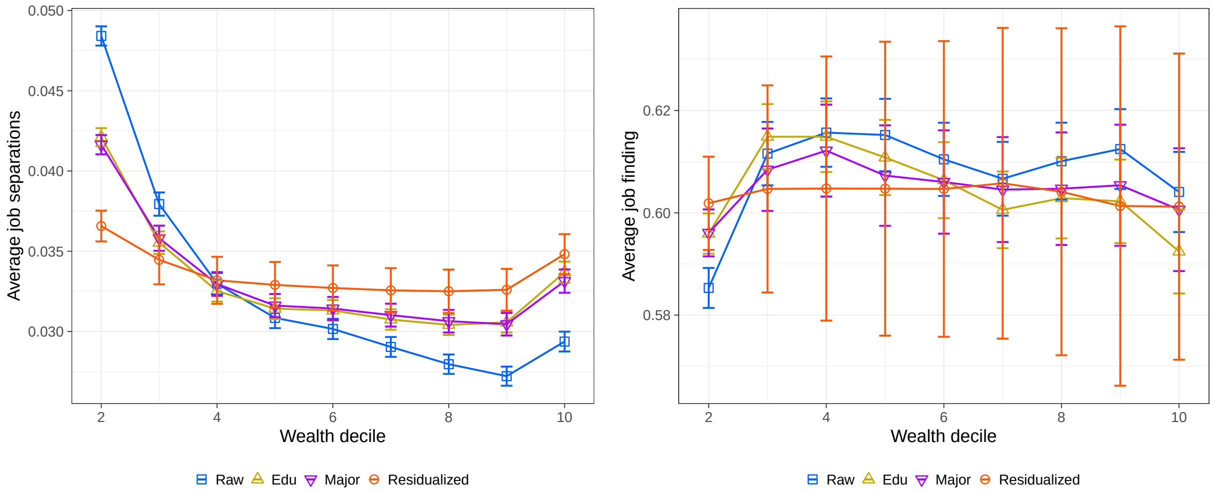
Note: The employment rates are calculated over the first five years after labor market entry, which is defined as the year when the highest observed degree was obtained. We control for interacted cohort and calendar year fixed effects ("Raw" series), and progressively add interactions with years of schooling ("Edu"), educational major ("Major"), municipality of residence, and a third-order polynomial in parental earnings ("Residualized"). The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

examine the flows into and out of employment. We measure the average job separation rate as the fraction of individuals who are employed (E) in year t and who experience non-employment (NE) in year $t+1$. Similarly, the job finding rate is the average proportion of workers without a job in year t who then are employed in year $t+1$.

The raw series in Figure 4 show that low-wealth individuals have a significantly higher probability of losing their job and a lower probability of switching from non-employment to employment compared to their wealthier counterparts. This difference is most striking for the job separation rate (E-NE transition) with the poorest workers being almost half as likely to move into non-employment than those at the median and almost double that of the ninth decile of the family wealth distribution (the left panel of Figure 4). As before, the top 10 percent of workers seem to be an exception as the job separation rate ticks upward for the wealthiest. Controlling for observables attenuates these gaps, again producing a non-monotonic (U-shape) relationship with the middle of the distribution having a lower E-NE transition rate than at the tails.[8] While the relationship between wealth and job finding rate is less stark, it is still the mirror image of job loss, with lower values at the top and bottom of the wealth distribution than in the middle (the right panel of Figure 4). Controlling for observables, the difference in the magnitude of NE-E transitions across wealth deciles is negligible. Taken together, these graphs suggest that both entry and exit margins contribute to the non-monotonic relationship between employment and family wealth, with job loss having a larger impact quantitatively.

[8] This finding is consistent with the findings by Clymo et al. (2022) that show a U-shape relationship between individuals' current wealth and their employment-to-non-employment transitions using the Panel Study of Income Dynamics in the US.

Figure 4: Average annual employment and non-employment transition rates.



Note: The transitions where calculated using the first five years after labor market entry. We control for interacted cohort and calendar year fixed effects ("Raw" series), and progressively add interactions with years of schooling ("Edu"), educational major ("Major"), municipality of residence, and a third-order polynomial in parental earnings ("Residualized"). The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

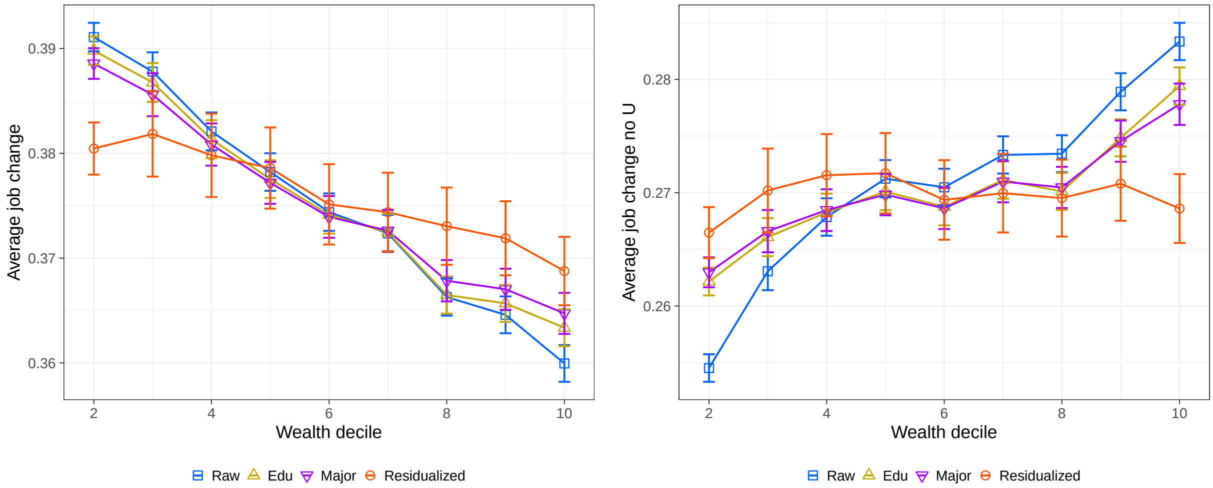
Figure 5 shows the rate at which workers change employers from one year to the next. The left panel presents all job switches and the right panel includes only those employer changes that do not involve interim spells of registered unemployment. When considering all job-to-job transitions, we observe a slight downward trend in the job switching rate across wealth deciles. Note that the difference in magnitudes by wealth decile is fairly small, moreover the curves flatten even more after we control for observable characteristics. When we exclude job changes with interim spells of unemployment, this relationship flips resulting in an upward trend across the wealth spectrum. Overall, it shows that less wealthy individuals experience more job churning, and they are especially more likely to separate from their jobs and move to non-employment or a different employer after a brief spell of unemployment.

Earnings growth

Higher job churning rates among less wealthy individuals have direct implications for income volatility, especially when job transitions involve non-employment spells. In the next step, we zoom in into earnings volatility by examining how earnings growth depends on family wealth. Figure 6 plots average annual growth of real income over the first five years upon entry, and its relationship with family wealth. We examine the growth rates separately for individuals staying with the same employer in the next year and workers that switch employers. The left panel shows the raw series that account for birth cohort and calendar year effects only, while the right panel uses fully residualized series.

Two key insights can be drawn from this graph. First, there is a significant disparity in annual income growth between job stayers and job leavers during the initial five years of their careers. Specifically, real earnings growth is entirely driven by those who switch employers, while job stayers face stagnation or even a decline in real earnings up to 5% for workers

Figure 5: Job change rate among employees, all job switches (left) and excluding those with interim spells of unemployment (right).



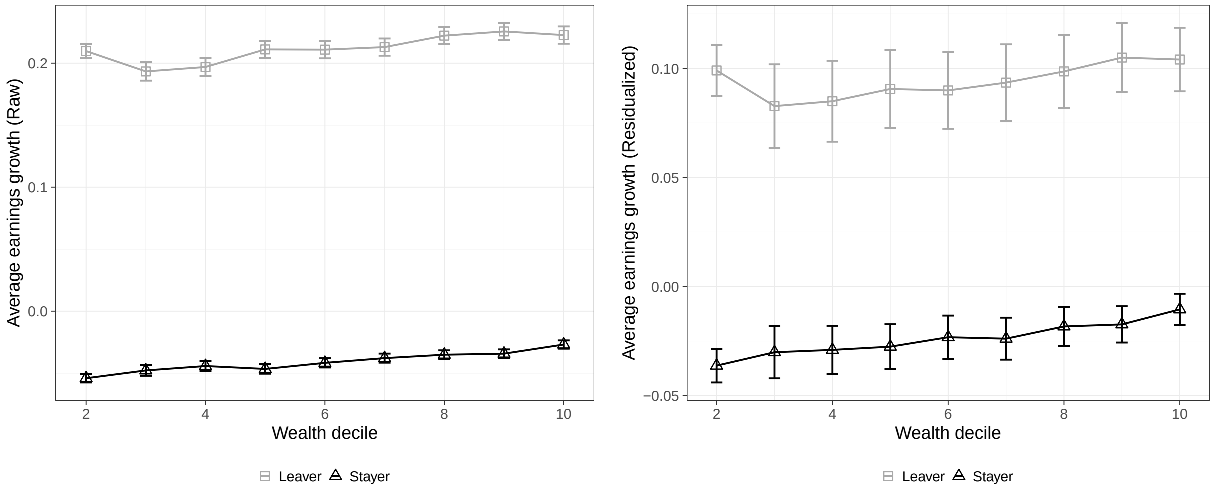
Note: The transitions where calculated using the first five years after labor market entry. We control for interacted cohort and calendar year fixed effects ("Raw" series), and progressively add interactions with years of schooling ("Edu"), educational major ("Major"), municipality of residence and a third-order polynomial in parental earnings ("Residualized"). The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

from the poorest households. In contrast, individuals who change employers experience, on average, a 10% increase in annual income. This evidence highlights the central role that job mobility plays in facilitating earnings growth at the start of workers' career.

The second insight concerns the relationship between earnings growth and wealth. The left panel of Figure 6 suggests that earnings growth increases steadily in family wealth, particularly among job stayers. However, once we account for observable characteristics, the differences across wealth deciles become negligible. Moreover, workers in the bottom two deciles of the distribution appear to benefit the most from switching employers.

To sum up, we find that even after controlling for a rich set of demographic characteristics (including parental earnings), individuals at the bottom of the family wealth distribution tend to have lower earnings, lower probability of being in employment, higher income volatility, and less stable jobs at the start of their careers compared to those with the median wealth. Moreover, there are two features that are common to the multiple graphs above, once we control for observables. First, we observe a sharp increase in earnings and employment (or a decline in job separations) as family wealth grows, followed by a flattening for the middle part of the distribution with young adults in deciles four to nine behaving very similarly. Second, there is a surprising reversal for the wealthiest 10% (or even 1%) of workers: they end up with lower earnings and employment probability, as well as a higher job separation rate, than the middle part of the distribution. In the next section, we will utilize the matched-employee nature of the data to investigate the role of firms in driving these relationships.

Figure 6: Annual earnings growth rates by wealth decile for job stayers and leavers.



Note: The series above show the average annual growth rate in real labor earnings over the first five years after labor market entry, split by the job stayers and job leavers status. The left panel is based on the "Raw" series that include interacted fixed effects for birth cohort and calendar year, while the right panel uses the "Residualized" series with additional controls for years of education, educational major, municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

4 Sorting across firms

The matched employer-employee component of the data allows us to explore whether individuals with low or high levels of parental wealth work at firms that are systematically different. We look at two characteristics of the firms – their average pay and job separation rate.

Firm-level earnings

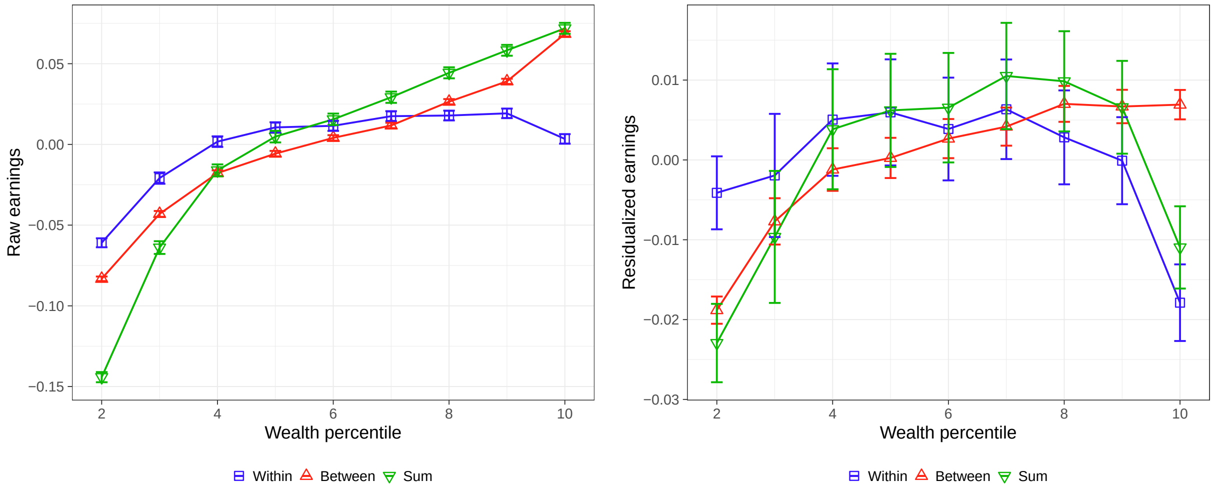
We start by decomposing workers' earnings across wealth deciles into between- and within-firm components. This is interesting since the between component highlights the potential role played by the allocation of workers across firms, whereas the within component highlights the potential differences in ability or labor supply.

Formally, the annual log earnings of individual i working at firm j in year t, y_{ijt}, can be expressed as the average log earnings within a firm plus a deviation from the firm's average, i.e.:

$$y_{ijt} = \underbrace{\frac{\sum_{i \in j} y_{ijt}}{N_{i \in j}}}_{\text{Between firm}} + \underbrace{y_{ijt} - \frac{\sum_{i \in j} y_{ijt}}{N_{i \in j}}}_{\text{Within firm}} = \underbrace{\overline{y}_{jt}}_{\text{Between firm}} + \underbrace{y_{ijt} - \overline{y}_{jt}}_{\text{Within firm}},$$

where $N_{i \in j}$ is the number of workers in firm j and $\overline{y}_{jt}$ is the average log earnings within a firm. Given that we focus on young adults during the first five years of their careers, we need to construct a firm-level average wage for a comparable group of workers. To do so, we calculate the average earnings for the cohort of young adults working at the same firm. Our baseline specification uses firms with at least five young adults. However, we repeated this

Figure 7: Within- and between-firm components of log earnings (Raw series on the left and Residualized on the right).



Note: Within- and between components have been calculated among individuals working in firms with at least 5 peers. The left panel is based on "Raw" series that include interacted fixed effects for birth cohort and calendar year, while the right panel uses "Residualized" series with additional controls for years of education, educational major, municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

analysis with a higher and lower threshold than five individuals, as well as using the entire firm's workforce over different minimum firm sizes, and the results are qualitatively similar.

Figure 7 shows this decomposition for the raw and residualized earnings averaged across household wealth deciles. A striking pattern emerges. We see a positive relationship between household wealth and the *between-firm* component, which remains even after we control for a comprehensive set of demographic characteristics (right panel of Figure 7). In contrast, the within-firm component shows an inverse U-shape relationship, with a particularly sharp drop in earnings among the top decile for both the raw and residualized series. Moreover, we conduct a similar decomposition using 3-digit occupation codes to see whether the observed patterns can be explained by individuals sorting into different occupations and find no evidence for it (see Appendix A for details). This suggests that sorting of wealthier workers into better paying firms is not a result of the occupational choice alone.

We can quantify the above relationships with a simple covariance decomposition. The covariance between an individual's annual log earnings over the first five years, y_{ijt}, with family wealth measured at age eighteen, a_i, can be decomposed into the covariance between wealth and each of the two (within and between) firm or occupation components:

$$\mathrm{Cov}(y_{ijt}, a_i) = \underbrace{\mathrm{Cov}(\overline{y}_{jt}, a_i)}_{\text{Between}} + \underbrace{\mathrm{Cov}(y_{ijt} - \overline{y}_{jt}, a_i)}_{\text{Within}}.$$

Table 2 shows the within and between contributions to the covariance between wealth and log earnings over the first five years after labor market entry. We present these statistics for the sample of firms at least 5 young adults ($N > 5$; our preferred specification), all

Table 2: Covariance decomposition between earnings and family wealth into within- and between-firm (or occupation) components.

		All		Deciles 1–9		Decile 10	
		Covariance	Between	Covariance	Between	Covariance	Between
Firm	Raw	0.152	57.4%	0.401	52.9%	47.1%	-0.006
$N \geq 5$	Resid.	0.069	103.1%	-3.1%	0.061	77.5%	22.5%
Firm	Raw	0.424	62.0%	38.0%	0.419	58.5%	41.5%
$N \geq 1$	Resid.	0.052	102.6%	-2.6%	0.069	82.2%	17.8%
Firm	Raw	0.407	55.5%	44.5%	0.397	50.8%	49.2%
$N \geq 10$	Resid.	0.039	111.0%	-11.0%	0.055	79.1%	20.9%
Occ.	Raw	0.236	-8.7%	108.7%	0.222	-9.3%	109.3%
	Resid.	-0.055	76.5%	23.5%	0.004	45.7%	54.3%

Note: Firm components are calculated with a lower bound of peers (N) of one, five or ten; no such restrictions were necessary for the between-occupation components as the minimum number of peers per occupation was 24. We use log of earnings and log of family wealth plus one when calculating the covariances.

firms ($N > 1$), and at least ten young adults ($N > 10$). We find that in the raw data, the between-firm component accounts for just over a half of the observed covariance between parental wealth and child log earnings. Recall that individuals from the top wealth decile behave differently from the rest of the population, which can be seen from the last three columns in Table 2. For the wealthiest workers, the covariance between family wealth and log earnings is negative and can only be explained by the within-firm component.

When we control for the full set of observable characteristics, the between-firm differences can explain virtually all of the covariance between earnings and wealth (that share is somewhat lower when we exclude the top decile, as for the bottom part of the distribution the within-firm component moves in the same direction as the between-firm component). This confirms that earnings differences across wealth deciles are largely driven by the allocation of individuals across firms. As the within-firm component captures mainly demographic (or labor supply) differences across individuals, it is not surprising that it explains a larger share of covariance for the raw series and almost nothing (and flips the sign) for residualized series.

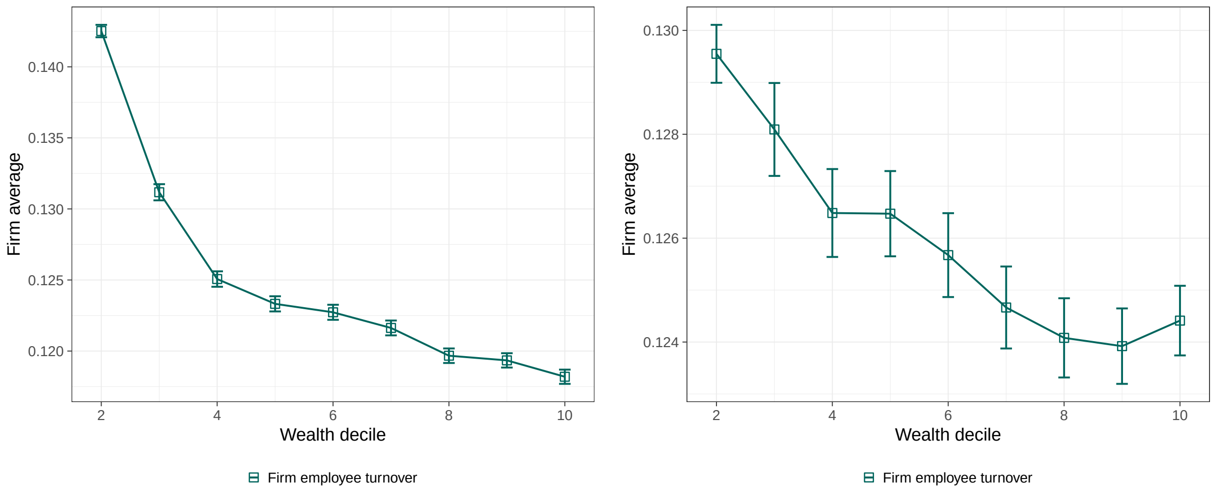
For occupations, the share of covariance between family wealth and earnings that can be explained by the between-occupation component is fairly small and negative in the raw data, and the overall covariance is negative in the residualized data.

Taken together, this evidence suggests that the allocation across different types of firms drives the increase in earnings over the wealth spectrum; while the relative drop in earnings among the wealthiest individuals can be attributed to the labor supply factors (such as preferences or unobserved human capital).

Firm-level separations

Using the universe of workers and their employers, we construct the average job separation rate for each firm as the fraction of the firm's workforce in year t that are no longer employed at that firm the following year. We then run the same regressions as in Equation (1) to control for individual worker's characteristics using firm-level job separation rate as an outcome variable. Figure 8 shows that young adults from poorer households tend to work at employers that have higher worker turnover rates. This holds true when using both raw (left panel) and residualized (right panel) series and across the whole wealth spectrum.

Figure 8: Firm-level average annual job separation rates, by wealth decile.



Note: The left panel is based on "Raw" series that include interacted fixed effects for birth cohort and calendar year, while the right panel uses "Residualized" series with additional controls for years of education, educational major, municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals after adjusting for the loss of degrees of freedom from residualization.

Overall, the evidence drawn from the firm-level data suggests that individuals from poor households are more likely to be employed in low-paying and high-turnover firms, even after we control for a comprehensive set of observable characteristics.

5 Model

In the preceding section, we show that, after controlling for detailed demographic characteristics, the allocation of workers across firms is a key determinant of the differences in earnings across the parental wealth spectrum. To explain the observed relationships, we propose a simple search model, in which parental wealth can act as an insurance mechanism in the children's job search process, i.e. higher parental wealth enables workers to extend their search period and hold out for better matches. In particular, we consider a partial equilibrium on-the-job search model with assets, heterogeneous wages and job destruction rates, and a disutility cost of working.[9] The model builds on Lise (2013) and is similar to

[9]The model can be extended to a general equilibrium analysis relatively easily using the bargaining protocol in Elsby and Gottfries (2022). However, since we focus on a small segment of the labor market, we maintain a partial equilibrium setting.

Clymo et al. (2022) but includes on-the-job search.

We use the model for three purposes. First, we assess whether a relatively parsimonious model can replicate the patterns documented above. Second, we use the model to infer the average proportion of their parents' wealth that children have access to. Finally, we evaluate the positive and normative effects of introducing additional unemployment benefits (which can be thought of as a subsidy for search) upon initial entry into the labor market.

5.1 Setup

Preferences and saving: Time is continuous, and workers maximize expected discounted lifetime utility over the infinite planning horizon:

$$E_0 \int_0^\infty e^{-\rho t}\big(u(c_t) - u_t^d\big)dt,$$

where ρ is the discount rate (adjusted by the death rate, at which workers leave the market). Workers gain utility from consumption flow, c_t, which is determined optimally by the individual. Finally, u_t^d represents non-pecuniary costs of working, which is positive if a worker is employed and equal to zero otherwise.

The per period utility from consumption is given by:

$$u(c) = \frac{c^{1-\alpha} - 1}{1-\alpha}, \tag{2}$$

where α determines the relative risk aversion. The worker chooses how much to consume and save each period. Hence, the asset accumulation equation can be written as:

$$\dot{a}_t = ra_t + y_t - c_t, \text{ subject to } a_t \geq 0 \tag{3}$$

where r is the common interest rate, a_t is the asset level at time t, y_t is the labor income equal to wages if employed or unemployment benefits if unemployed, and c_t is the consumption flow at time t. We impose a borrowing constraint such that assets cannot be negative. This is a plausible assumption given that we model young adults starting their careers, while explicitly accounting for their parental wealth.

Matching and job transitions: Workers begin life unemployed and receiving the minimum benefit level b_{min}, which corresponds to around 670 SEK per week ($\approx$ 60 US dollars). This reflects the fact that workers who have zero work experience do not qualify for UI benefits and can only apply for other benefits (if at all) that are typically quite low, especially for younger individuals.[10] Upon entry, a worker is randomly assigned an initial level of assets for a given decile. We produce an initial asset distribution proportional to the family wealth distribution, with a scale parameter ψ.

[10]For example, unemployed young people between 18 and 24 years old can apply for Development allowance (*utvecklingsersättning*) through participation in active labor market programmes or, alternatively, claim means-tested social assistance (*Försörjningsstöd*). See Appendix B for more details on UI system in Sweden.

Workers receive job offers at Poisson rates λ_0 when unemployed and λ_1 when employed. An offer is a wage level w drawn from an exogenous distribution, F. When an offer arrives, the worker will accept it if the value of working at the offered wage exceeds the value of remaining unemployed, in which case the worker exits unemployment. Similarly, the worker will change jobs if the value of employment at a newly received offer is higher than that of continuing working in their current job. Whilst employed, workers receive a job destruction shock at rate $\delta(w)$, upon which they transition into unemployment. Notably, we allow for the job destruction rate to depend on wage, which is key to generating the decline in job separations over the lower levels of the initial asset distribution.[11] Finally, there is an exogenous reallocation shock that arrives at rate λ^r, at which point the worker accepts a new job offer randomly drawn from the wage distribution, F.[12] Finally, similarly to Clymo et al. (2022), we assume that employed workers receive an opportunity to quit at rate χ. This parameter is meant to capture the need to give an advance notice to the firm when resigning, as well as to negotiate mutually agreeable termination terms so that workers are still eligible for the UI benefits when unemployed.

Immediately following job loss, workers receive unemployment benefits $b(w) = 0.8w$ (see Appendix B for details on the Swedish unemployment system), which run out at rate ϕ. (In the calibration, we choose the value of ϕ to reproduce the average duration of UIBs of one year). After that, workers receive basic benefits $b^L(w) = 0.5w$, approximately consistent with the Swedish unemployment insurance system. For new entrants into the labor market, we assume that b_{min} corresponds to 60% of the lowest wage.

Hamilton-Jacobi-Bellman equations

The model can be represented using the continuous time Hamiltonian-Jacobi-Bellman (HJB) equations for the value of being unemployed with assets a and previous wage w for two levels of benefits; as well as the value of being employed with assets a and wage w. Let $U(w,a)$ and $U^L(w,a)$ denote the value of unemployment, and unemployment at the lower unemployment benefit level, respectively.[13] Let $W(w,a)$ denote the value of employment. Beyond a worker's optimal consumption level, there are two reservation wages associated with accepting job offers from unemployment that the worker must determine.

[11] While Clymo et al. (2022) do not link the destruction rate to wages, they have a similar mechanism in their model where less wealthy individuals are more likely to accept inherently riskier jobs to move out of unemployment faster.

[12] The exogenous reallocation shock is standard in the literature and helps capture job changes due to other factors not captured in the model (e.g. family relocation) or non-wage job characteristics, as well as involuntary reallocations (Jolivet et al., 2006; Bagger and Lentz, 2018). The latter reflect job losses followed by the immediate finding of a replacement job, or, alternatively, a worker's response to a formal or informal advance notice. For example, Grindaker et al. (2023); Simmons (2024) show that many job switches occur due to workers acknowledging large declines in job security within a job. This feature of the model helps generate job-to-job transitions associated with a drop in wages, that are relatively frequent in the data.

[13] Given the Poisson arrival rates of shocks, the value functions are stationary and we can drop time subscripts from our notations.

The two reservation wages $w^U(w,a)$ and $w^L(w,a)$ for unemployed workers with asset level a, previous wage w, and higher or lower level of benefits, respectively, solve the following equations:

$$W\big(w^U(w,a),a\big) \coloneqq U(w,a) \quad \text{and} \quad W\big(w^L(w,a),a\big) \coloneqq U^L(w,a). \tag{4}$$

Those in employment accept offers that are greater than their current wage since $W_w > 0$, which also entails a unique solution for (4).

The HJB equations for the value of unemployment and unemployment at the lower level of benefits are, respectively, written as:

$$\rho U(w,a) = \max_c \Bigg\{ u(c) + \lambda_0 \int_{w^U(w,a)} \big(W(x,a) - U(w,a)\big) dF(x) \\ + \phi[U^L(w,a) - U(w,a)] + U_a(w,a)\dot{a} \Bigg\}, \tag{5}$$

where assets evolve according to:

$$\dot{a} = ra + b(w) - c,$$

and

$$\rho U^L(w,a) = \max_c \Bigg\{ u(c) + \lambda_0 \int_{w^L(w,a)} \big(W(x,a) - U^L(w,a)\big) dF(x) + U^L_a(w,a)\dot{a} \Bigg\}, \tag{6}$$

where assets evolve according to:

$$\dot{a} = ra + b^L(w) - c.$$

The HJB equation for an employed worker with assets a and wage w is:

$$\rho W(w,a) = \max_c \Bigg\{ u(c) - u^d + \underbrace{\delta(w)[U(w,a) - W(w,a)]}_{\text{job destruction shock}} \\ \underbrace{+ \lambda_1 \int_w \big(W(x,a) - W(w,a)\big) dF(x)}_{\text{voluntary job-to-job transition}} \\ \underbrace{+ \lambda_r \int \big(\max\{W(x,a), U(w,a)\} - W(w,a)\big) dF(x)}_{\text{reallocation shock}} \\ + \underbrace{\chi\big(\max\{W(w,a), U(w,a)\} - W(w,a)\big)}_{\text{voluntary quit into unemployment}} + W_a(w,a)\dot{a} \Bigg\}, \tag{7}$$

where assets evolve according to:

$$\dot{a} = ra + w - c.$$

If employed, the worker might choose to quit if the value of unemployment exceeds that of employment (conditional on receiving an opportunity to do so). This might happen as assets grow and the reservation wage exceeds the current wage. Finally, we impose a zero borrowing constraint:

$$a \geq 0. \tag{8}$$

Behavior

The continuous time setup renders simple first order conditions for the optimal level of consumption in each state (if the borrowing constraint is not binding). For example, the workers' optimal level of consumption in unemployment and employment solve:

$$u'(c^U(w,a)) = U_a(w,a) \quad \text{and} \quad u'(c^E(w,a)) = W_a(w,a). \tag{9}$$

These are standard intertemporal optimality conditions that state that the marginal utility of consumption needs to be equal to the marginal value of assets, implying that the expected utility cannot be increased by additional saving or borrowing.

We assume that workers with different asset levels face the same wage offer distribution. Hence, the observed differences in wages across the wealth spectrum are driven solely by differences in the job search behavior of individuals. For the purposes of our discussion, we will focus on the reservation wage $w^U(w,a)$ – the minimum accepted wage to exit unemployment with full UI benefits, which is key to generating the observed dynamics of wages and job flows. A similar argument can be made for the reservation wage from low-benefit unemployment, $w^L(w,a)$. The results below are well known in the literature, but we describe them here for clarity and completeness, as well as to highlight other model features such as the difference in search efficiency in unemployment and employment that are required to produce these results.

The derivative of the reservation wage from unemployment with respect to assets can be written as:

$$w^U_a(w,a) = \frac{U_a(w,a) - W_a(w^U(w,a),a)}{W_w(w^U(w,a),a)} = \frac{u'(c^U(w,a)) - u'(c^E(w^U(w,a),a))}{W_w(w^U(w,a),a)}. \tag{10}$$

This derivative is positive if $u'(c^U(w,a)) > u'(c^E(w^U(w,a),a))$, or equivalently $c^U(w,a) < c^E(w^U(w,a),a)$ given the concavity of the utility function. This expression outlines that if consumption is lower in unemployment than in employment at the corresponding reservation wage, then the reservation wage is increasing, and the corresponding exit rate from unemployment is falling, in assets. The key to generating this feature quantitatively is to ensure that the offer arrival rate when unemployed is higher than when employed (i.e. $\lambda_0 > \lambda_1$), so that the reservation wage $w^U(w,a)$ is higher than $b(w)$, the benefit level a worker receives whilst unemployed. Moreover, the additive disutility costs from working imply that the reservation wage has to be even higher than UI benefits to compensate workers for the drop in utility upon switching to employment.

If the reservation wage from unemployment increases in assets then, as assets grow, the reservation wage might exceed the worker's current wage and the worker decides to quit into unemployment. The presence of the disutility costs of working is key for matching this result quantitatively. The intuition for this result is straightforward when we consider instantaneous utility and can be easily extended to value functions. That is, continuing to work at the same job and earning one extra krona of wages increases worker's utility by $u'(c)$. Alternatively, if the worker quits into unemployment, she loses part of her income (since the replacement rate is lower than one) but gains the utility from leisure, u^d. As the level of assets (and hence consumption) grows, the marginal utility from consumption falls, while the disutility from working remains the same. This means that job separations increase at high levels of assets both due to voluntary quits into unemployment and as a response to the exogenous reallocation shock λ^r, where the new job offer is below the reservation wage $w^U(w, a)$.

To sum up, two elements of the model are necessary to replicate the U-shape relationship in the job separation rate by family asset decile. First, as workers with lower assets accept lower paying jobs, an exogenously higher job destruction rate at low wages generates the initial fall in job separations at the bottom of wealth distribution. Second, the presence of non-pecuniary disutility means that workers with high levels of assets are more likely to quit to non-employment.

5.2 Model predictions and supporting empirical evidence

Earnings convergence

In the model, the curvature of the utility function implies a non-linear relationship between the reservation wage and asset levels. As can be seen from Equation (10), as the level of assets (and consequently consumption) increases, the difference in the marginal utility across employment states becomes smaller. This means that the reservation wage from unemployment, along with the average accepted wage, follows an increasing but concave relationship with wealth – a pattern characteristic of job search models involving risk-averse individuals (e.g. Rendon (2006)). This theoretical prediction aligns well with empirical data: among observationally similar workers, the disparity in labor earnings is greatest for those with low-wealth parents (in the bottom three deciles) and diminishes progressively, becoming negligible by the fifth decile.

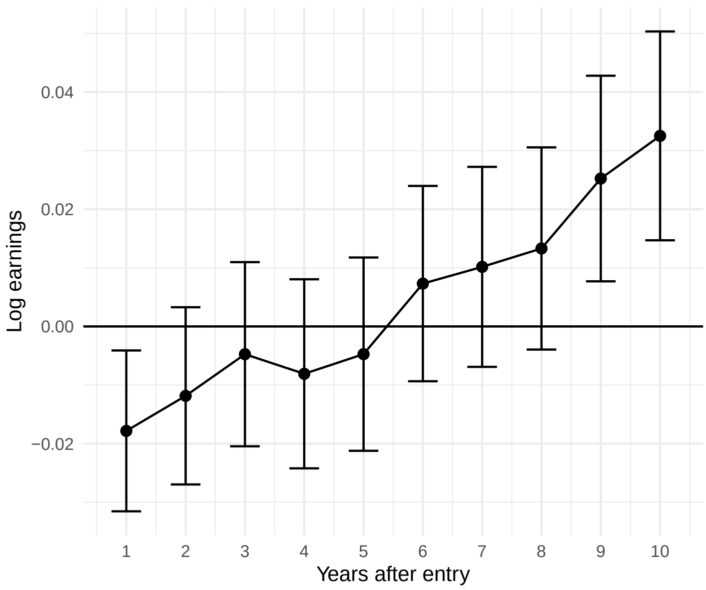
The same mechanism implies that earnings disparities due to differences in initial wealth will decrease as individuals start building up their own assets, reducing the role of parental wealth. That is, we expect to see convergence in earnings between low and high family wealth individuals over time. To test this prediction in the data, we examine how earnings evolve over the first ten years of workers' careers for observationally equivalent workers from poor and richer family background. In particular, we run a matched regression, in which individuals from deciles 1 and 2 are considered treated and young adults from deciles 4 to 9 are used as potential controls. We use coarsened exact matching (CEM) and match individuals based on year of labor market entry, years of education, age at graduation, gender, municipality of residence, and earnings rank of parents (Iacus et al., 2011):

$$y_{itp} = \alpha_i + f(earn_p) + \sum_{\tau=0}^{10} \beta_\tau D_{i,\tau} + \theta_{p,t} + \gamma_m + \varepsilon_{itp} \tag{11}$$

where y_{itp} is log earnings of individual i in the matched pair p at time t, α_i is an individual FE, $f(earn_p)$ a polynomial in parental earnings, $D_{i,\tau}$ is the treatment variable in τth year after labor market entry, $\theta_{p,t}$ is an interacted matched pair and time FE, and γ_m is an education major fixed effect.

The results are presented in Figure 9. Upon entry, the workers from the bottom part of the wealth distribution have 2-3% lower earnings than those with wealthier parents. This gap gradually diminishes over time and becomes statistically insignificant five years after graduation.

Figure 9: Earnings gap by years since graduation.



Note: The estimated coefficient shows the difference in earnings between the treated (those with parents in wealth deciles 1-2) and control group (those with parents in wealth deciles 4-9) using coarsened exact matching (CEM) regression, where we match individuals based on year of entry, years of education, age at graduation, gender, municipality of residence, and earnings rank of parents.

We take this evidence as indicative of parental wealth as an insurance mechanism. We do not expect to see a similar convergence in earnings in other models that link children's earnings with parental wealth. For example, if the gap in earnings by parental wealth is driven by intergenerational transmission of work attitudes (Galassi et al., 2024), risk preferences (Fagereng et al., 2021), or ability (Bjorklund et al., 2006), we would expect differences in earnings to persist over time, as well as across the whole spectrum of parental wealth.

Finally, we examine an alternative explanation for the observed sorting of individuals from wealthier backgrounds into higher-paying firms: parental networks. Specifically, wealthier parents may leverage their professional connections to help their children secure better jobs, especially for their first job after graduation.[14] Using matched employer-employee data for whole population of Sweden, we construct an extensive social network of parents based on their employment histories. In particular, we identify all employers and co-workers of the parents during the preceding ten years and split young workers into two groups: those working in the same firm as their parents or with their parents' former colleagues and those working outside of the "parental network" (see Appendix A for details). On average, we find that about 12% of young adults work in parent-connected firms and that this fraction is stable across the wealth spectrum. Moreover, the earnings-by-wealth schedule among those not belonging to the professional network of their parents is nearly identical to that of all workers, suggesting that this mechanism is not the main driving force of the observed patterns.

Local labor markets

In the model, higher parental wealth serves as a safety net enabling workers to extend their search period and hold out for better matches. The role of parental wealth as insurance is more important during periods (or in localities) of high unemployment when jobs are scarce. The higher the job offer arrival rate in unemployment, the easier it is to find a (higher paying) job. As a result, workers do not stay unemployed for long, and thus do not need to rely on family savings to finance their consumption.

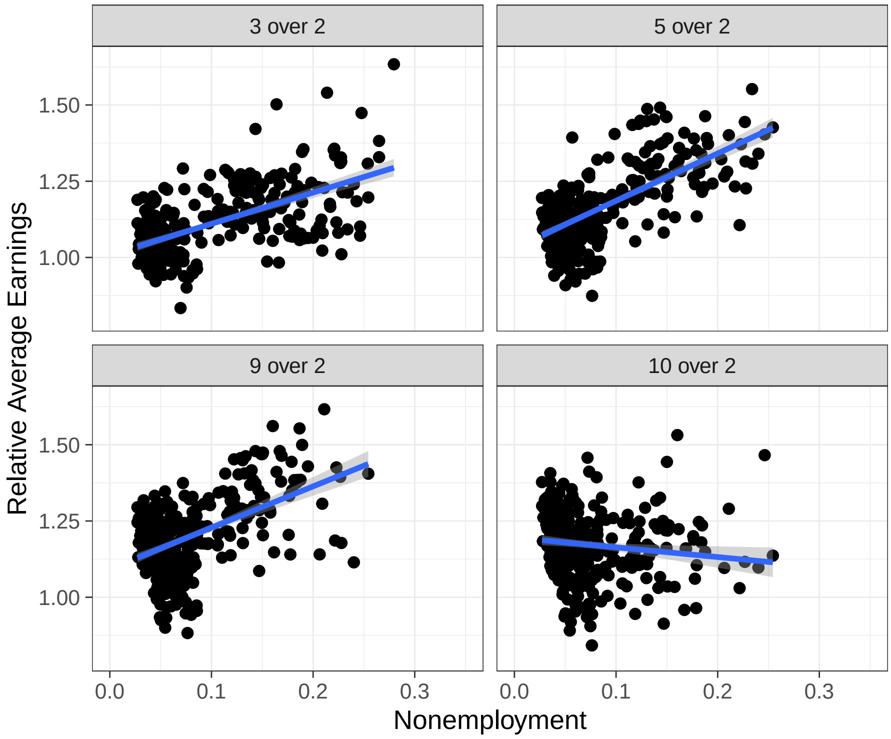
To test this hypothesis in the data, we examine whether local labor market conditions (captured by the local non-employment rate) are correlated with the steepness of the wealth-earnings profile. We define local labor markets (LLMs) using municipality-year-age-education cells. We consider two levels of education in this analysis —tertiary and less than tertiary —to have a large enough observations per cell.[15] Then, we calculate the non-employment rate for each LLM and the average labor earnings among individuals from different wealth deciles. We then compute relative earnings of individuals from wealth decile $X = \{3, 5, 9, 10\}$ to the average earnings of the bottom two deciles within each LLM.

Figure 10 shows that the wealth-earnings gradient increases with a higher non-employment rate, again with the exception of the top 10%. This pattern is consistent with parental wealth providing insurance for the unemployed. In general, higher consumption levels in unemployment increase workers' reservation wages. However, we expect that the benefit of being able to afford a longer search period to become smaller as the frequency of

[14]The literature on the role of social networks for labor market outcomes (e.g., Kramarz and Nordström Skans, 2014; Staiger, 2021; San, 2022) finds that parents are important for determining the workplace of a child.

[15]We restrict our analysis to observations with at least 100 individuals in each group.

Figure 10: The relative earnings of wealthier to poorer individuals by local non-employment rates.



Note: Local labor markets (LLM) are defined using municipality-age-year-education cells. The four panels plot the ratio of average earnings of individuals from wealth decile $X = \{3, 5, 9, 10\}$ relative to decile 2 for each LLM. We compare cells, in which the corresponding two wealth groups contain at least 100 individuals each. The blue line represents the fit of a linear regression.

receiving job offers increases (i.e. when the non-employment rate is low). This is exactly what we observe in the data —the ratio of average earnings of wealthier to poorer individuals increases in local non-employment.[16]

6 Quantitative results

6.1 Calibration

The model is calibrated at a quarterly frequency and aggregated to annual moments to match the empirical moments. To obtain those, we solve for an equilibrium of the model and calculate the ergodic distribution of assets, wages, and job flows at the quarterly frequency. We then aggregate the simulated models at the annual frequency to replicate the way the information is recorded in the data.

A key question we are interested in is the variation in labor market outcomes in relation to the initial wealth upon labor market entry. We assume that the assets children can access are equal to their own plus some fraction, ψ, of their parents'. Recovering this parameter is one of the primary goals of our quantitative model. All simulated moments are then computed against the initial parental wealth deciles.

We make two further parametric assumptions in order to calibrate the model. First, we assume that wage offers are drawn from a Beta distribution, $w \sim Beta(\eta_w^1, \eta_w^2)$. Second, we suppose that the mapping of wages to job destruction follows $\delta(w) = \delta^H - (\delta^H - \delta^L)w^{\delta^i}$, where δ^H and δ^L are the highest and lowest level of δ, and δ^i governs interpolation where $w \in [0, 1]$ (Bagger and Lentz, 2019).

We choose the discount rate of 5% annually, and assume that workers are in the labor market for 40 years on average. We set the interest rate to 3% annually, and choose the CRRA parameter $\alpha = 3$.[17] We choose the unemployment benefits to replicate an 80% replacement rate, which expires at a rate of $\phi = 1/4$, implying average duration of UI benefits of one year. When unemployment insurance (UI) expires, it is replaced by a basic benefit with a replacement rate of 50%. In addition, we assume that the opportunity to quit arrives once a quarter on average, i.e. $\chi = 1$. We base it on the fact that workers who want to resign in Sweden typically must give a one-month advance notice to their employer, moreover they have to wait for 9 weeks after resignation to received unemployment benefits.[18]

This leaves us with the remaining 10 parameters to calibrate, $\theta = \{\eta_w^1, \eta_w^2, \lambda_0, \lambda_1, \lambda^r, \delta_H, \delta_L, \delta_i, u^d, \psi\}$. Next, we turn to identification.

[16]This pattern is robust to other specifications. For example, it holds we restrict the sample to wage employees only when calculating average wage earnings (i.e. excluding non-employed and self-employed) or when we use the 3rd wealth decile 3 as the reference group (see Appendix A).

[17]This is within the range found in the literature. For example, Lise (2013) uses a CRRA value of 2, while Clymo et al. (2022) use 4.

[18]See https://www.akademikernasakassa.se/en/benefits/rules-and-terms/voluntary-resignation.

Identification

Wage distribution parameters: We choose the variance and skewness of wages to pin down η_w^1 and η_w^2.

Job finding and job-to-job transition rates: We calibrate λ_0 and λ_1 by matching job transition rates for both unemployed and employed individuals. We let the extent of job-to-job transitions with negative wage growth pin down the exogenous reallocation shock, λ^r.

Job destruction shock: We use the decreasing E-NE transition rate over the low wealth deciles to pin down the δ_H, δ_L and δ_i.

Disutility costs of working: The increase in the E-NE transition rate at the top of the wealth distribution determines the disutility costs of working.

The share of available parental wealth: The share of parental wealth that children have access to at the start of their careers, ψ, determines the resulting assets to income ratio in the model in the steady state.

We estimate the model by indirect inference. That is, we numerically solve the model, calculate moments on simulated data, and solve for θ that minimizes the distance between the simulated moments, $m^s(\theta)$, and empirical moments, m. The indirect inference estimator is as follows:

$$\hat{\theta} = argmin_{\theta}\Big\{\big[m - m^s(\theta)\big]W\big[m - m^s(\theta)\big]\Big\}.^{19} \tag{12}$$

Our numerical procedure uses a Metropolis-Hastings algorithm followed by a simplex algorithm. See Appendix C for detailed information regarding the solution and estimation procedure.

6.2 Results

Calibrated parameters

Table 3 shows the pre-determined and internally calibrated parameters. In the previous subsection, we showed that to generate the precautionary motive for search required a higher efficiency of search in unemployment than in employment. Indeed, we find that unemployed workers face about a 3.5 times higher offer arrival rate than their employed counterparts.[20] We also observe an extremely skewed job destruction distribution, where workers in low-pay jobs undergo 8 times higher unemployment risk, which decreases dramatically with wages. Our model implies that children behave as if they have access to 9% of their parents' wealth.

[19] We use the inverse of empirical moments on the diagonals as the weighting matrix.

[20] Our results are similar in magnitude to other studies. For example, Faberman et al. (2022) using survey data from the US show that the unemployed's offer yield is 4.2 times that of the employed. It is important to acknowledge that search efficiency, as captured by the offer arrival rate, is the product of search effort and the offer yield. In fact, Faberman et al. (2022) find that the offer yield is significantly higher among the employed, even if the resulting arrival rate is lower.

Table 3: Parameter values

Parameters	Name	Value	Reason/moments
		Pre-set	
ρ	social discount rate	$(-\log(0.95)+1/40)/4$	5% annual and 40 year life
r	interest rate	$-\log(0.97)/4$	3% annual
α	CRRA	3	exogenously set
		Internally calibrated	
η_w^1	w distribution	8.69	$var(w)$ and $skew(w)$
η_w^2	w distribution	13.1	$var(w)$ and $skew(w)$
λ_0	offer arrival rate in NE	0.24	NE-E schedule
λ_1	offer arrival rate in E	0.07	J2J schedule
λ^r	reallocation	0.005	share of J2J with wage decline
δ_H	highest job destruction	0.08	E-NE schedule at low assets
δ_L	lowest job destruction	0.01	E-NE schedule at low assets
δ^i	interpolation parameter	0.03	E-NE schedule at low assets
u^d	work disutility	0.03	wage-wealth relationship and E-NE schedule at the top
ψ	scale parameter	0.092	wealth to income ratio

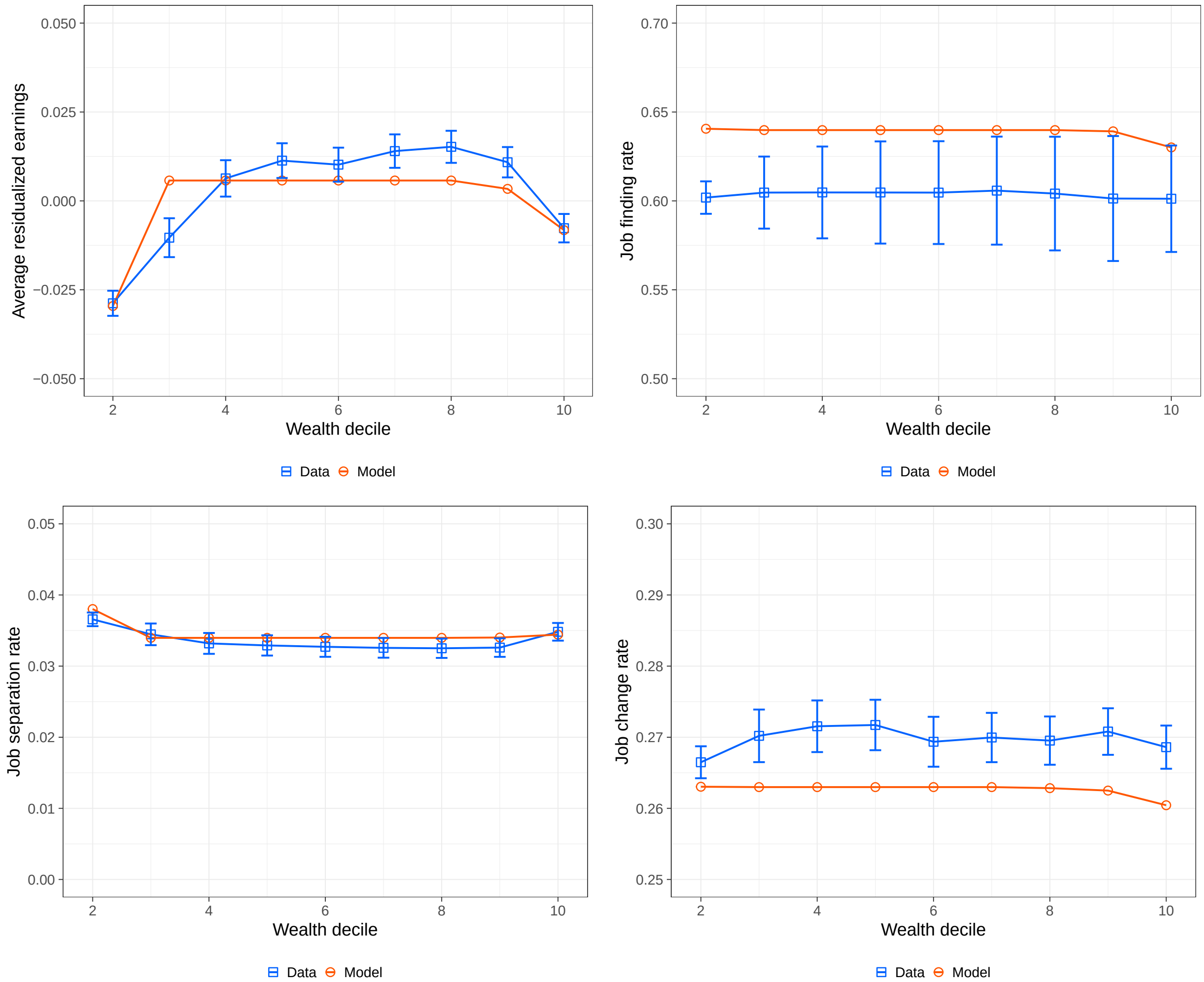
Moments

Table 4 shows the empirical variance and skewness of the wage distribution during the first five years, and the corresponding moments in the model. Figure 11, shows the residualized wages, job separation, job finding, and job change rates across the initial wealth distribution against the data counterparts. We see very similar dynamics in the data and model counterparts, although we are currently understating the U-shape in the employment to unemployment rate, especially among the poorest workers, and fit slightly higher levels for the job finding probability, and lower levels for the job change probability. Some of the difficulty in matching job flows data is due to time aggregation and we discuss it in more details in Appendix D.

Table 4: Targeted moments

Moments	Data	Model
$var(w)$	0.5	0.4
$skew(w)$	-1.9	-1.8
share of J2J with wage decline	0.35	0.33
wealth to income ratio	0.43	0.43

Figure 11: Empirical and simulated moments: wages and job transitions



Earnings decomposition

A key contribution of this paper is to show how workers from different parental wealth backgrounds sort differently across firms. Empirically, we find that workers with higher wealth systematically sort into higher paying firms, while the wealthiest (top 10%) earn less within those firms. Figure 13 plots the non-targeted within- and between-firm wage components across the initial wealth spectrum generated by the model.[21]

The model delivers very similar patterns to those observed in the data (see Figure 7). As discussed in Section 5.1, these patterns are driven by the two key behavioral responses to an increase in wealth. First, individuals with lower initial asset levels are more willing to accept lower paying jobs. They become more selective as assets grow, which increases the average firm-level wages (reflected in a growing between-firm component over the wealth spectrum). In contrast, individuals with higher wealth are more likely to spend time non-employed,

[21] Note that in the model, there is no distinction between a firm or a job. Thus, the between-firm component is straightforward in the data and reflects the average wage rate for an individual's job. The within-firm component in the model is a product of time aggregation and is driven purely by the extensive employment margin. That is, workers with higher job churning rates (within a given wage bin) will have lower annual earnings than those staying in the same job for a whole year.

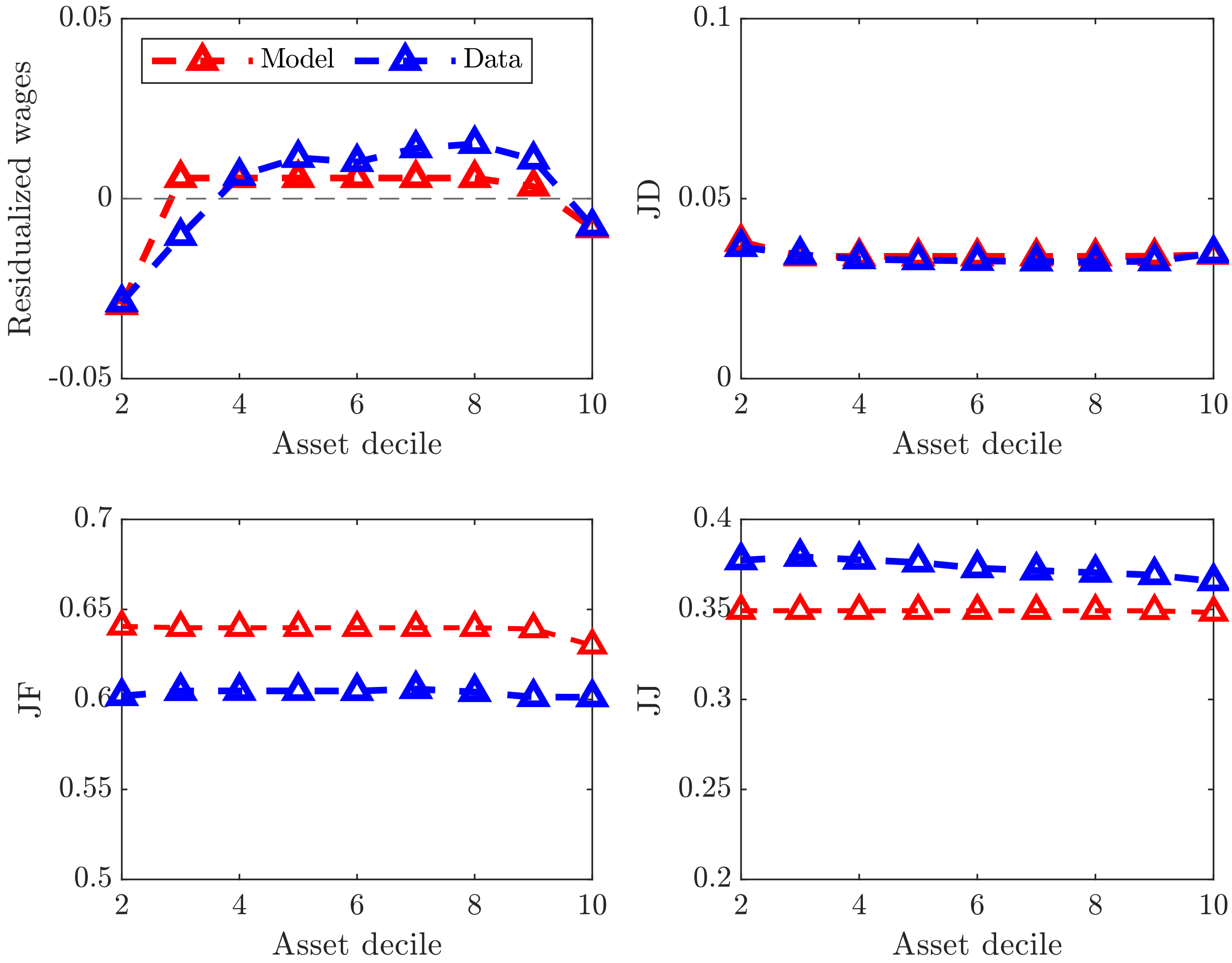
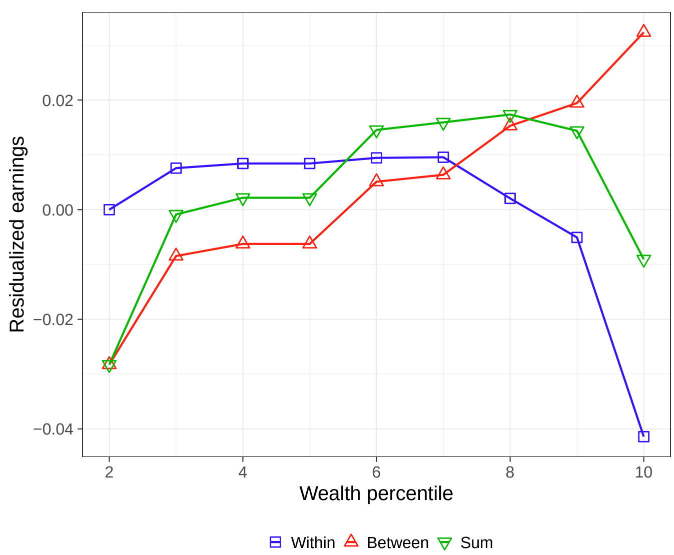


Figure 12: Caption

Figure 13: Simulated within- and between-firm components of log-earnings



largely due to a higher incidence of quits. Since earnings are measured annually, this lowers the within-firm component for the wealthiest individuals as they spend a larger fraction of the year not earning.

6.3 Financing job search upon labor market entry

In this section, we use the calibrated model to simulate how the differences in benefit levels that workers receive upon entry, b_{min}, impact earnings in the first five years of their careers. To do this, we finance the increase in benefits through a labor income tax on the steady-state distribution of wages.[22] Thus, we impose the following budget constraint:

$$E(b_{min}) = \tau E(w), \tag{13}$$

where average benefits and wages are measured at steady-state. We then consider the impacts from such a policy on earnings and welfare.

The main channel through which increased liquidity at entry changes labor market outcomes in our model is through the acceptance behavior of unemployed workers. In particular, it raises workers' reservation wages and, as a consequence, average earned wages and job stability through a lower job destruction rate. This is in line with empirical and theoretical work that shows that the benefit level may impact future job quality of the unemployed (Nekoei and Weber, 2017).[23] Our results suggest that small changes in benefit levels could have a large impact on earnings outcomes, especially among low-asset individuals.

In the baseline model, we assume that the benefit level upon entry, b_{min}, equals to 670 SEK (around 60 US dollars) per week, in line with the Swedish UI system. This amounts to about 25% of the average weekly earnings in our sample. After the first job, the benefits follow the standard income-based UI benefits, $b(w)$. Below, we consider policies that increase the amount of income that workers receive upon entry, b_{min}, and finance them through labor tax as explained above.

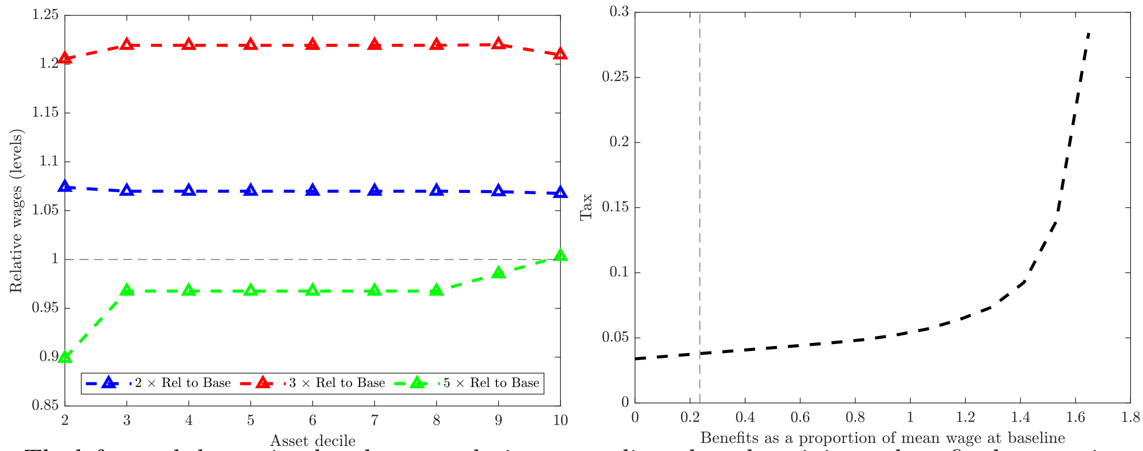
The left panel of Figure 14 depicts the resulting increase in earnings relative to the baseline when the minimal benefits are multiplied by 3 and 5 times. Two points are worth noting. First, this policy has a larger effect on the earnings of low-asset workers. For example, tripling the benefits increases early career average earnings for the lowest two deciles by over 10%, while the effect for higher deciles plateaus at about 5%. Second, raising benefits too much (e.g. five times), can lead to an overall decline in average wages due to a higher tax burden. This can be seen in the right panel of Figure 14, which depicts the implied tax rate that is needed to finance UI benefits. The fact that the tax rate schedule is convex suggests that the policy has decreasing marginal returns (primarily driven by the concavity of the

[22]We use the steady-state employment and distribution of wages to reflect the fact that the labor tax would apply to the whole working population and not only to young adults. Note that workers' average per period wages in steady-state are around twice as large as those earned over the first five years, as workers accumulate assets and continue to climb up the job ladder.

[23]In recent work, Grindaker and Simmons (2024) found that unemployment insurance impacts the search behavior and acceptance decisions of the employed.

utility function).

Figure 14: Simulated increase in benefits: the effect on average wages (left panel) and implied labor tax rate (right panel)



Note: The left panel shows simulated wages relative to paseline when the minimum benefits b_{min} are increased 3 and 5 times. The right panel plots the implied equilibrium payroll tax rate required to finance each level of benefits.

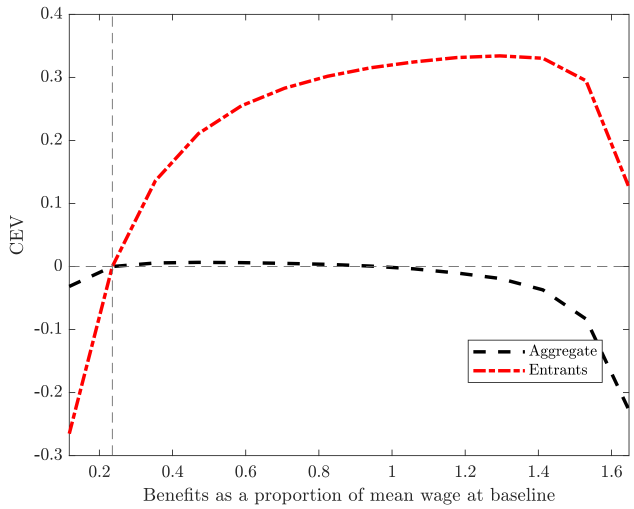
Finally, we use the model to consider the optimal level of benefits a worker receives upon entering the labor market. To do this, we consider the aggregated level of consumption equivalent variation (CEV), γ, that solves:

$$\mathbb{E}_0\left[\int_{t=0}^{\infty} e^{-\rho t}\big(u(c_t(1+\gamma)) - u^d\big)dt\right] = \mathbb{E}_0\left[\int_{t=0}^{\infty} e^{-\rho t}\big(u(\tilde{c}_t) - \tilde{u}^d\big)dt\right], \tag{14}$$

where $\tilde{c}$ and $\tilde{u}^d$ are consumption and disutility in the counterfactual.

Figure 15 shows the resulting CEV across different levels of unemployment benefits upon entry for labor market entrants and all workers. Evidently, labor market entrants gain significantly from this policy when the benefits are increased. However, small positive gains in welfare can be achieved in the aggregate for benefit increases from 25 up to 100 percent of the average wage (about 4 times the benefit level that workers receive in the baseline). This takes into account that the higher benefit level results in an increase in the tax rate.

Figure 15: Consumption equivalent variation



Overall, the results in this section suggest that increasing benefits upon labor market entry can be a relatively inexpensive and powerful policy for workers, both in terms of efficiency (or wages earned), equity and welfare.

7 Conclusion

In this paper, we document the labor market outcomes of children in the first five years of their careers and how they depend on their family wealth distribution. Most notably, and even after controlling for a detailed array of observable characteristics through interacted group effects, wealthier individuals earn more, have a higher employment rate, lower variance of earnings and a lower probability to separate from their jobs. Interestingly, this relationship breaks down at the very top of the wealth distribution. After controlling for observable characteristics, the wealthiest 10% have lower earnings and employment rates than the median worker.

To determine the role of firms in driving these patterns, we perform a within- and between-firm decomposition of earnings and show a clear pattern of wealthier individuals sorting into higher-paying firms, along the whole wealth spectrum. In contrast, the relative drop in earnings among workers at the top of the distribution is attributable to the within-firm component, which may reflect labor supply factors such as preferences and unobserved ability. In addition, we also show that children from poorer households tend to work in firms with higher average worker turnover rates.

Finally, we interpret our results through a search model with savings, search on and off the job, and disutility of work. Our results suggest that parents' wealth provides insurance to their children, which enables them to search longer for higher-paying and more stable jobs. We provide suggestive evidence in support of this model, in particular that the difference in earnings across wealth deciles (controlling for observables) decreases over time, suggesting earnings convergence. We then show that a relatively inexpensive policy of providing higher unemployment benefits upon entry (financed through a labor tax) can reduce the earnings gap across family wealth deciles and increase overall welfare.

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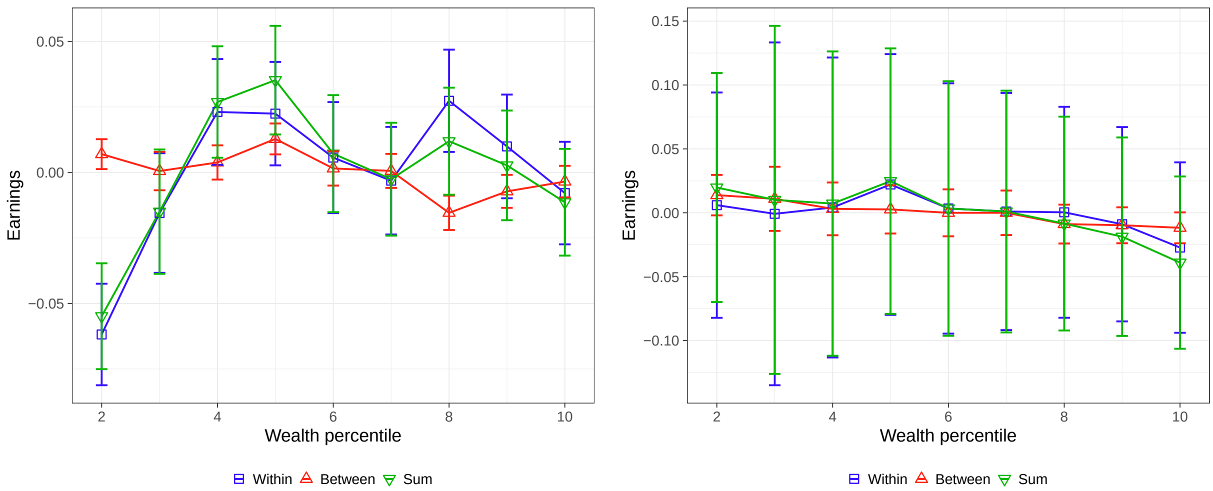
Figure A.1: Within- and between-occupation components of log earnings (Raw series on the left and Residualized on the right.



Note: Within- and between components have been calculated among individuals working in 3-digit occupations with at least 5 peers. In the Raw data, we control for interacted cohort and calendar year fixed effects. In the Residualized data we also control for years of education, educational major, municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

Appendix A. Additional empirical facts on early labor market outcomes and parental wealth

Sorting into occupations

Similarly to the firm-level analysis described in Section 4, we decompose log labor earnings into within- and between-occupation components using detailed 3-digit occupation codes. Given changes in the occupational classification over time, a significant number of workers have missing or inconsistent occupational information. Therefore, we disregard employees with imputed or out-of-date occupational codes, which in turn reduces our sample size and increases standard errors. Figure A.1 shows that, unlike the firm-level analysis, the between-occupation component is relatively similar across the wealth spectrum for both raw and residualized series. This suggests that the earnings gap by wealth decile is not a result of the occupational choice alone.

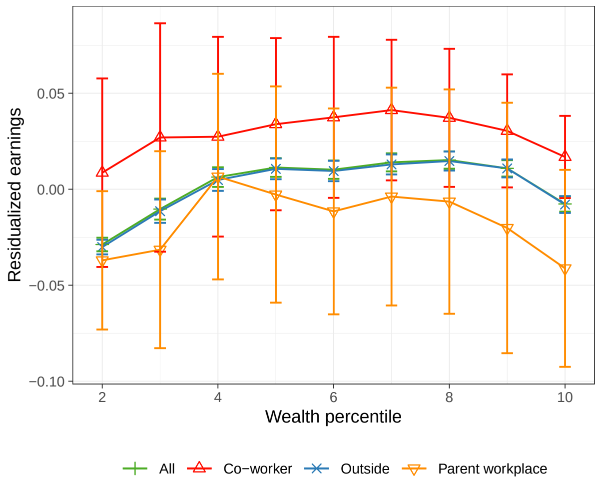
Parental networks

Using matched employer-employee data for whole population of Sweden, we construct an extensive social network of parents based on their employment histories. In particular, we identify all employers and co-workers of the parents during over the preceding ten years and match them with their children's current colleagues and/or employers.

The left panel of Figure A.2 presents the proportion of young adults employed in either a current or former firm of one of their parents within the first five years of entering the labor market ("Parent workplace" line). It also displays the proportion working with any former co-worker of their parents from the past ten years ("Co-worker" line). Among individuals in the bottom fifth of the wealth distribution, fewer than 10% are employed at a firm connected to their parents, with roughly equal representation between employer and co-worker links. This share rises to approximately 12% by the third decile and remains stable across the wealth distribution, with a slight shift in the composition of connections towards a higher share of co-worker links (up to a 3:2 ratio).

The right panel of Figure A.2 displays the average residualized log earnings for individuals employed at their parent's current or former firm, with a parent's current or past co-worker, outside of their parent's network, and the overall average. According to the nepotism hypothesis, working at a parent's firm should lead to higher earnings, particularly for individuals from the upper end of the parental wealth distribution. However, our findings indicate that young adults employed at their parent's (current or former) firms do not earn more than the average worker with similar characteristics. In contrast, working with a parent's former colleague is associated with higher earnings across the wealth distribution. However, the difference in earnings between individuals working within and outside of the parents' network is not statistically significant. Furthermore, the earnings-wealth profiles for all individuals and for those employed outside of parental networks are nearly identical. Combined with the relatively low proportion of young adults employed in parent-connected firms across the wealth distribution, these findings suggest that parental networks alone cannot account for the sorting patterns documented above.

Figure A.2: Proportion of individuals working in a parent-connected firm (left panel), and the average residualized earnings by connection type (right panel).

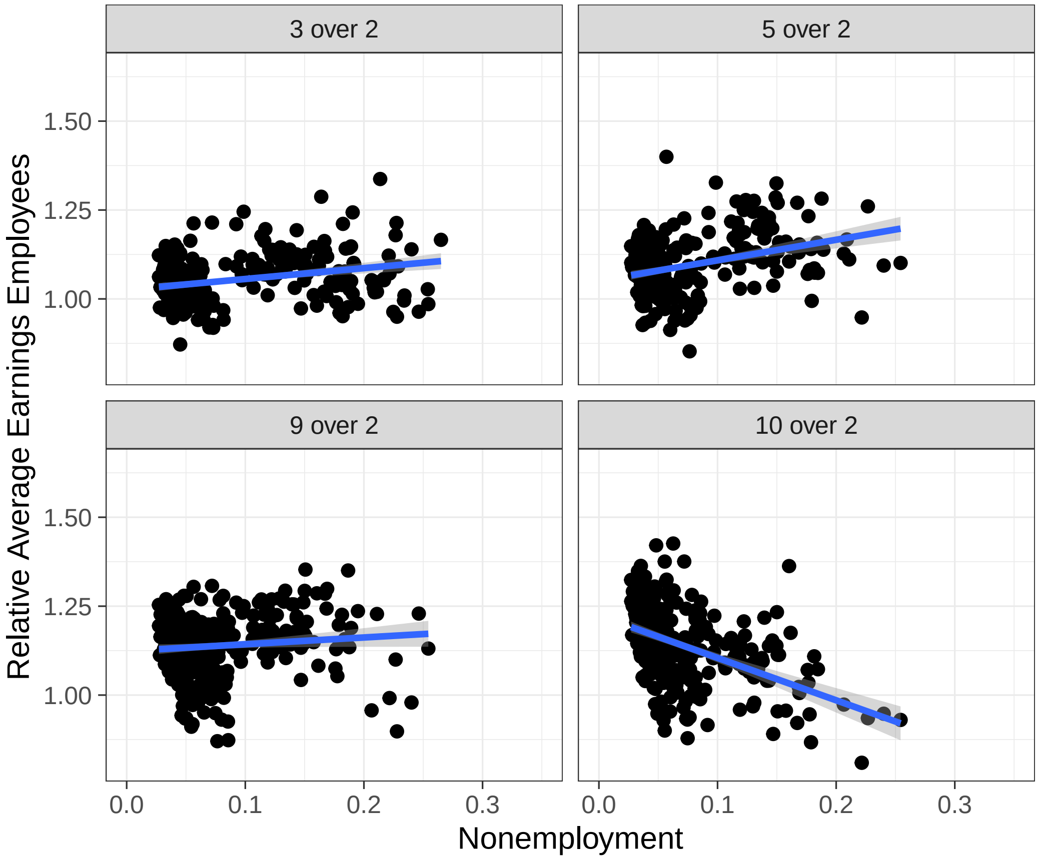


Note: Parental networks are defined using a rolling 10-year window tracing the workplaces and co-workers of each parent. "Parent workplace" line shows the share of workers employed in their parents' current/former firm in the first 5 years after the labor market entry. "Co-worker" series include those working with their parents' former co-workers. "Outside" line shows those working outside of their parents' network (i.e. excluding the two groups above). The error bars represent 95% confidence intervals.

Local labor markets and parental wealth

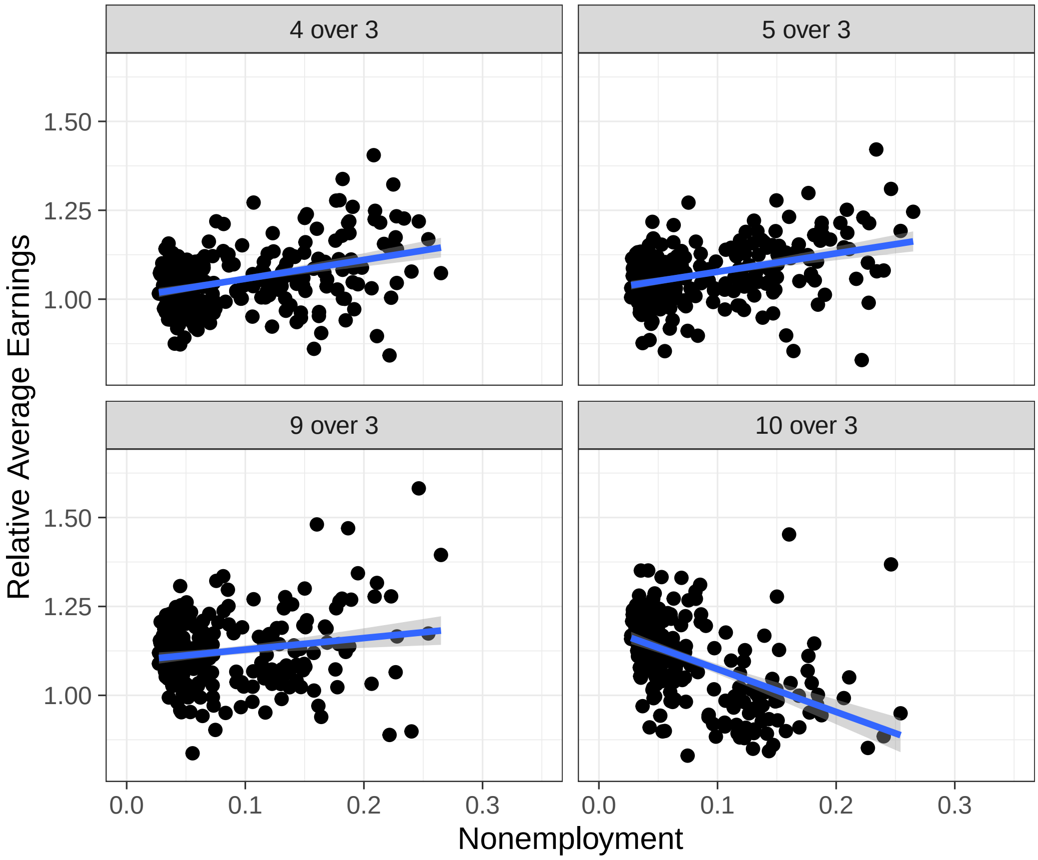
This appendix provides some additional figures related to the analysis in Section 5.2.

Figure A.3: The ratio of earnings of wealthier to poorer individuals (wage employees only).



Note: Local labor markets are defined using municipality-age-year-education cells. The four panels plot the ratio of average earnings of individuals from wealth decile $X = \{3, 5, 9, 10\}$ relative to decile 2 for each LLM. We only compare cells in which both wealth groups contains at least 100 individuals. The blue line represents the fit of a linear regression.

Figure A.4: The ratio of earnings of wealthier to poorer individuals by local non-employment rates (relative to wealth decile 3).



Note: Local labor markets are defined using municipality-age-year-education cells. The four panels plot the ratio of average earnings of individuals from wealth decile $X = \{4, 5, 9, 10\}$ relative to decile 3 for each LLM. We only compare cells in which the corresponding wealth groups contain at least 100 individuals each. The blue line represents the fit of a linear regression.

Appendix B. Unemployment insurance in Sweden

This appendix provides a brief overview of unemployment insurance in Sweden.

Unemployment insurance (UI) is voluntary in Sweden and administered by trade union-linked funds with publicly subsidized fees following a Ghent system (Clasen and Viebrock, 2008). For the period 2000–2020, the initial replacement rate has been 80% of the previous wage up to a nominal ceiling of 2900–4550 SEK per week (approximately 290–455 USD), while the lower bound, given that the unemployed had full basic coverage, varied from 1225 to 1825 SEK per week. When considering the wage employed during the first five years in the labor market from our sample, we find an average weekly earnings rate of 4080 SEK. Unions can provide additional insurance to top up the replacement rates for workers earning more than the nominal ceiling in the publicly provided UI (Kolsrud, 2018). However, in order to qualify for UI, the individual must fulfill a work requirement which demands at least half-time employment for the past six months prior to becoming unemployed. Qualifying for the union top up requires that you qualify for the public UI, and also in general that you have paid the union insurance fee for at least 12 months. In the public insurance, the replacement rate is 80% for the first 40 weeks, then it drops to 70% for an additional 20 weeks. After 60 weeks, the individual must participate in active labor market programs to qualify for further benefit payments capped at a 65% replacement rate (Kolsrud, 2018).

Unemployed individuals who do not qualify for UI can get benefits through participation in active labor market programs and receive *"aktivitetsstöd"* (for people over the age of 25) and *"utvecklingsersättning"* (for individuals aged between 18–24). In 2009, the benefits for the older unemployed who did not qualify for UI were 1115 SEK per week and for younger workers 670 SEK per week (Sibbmark and Martinson, 2010).

Appendix C. Model solution and calibration

Before describing the solution algorithm, it is important to note that using this method relies on the software's ability to recognize the sparsity of the matrices that consist mainly of zeros. If we cannot identify sparse matrices, the limits on the size of objects within our software (Matlab) would render the methodology unusable. For a thorough discussion of this topic, see Achdou et al. (2022).

Using the solution method described in Section 5, it is possible to estimate the parameters of the model using the simulated method of moments. To do so, we select key moments from the data discussed in the main text, solve the model, calculate the equilibrium distribution, and simulate data where needed. We then calculate the same moments as in the data, and calculate the value for the criterion. Following this, we choose optimization procedures to pick parameter values to minimize the criterion function, shown in the text. The following optimization routine is employed.

We employ a Metropolis-Hastings style algorithm (as e.g., Lise, 2013; Jarosch, 2021). First, we make an initial guess for the parameter values. Then, we solve the model and calculate the criterion function. Next, we sample new parameter values from a normal distribution, with a standard deviation proportional to the current parameter value. We set the standard deviation to one-sixth of the parameter value during estimation. If the new parameter values yield a lower criterion, we accept them; otherwise, we reject them and continue with the old set. Each iteration forms a chain. We generate 1000 chains, each with a length of 50.

We use the 10 sets of parameter values from the chains that yield the lowest criterion values as starting points. Next, we apply the Nelder-Mead simplex algorithm to find a local minimum. The parameters corresponding to the minimum value obtained serve as our parameter estimate, $\hat{\theta}$. The following summarizes the procedure:

1. Make sensible guesses for the parameter values.
2. Solve the model numerically.
3. Simulate data from the model.
4. Calculate the same moments as in the empirical data and calculate the criterion function.
5. Pick new parameter values using a Metropolis-Hastings style algorithm followed by the Nelder-Mead simplex algorithm.
6. Iterate over steps 2 to 5 until the criterion is minimised.

Appendix D. A note on time aggregation

We simulate the model at a quarterly frequency and aggregate the moments to an annual basis to replicate the records we observe in the data. This makes matching of the moments, in particular the job flows, in the data and in the model more difficult. To illustrate it further, suppose that we want to reproduce an unemployment to employment transition we observe in the data. That requires an unemployed worker to get a job offer (and accept it), as well as remain in the job for the rest of the year. Let

$$T_1 \sim exponential(f) : \text{time to find a job}$$

$$T_2 \sim exponential(\delta) : \text{time to lose a job}$$

Note that the job finding probability, f, in the model is the product of the job offer arrival rate, λ_0, and the acceptance probability $1 - F(w^U(w, a))$. For simplicity, we ignore the reallocation shock that can lead to unemployment as well. We are interested in the probability of a joint event of finding a job and not separating from it within the same year:

$$P(T_1 < \mathcal{T} \;\;\&\;\; T_2 > \mathcal{T} - T_1) = \int_0^{\mathcal{T}} f e^{-ft} e^{-(\mathcal{T}-t)\delta} dt,$$

where $\mathcal{T}$ is the length of the observed period, so 4 quarters in the calibrated model. That is, the probability of finding a job at some instance t, fe^{-ft}, is multiplied by the survival probability $e^{-(\mathcal{T}-t)\delta}$, which is then integrated over all t within period $\mathcal{T}$. We can solve for the probability analytically as

$$P(T_1 < \mathcal{T} \;\;\&\;\; T_2 > \mathcal{T} - T_1) = \frac{f}{\delta - f}(e^{-\mathcal{T}f} - e^{-\mathcal{T}\delta}). \tag{D.1}$$

This probability is naturally increasing in the job finding rate f, but it is also decreasing in δ. In our model, the workers who are willing to accept low-paying jobs (low-asset workers), are also more likely to lose them, thus creating a tension between the two job transition rates. Figure D.5 shows that a decreasing acceptance probability (and hence the job finding rate) and a decreasing job destruction rate in wealth generate a relatively flat relationship between annual non-employment to employment transitions and wealth, similar to what we see in the data.

Figure D.5: Acceptance probability, and job destruction rate, $\delta(w)$