Parental Wealth and Early Labor Market Outcomes

Johan Holmberg Michael Simmons Ija Trapeznikova*

October 29, 2024

Abstract

We use employer-employee data matched to detailed wealth records for the population of Sweden to study the relationship between initial wealth and labor market outcomes in early careers. Controlling for a detailed array of observable characteristics, including the educational major and parents' earnings before labor market entry, those with higher levels of wealth earn more. The relationship, however, is non-monotonic —the wealthiest and poorest earn less than those in the middle of the initial wealth distribution. We show that the correlation between initial wealth and average earnings in early careers is largely driven by between-firm differences, suggesting an important role for the allocation of workers across firms, and provide some descriptive evidence suggesting parental connections do not play a major role. We document several features of worker flows by parental wealth. We build a search model with on-the-job search, savings, disutility of work and heterogeneity in job destruction to understand these patterns. The model is able to replicate the dynamics of within and between firm variation in earnings across the initial wealth spectrum. Providing greater benefits to workers upon labor market entry, taxed through labor income, can significantly increase wages and welfare.

*Holmberg: Umeå University (johan.holmberg@umu.se); Simmons: Umeå University (michael.simmons@umu.se); Trapeznikova: Royal Holloway (ija.trapeznikova@rhul.ac.uk). Holmberg and Simmons thank Handelsbankens forskningsstiftelser for financial support (grant number W21.0048). We thank seminar participants at Umeå University, Royal Holloway, Strathclyde, Copenhagen Business School, Copenhagen University, the Baltic Economic Conference and EALE for helpful comments.

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 by studying intergenerational mobility highlighting the role of parental *wealth* over and above parental earnings. Following Chetty et al. (2014a), we estimate quantitatively similar rank-rank correlations between individual earnings and parental earnings (0.17) and between individual earnings and parental wealth (0.145). However, the rank-rank correlation between parental wealth and a child's earnings remains significant even within each parental earnings decile (0.091 on average), suggesting that even among children of parents with similar income, those with wealthier parents tend to outperform their peers.

We then proceed to the main part of our empirical analysis that examines in detail the link between parental wealth and children's earnings in 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 26% more than those from the lowest two deciles. Most of this gap (16 percentage points) 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 5% less than the median, whilst those from the top decile earn 3% 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.

We explore two potential mechanisms that can explain why wealthier individuals work for higher-paying firms. First, we examine the role of parental social networks that we construct using employment histories of parents over the preceding 10 years. We find that about 10% of children work in the same company as their parents or with their parents' former coworkers, and that share is relatively stable across wealth deciles. 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. This suggests that parental networks are unlikely to drive the observed earnings differences across the wealth spectrum. Our second, and preferred, explanation for wealthier individuals sorting into better-paying firms is the role of parental wealth as a financial safety net that affects the job search behavior of workers (e.g., Lise, 2013). That is, wealthier individuals can afford to search longer for higher paying and more stable jobs. We provide tentative evidence for this channel by showing that wealth-earnings profile becomes steeper in local labor markets with higher non-employment rates, suggesting that parental wealth is more important when jobs are scarce.

Finally, we build a partial equilibrium job search model with savings to interpret our results. 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 disutility of working, but where ours is stochastic, which is key to replicating the increase in the job separation rate observed among the wealthiest individuals. The main mechanism through which parental wealth induces sorting into higher-paying jobs is by providing additional consumption to unemployed children, which increases their reservation wages.[1] We use this model to estimate the perceived distribution of assets children can access when entering the labor market (i.e., the fraction of family wealth they can use for consumption smoothing). 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., 2014b, 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. In support of this conjecture, our data shows only a relatively weak correlation between the average earnings rank of parents

[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). Herkenhoff et al. (2016) shows that increasing credit limits also prolongs job search in unemployment.

and their level of wealth. Furthermore, we document that even within parental earnings ranks, there is a positive correlation between the parental wealth rank and the earnings rank of children.

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., 2016, 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 explores the empirical relationships between children's earnings and their parents' earnings and wealth. In Section 4, we examine differences in early career labor market outcomes based on parental wealth, focusing on labor earnings and market transitions. Section 5 examines the role of firms in generating the observed differences in earnings by wealth decile and discusses potential channels that explain these patterns. Section 6 introduces a model that we apply in Section 7 for policy experiments, while Section 8 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. 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]

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 have 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.

[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 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	5.6	32.4	88.2	165.5	183.2	258.9	461.7	1226.9	5810.5
Mean wealth	0.6	10.5	37.3	91.4	165.9	233.4	333.0	558.5	2913.6	16752.2
Std. dev. wealth	2.5	11.4	23.6	49.4	113.9	205.6	299.6	460.2	139879.8	442740.8
Education years	12.2	12.6	13.0	13.2	13.3	13.4	13.6	13.9	14.3	14.5
Bachelor (%)	18.6	23.7	28.	32.7	35.3	37.4	41.3	46.6	54.6	59.6
Age at graduation	22.3	22.6	22.9	23.1	23.2	23.3	23.6	23.9	24.3	24.6
Empl. rate (%)	77.2	83.5	86.5	87.8	88.0	88.3	89.6	90.3	90.4	88.6
Self-employment (%)	0.8	0.8	0.9	1.0	1.1	1.2	1.2	1.4	2.1	3.3
Obs.	172335	86554	86760	86738	86714	86715	86749	86779	86855	8657

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.

Individuals without records 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.

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

3 Parental wealth vs parental earnings and intergenerational mobility

Before we proceed to the main analysis, we perform several exercises highlighting the differences between using parental wealth and parental earnings in the context of intergenerational mobility. The previous literature has relied on the strength of the relationship between parents' and children's income or education to measure a country's intergenerational mobility. Frequently employed metrics include the intergenerational elasticity of income, derived from regressing the logarithm of a child's income on the logarithm of the parent's income (as surveyed by Solon, 1999; Black and Devereux, 2011), and the rank-rank slope (RRS). The RRS is defined as the correlation between the relative positions of children and parents within their respective income distributions (e.g., Dahl and DeLeire, 2008; Chetty et al., 2014a; Acciari et al., 2022). It is worth noting that alternative measures can also be utilized, such as the probability of upward or downward movements between quantiles, as demonstrated in Chetty et al. (2014b).

The goal is to compare the permanent earnings of parents with the earnings of their children. An important challenge is accounting for idiosyncratic changes in earnings when constructing the parental earnings rank. As demonstrated by Solon (1992) and Zimmerman (1992), the noise resulting from idiosyncratic shocks can lead to a substantial downward bias in the correlation coefficient. This bias can be mitigated by averaging parental earnings over an extended duration, as suggested by (Björklund and Jäntti, 1997). Chetty et al. (2014a), for instance, employs a five-year average of earnings to estimate a parent's permanent earnings component. Conceptually, given that wealth is a stock, there is less apprehension about idiosyncratic changes affecting the parent's rank.

Chetty et al. (2014a) demonstrates that the rank-rank correlation offers a more stable statistical measure for the intergenerational transmission of income. Consequently, we adopt their methodology and calculate the RRS for both parent-child income and wealth-income relationships. However, our primary emphasis is on the relationship between children's income and parents' wealth, as this provides a more comprehensive measure of the stock of economic resources available for children's use.

We assign an earnings rank to parents derived from their average real labor income when their child is between 15 and 19 years old. Similarly, we assign a wealth rank based on their financial wealth when their child reaches 18. By averaging income over a five-year period, we reduce the impact of short-term fluctuations in parents' income. In line with existing literature, we assess children's income at ages 29 to 30 and rank them in relation to their peers within the same birth cohort.

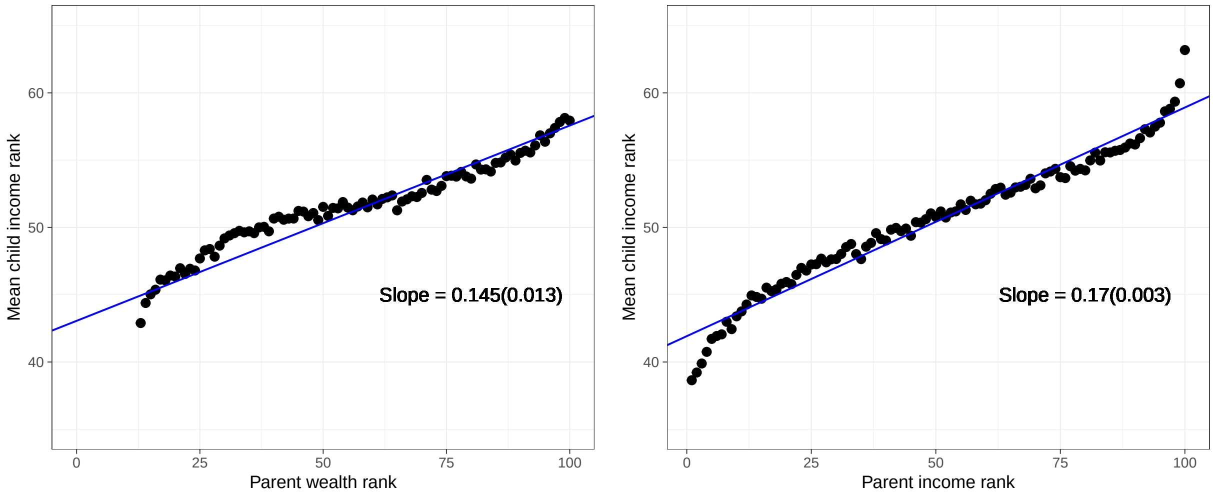
3.1 Intergenerational correlations

Figure 1 presents a binned scatterplot of the mean percentile rank of children's income versus their parents' percentile wealth (left panel) or income (right panel) rank. We find quantitatively similar correlation coefficients between parental wealth and parental earnings on child earnings. The RRS is 0.145 for parental wealth and children's earnings, and 0.17 for parental earnings and children's earnings.[5] There are interesting differences, however, at the extremes. For parental wealth, the relationship is relatively linear, whereas for parental earnings, the relationship shows an S shape —the predictive power is stronger at the extremes for parental earnings.

Since the correlation coefficients between parental wealth and parental earnings on children's earnings are similar in magnitude, one may wonder whether parental wealth and

[5] On average, our income-income rank correlation is similar in magnitude to the estimates found for Denmark (Boserup et al., 2017), lower than the range of estimates between 0.2 and 0.24 found in Australia (Deutscher and Mazumder, 2020), Canada (Corak, 2019), and Italy (Acciari et al., 2022) and half the estimate reported for the US (Chetty et al., 2014a). Boserup et al. (2017) also find similar correlation magnitudes for wealth ranks of children and parents using Danish data. In particular, they find the RRS coefficient of 0.35 when children move into adulthood (age 20), going down to 0.17 in the mid-twenties and then moving gradually up again to 0.27 in the forties.

Figure 1: Mean child income rank conditional on parent income or wealth rank.



Note: The wealth rank of parents is measured when the child is 18, the earnings rank of parents is measured using the average earnings when the child is between 15–19 years old, and the earnings rank of children is measured as the average earnings when the child is 29–30 years old.

earnings are close to perfectly correlated. If this is true, having information on parental wealth is less useful when measuring the extent of intergenerational mobility.

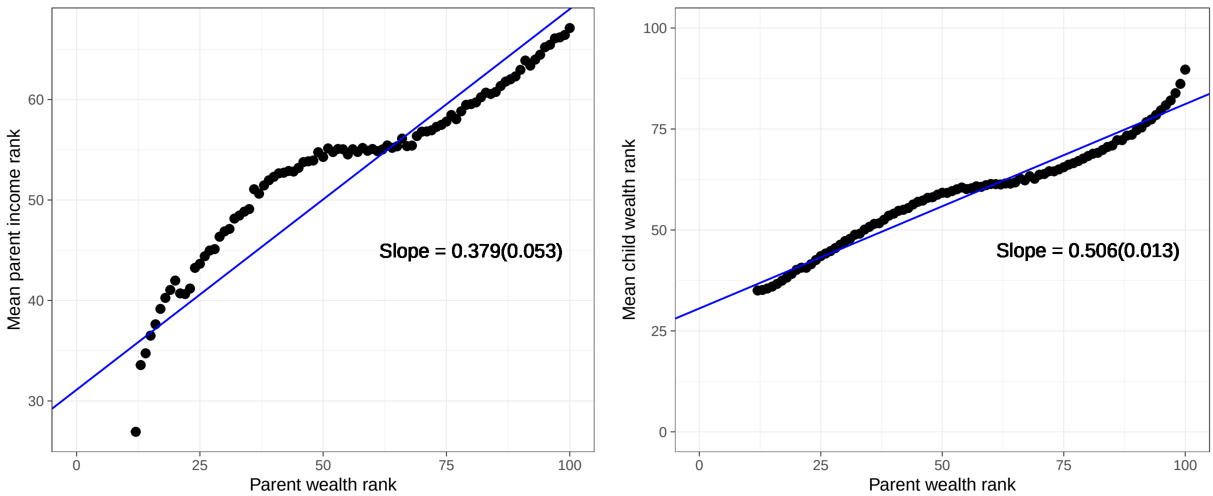
The left panel of Figure 2 shows the rank-rank correlation between parental wealth and earnings. A key finding is that the parents' earnings and wealth ranks are far from perfectly correlated, with a RRS of 0.379, suggesting that parental wealth measures something beyond parental earnings. To highlight this further, we calculate the rank-rank correlation between parental wealth and children's earnings separately for each parental earnings decile. Controlling for parental earnings reduces the correlation between parental wealth and children's earnings; however, it remains consistently greater than zero, with an average of 0.091 across parental income deciles. That is, even when having parents with similar income, children from wealthier households earn more.

Our third empirical fact is that the wealth of children at age 18 is strongly correlated with parental wealth. The right panel of Figure 2 shows a virtually linear relationship with a slope of 0.506. Since children are unlikely to have earned their wealth at the age of 18, the natural interpretation of this strong correlation is bequests (from deceased grandparents, for example) or *inter vivos* transfers.[6] This suggests that parents provide considerable insurance for their children as they enter the labor market, which in turn may impact their early labor market outcomes.

Our takeaway from these facts is that, while both parental wealth and earnings are correlated the future income of their children, parental wealth has additional predictive power for children's earnings beyond parents' income. Importantly, the strong correlation between parents' wealth and children's wealth at the age of 18 suggests that children receive

[6] Boserup et al. (2018) using the data drawn from Danish administrative registers show that the share of children who own assets increases sharply from 10% at age 12 to about 91% at age 15, which is only slightly below its level in adulthood of around 97%. Most of these assets are bank deposits.

Figure 2: The relationship between parents' income and wealth (left panel), and parents' wealth and children's wealth (right).



Note: The wealth rank of parents and children is measured when the child is 18, the earnings rank of parents is measured using the average earnings when the child is between 15–19 years old, and the earnings rank of children is measured as the average earnings when the child is 29–30 years old.

inter vivos transfers from parents, which may then be used to smooth income shocks even at the very early stages of the labor market.

4 Early career labor market outcomes

The previous section demonstrates that parental wealth is predictive of earnings outcomes of children. In this section, we utilize the richness of the Swedish data to better understand the potential mechanisms that may account for this relationship. We start by examining the role of demographic characteristics, and then proceed to analyzing labor market transitions before and after controlling for observables.

4.1 Demographic characteristics

Our main empirical analysis uses the constructed data set described in Section 2. We group children into family wealth deciles, and in some cases, percentiles. The analysis is conducted using 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 will 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." Furthermore, we will present outcomes where we also control for years of education "Edu," also including degree major "Major," and finally adding municipality of residence as well as a third-order polynomial in average parental earnings[7] "Residualized." When studying earnings, we only consider employees.

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 interacted fixed effects for group x in year t.[8] For the "Residualized" outcomes, we also control for a polynomial in parental earnings, $f(earn_p)$. The mean-zero error term, ϵ_{it}, gives the distribution of relative earnings conditional on these group characteristics. We then take the average of these residuals by wealth decile/percentile and plot them in the graphs below. When calculating standard errors, we adjust for the loss of degrees of freedom from the residualization.

4.2 Labor earnings

Figure 3 shows the average log earnings over the first five years after labor market entry for employees over household financial wealth deciles on the left and percentiles for the top decile on the right. There are large differences in raw earnings over the household wealth spectrum. Individuals in the bottom 20% of household wealth earn around 14% less than the average worker. Individuals in the top 30% of household wealth earn around 8% more than the average worker. A striking regularity, however, is present at the top decile. Children who come from households in the top one percent earn 7% less than those at the 99th percentile.

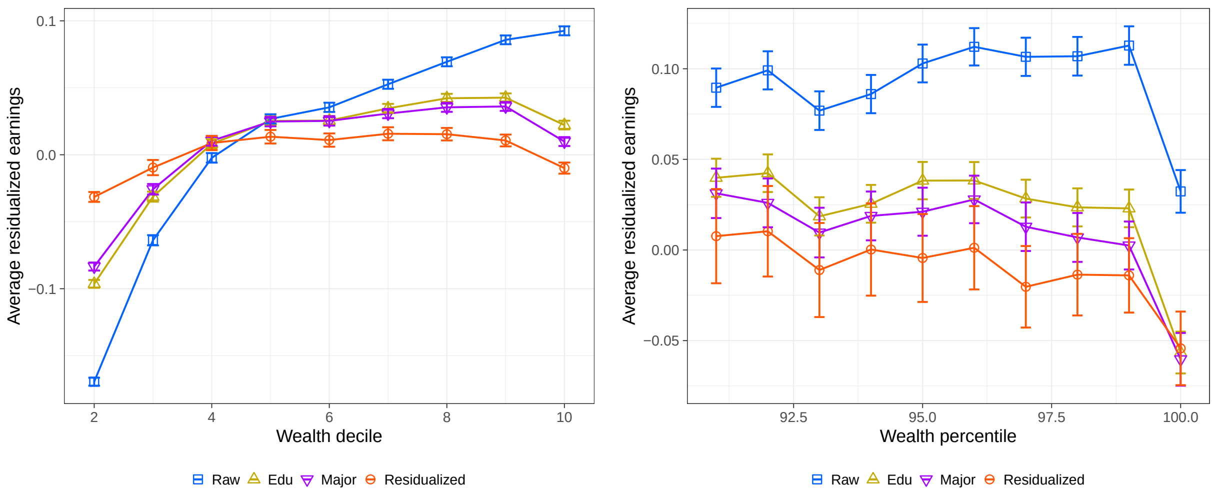
After controlling for years of education ("Edu" line), the bottom two deciles earn 10% less than the average, and the top decile earns 2% more than the average. Interestingly, adding fixed effects on educational majors, makes only a small difference beyond the effect of years of education. Finally, including municipality controls and a third-order polynomial in parental earnings reduces the gap for the bottom 2 deciles to -3% and for the top decile to -1%. This highlights a clear non-monotonic relationship for our fully residualized earnings outcomes. Those in the middle wealth deciles earn more than at the tails. Moreover, the right figure highlights that the decline in the top is largely driven by the wealthiest percentile.

Figure 4 shows the variance of annual log earnings over the first five years in the labor market. We see a general declining trend in the variance of earnings over the household wealth deciles —inequality tends to decline with household wealth. Again we observe a striking difference at the top percentile. Larger inequality is present in the top 1% than

[7]Parental earnings were deflated using the CPI with 2010 as the base year and averaged over the years whilst the child was thirteen to nineteen. 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.

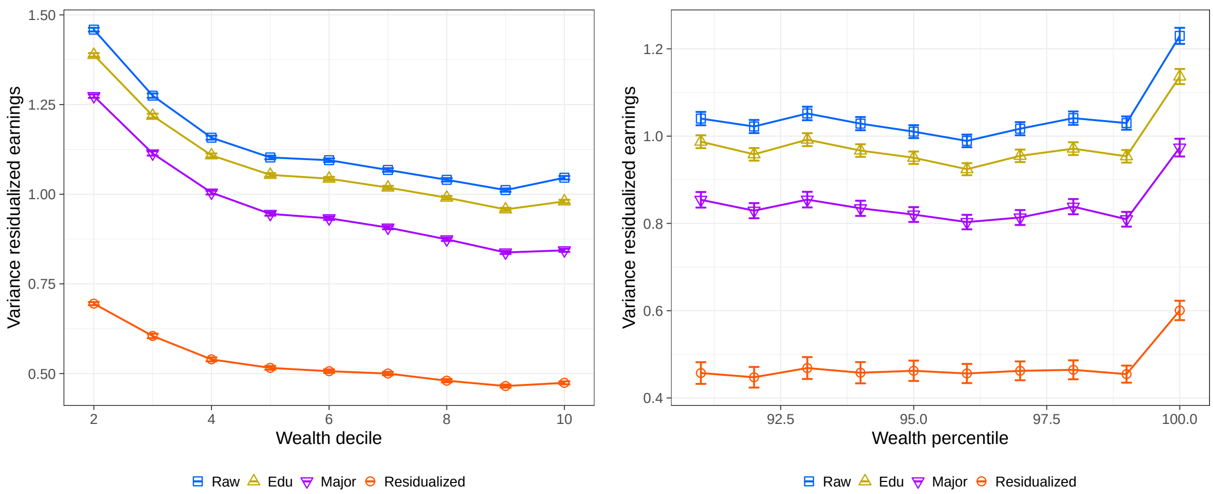
[8]We get 154 birth-year and age groups. When adding years of education we have 1,291 unique combinations. Adding major results in 89,090 groups. Finally, adding the municipality of residence results in 1,456,913 unique groups. Our sample has over 8 million observations.

Figure 3: Average log earnings, by family wealth decile.



Note: We use earnings among employees observed the first five years after labor market entry. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the Residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

Figure 4: Variance of log earnings, by family wealth deciles.



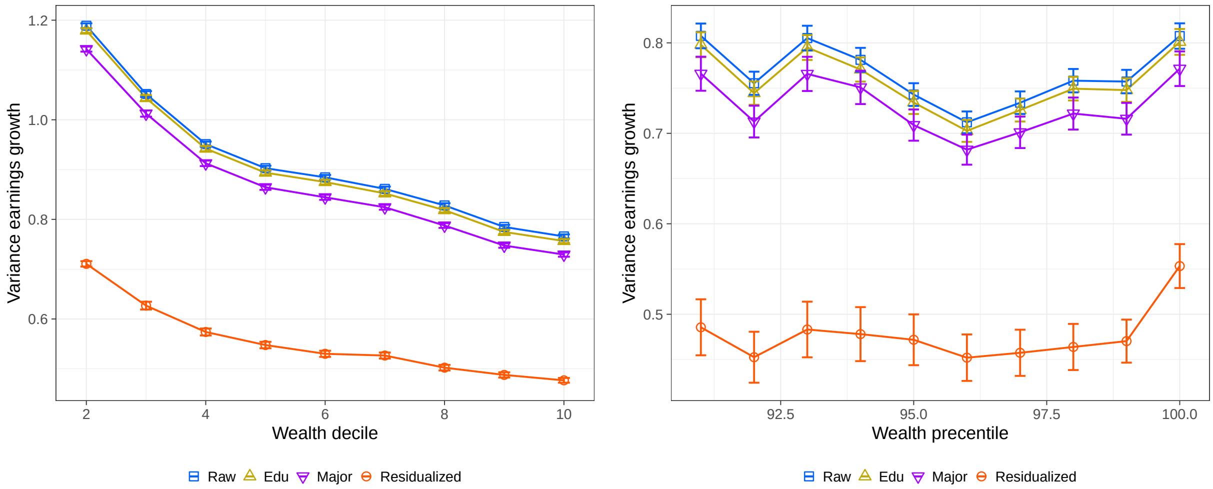
Note: We use earnings among employees observed the first five years after labor market entry. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the Residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

anywhere between the 90th and 99th percentiles.

Figure 5 shows the variance of the average log earnings growth over the household wealth deciles. The patterns are very similar to earnings inequality. Those at the bottom experience more growth volatility than those in the middle, whereas there is an increase in growth volatility for the top 1%.

The main takeaways from Figures 4 and 5 is that within-group inequality is larger among the poorest households, and children from poorer families experience more volatile earnings.

Figure 5: Variance of log earnings growth, by family wealth deciles.



Note: We use earnings among employees observed the first five years after labor market entry. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the Residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

This can to some extent be attributed to differential labor market transitions, which we will now discuss.

4.3 Employment rate and labor market transitions

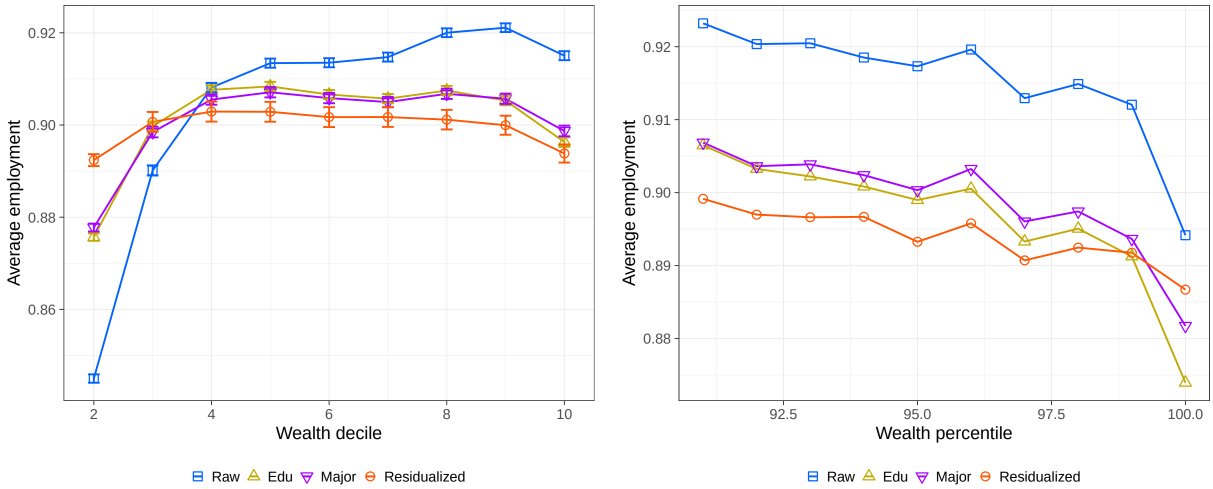
In this section, we establish relationships between parental wealth and transitions between labor market states. Figure 6 shows the relationship between family wealth and employment (as opposed to non-employment).[9] Young adults at the bottom of the wealth distribution have about 5 percentage points lower probability of being employed compared to those with above-median family wealth. Analogously to labor earnings, after controlling for observable characteristics the employment rate becomes non-monotonic in wealth. After residualization, individuals at the top of the wealth distribution are less likely to work than median workers, with the most prominent fall for those from the top 1 percent.

To better understand what drives the employment rate at each wealth decile, we 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 7 show that low-wealth individuals have a significantly higher

[9]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 the 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 a 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 for an average worker. For this reason, we consider two states only – employment and non-employment.

Figure 6: Average employment rate, by wealth decile.



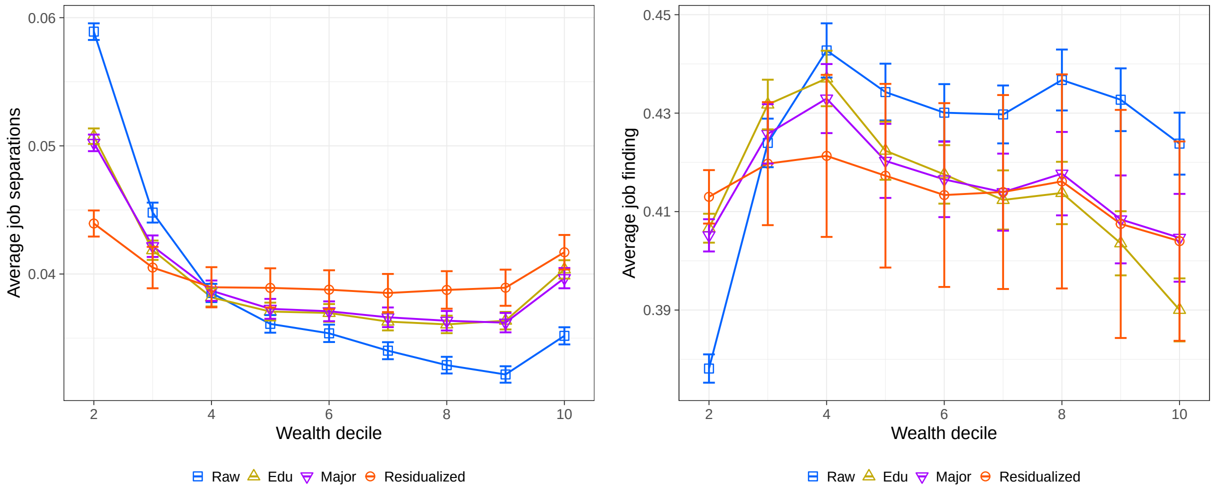
Note: The employment rates are calculated over the first five years after labor market entry defined as the year when the highest observed degree was obtained. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the Residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

probability to lose their jobs and a lower probability to switch 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 7). As before, the top 10 percent of workers seem to be an exception as the job separation rate ticks upwards for the wealthiest. Controlling for observables attenuates these gaps, again producing a U-shape relationship with the middle of the distribution having a lower E-NE transition rate than at the tails.[10] While the relationship between wealth and the 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 7). Taken together, these graphs reveal that both entry and exit margins contribute to the non-monotonic relationship between employment and family wealth.

Figure 8 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

[10]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. Given the results in the previous section, which suggest that an individual's wealth and their parents' wealth are highly correlated at the start of their labor market career, it is not surprising that our results echo Clymo et al. (2022).

Figure 7: Average annual employment and non-employment transition rates.



Note: The transitions where calculated using the first five years after labor market entry. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the Residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

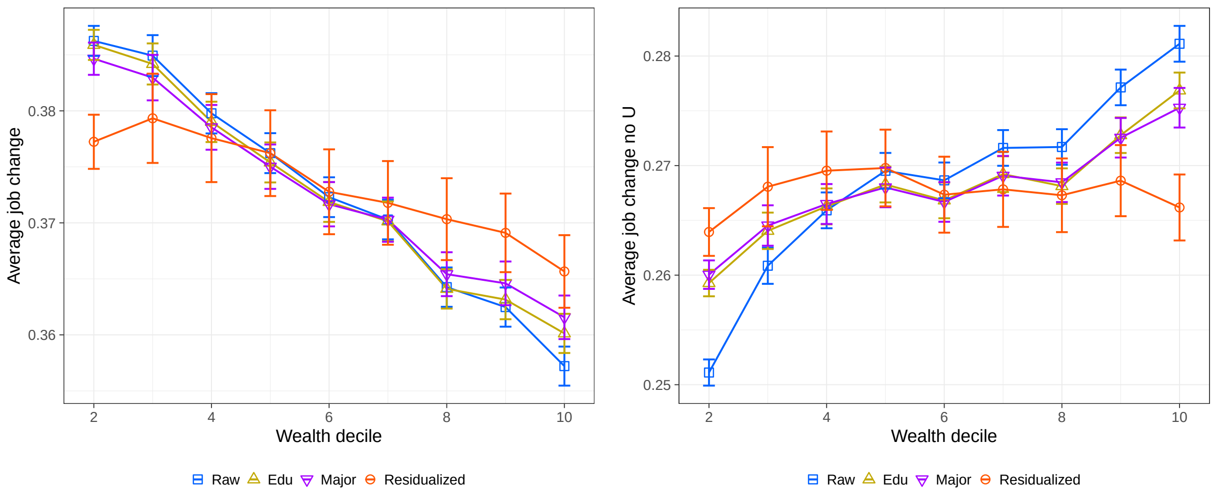
changes with interim spells of unemployment, this relationship flips resulting in an upward trend across the wealth spectrum. Overall, it shows that less wealthy individuals experience more job churning, and they are especially more likely to separate from their jobs and move to non-employment or a different employer after a brief spell of unemployment.

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. Surprisingly, the wealthiest 10% of workers have lower earnings and employment probability and a higher job separation rate than the middle part of the distribution, once we control for observable characteristics.

5 Firms and parental wealth

This section explores potential drivers of the patterns we document in Section 4. In particular, 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. First, we decompose child earnings dynamics across the household wealth spectrum into between- and within-firm components. We repeat this decomposition for occupations to test whether the wealth-earnings relationship is driven by occupational choice. Second, we propose two potential explanations for the observed sorting across firms along wealth dimension – parental (professional) connections and job search – and provide supporting evidence for the latter channel.

Figure 8: 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. In the Raw data, we control for interacted cohort and calendar year fixed effects, and in the Edu data, we add an interaction with years of schooling. Furthermore, Major outcomes are also residualized using educational major, and for the residualized data, we add an interacted fixed effect for the municipality of residence and a third-order polynomial in parental earnings. The error bars represent 95% confidence intervals.

5.1 Sorting across firms

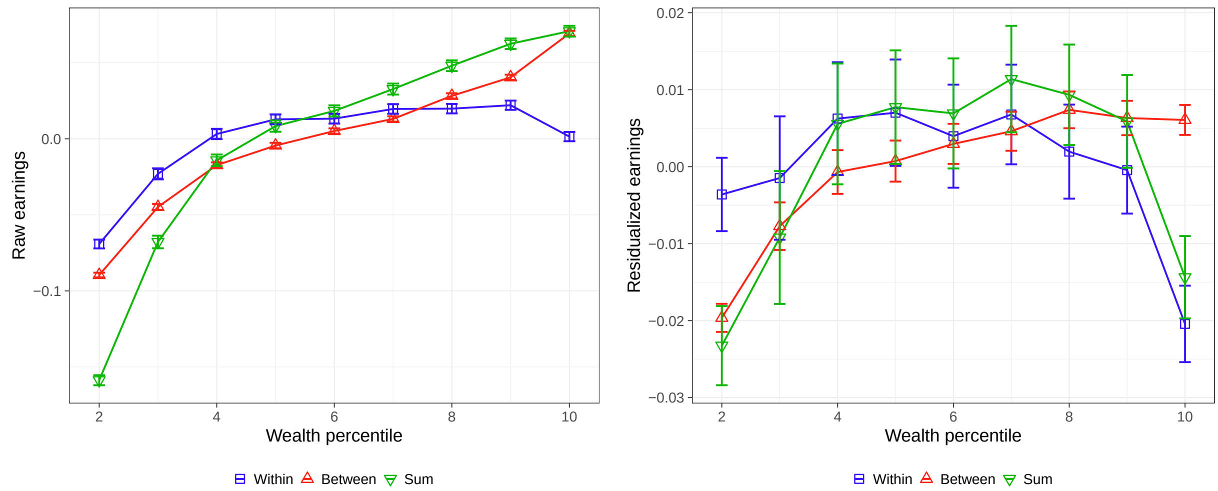
We aim to determine to what extent the gap in log earnings across wealth deciles can be attributed to between-firm or within-firm differences. This is interesting since the between component highlights the potential role played by the allocation of workers across firms, whereas the within component highlights 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. Then the variance in individual log earnings can be decomposed into the variance of between- and within-firm components. We focus on young adults during the first five years of their careers, and, therefore, 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 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 9 shows this decomposition for the raw and residualized earnings averaged across household wealth deciles. A striking pattern emerges. We see a positive relationship between

Figure 9: 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. 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.

household wealth and the *between-firm* component, which remains even after we control for a comprehensive set of demographic characteristics (right panel of Figure 9). 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.

We conduct a similar within- and between decomposition using 3-digit occupation codes to see whether the patterns observed for firms is the result of individuals sorting into different occupations. Figure 10 shows the earnings decompositions within and between occupations.[11] From this figure, we find that even in the raw data the between-occupation component is relatively similar across the wealth spectrum. This suggests that the sorting of wealthier workers into better paying firms is not the result of occupational choice alone.

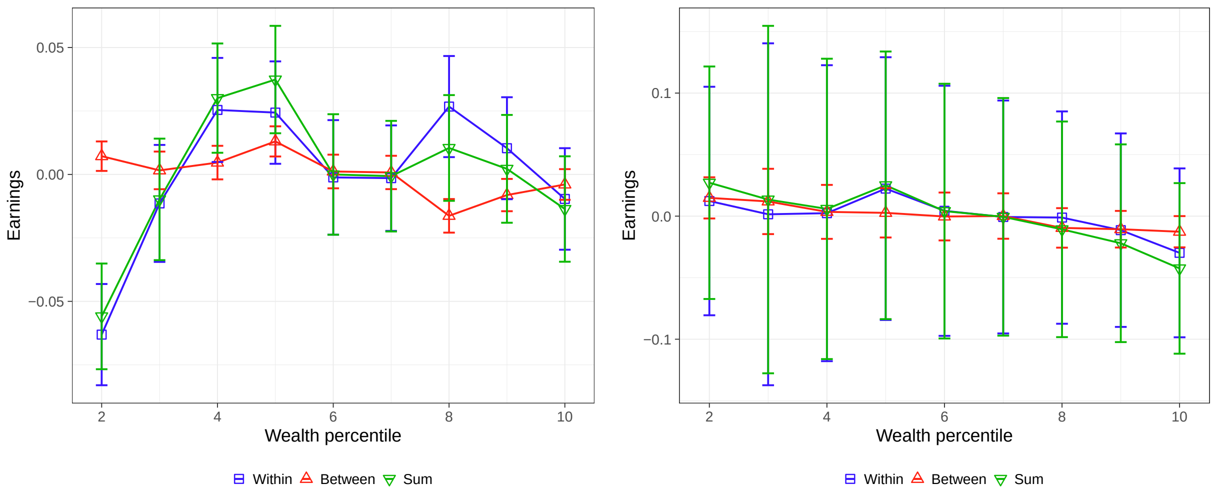
We can quantify the above relationships with a simple covariance decomposition. The covariance between an individual's annual log earnings over the first five years, y_{ijt}, with family wealth measured at age eighteen, a_i, can be decomposed into the covariance between wealth and each of the two (within 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 firms ($N > 1$), and at least ten young adults ($N > 10$). We find that in the raw data, the

[11] We do not observe any occupation with less than 24 peers within our sample. However, we disregard employees with imputed or out of date occupational codes, which reduces our sample size and increases the standard errors.

Figure 10: 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.

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 the 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 residualised 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).

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

		All			Deciles 1–9			Decile 10		
		Cov	Between	Within	Cov	Between	Within	Cov	Between	Within
Firm	Raw	0.411	57.4%	42.6%	0.401	52.9%	47.1%	-0.006	-87.4%	187.4%
$N \geq 5$	Resid.	0.045	103.1%	-3.1%	0.061	77.5%	22.5%	-0.008	4.7%	95.3%
Firm	Raw	0.424	62.0%	38.0%	0.419	58.5%	41.5%	-0.008	-21.8%	121.8%
$N \geq 1$	Resid.	0.052	102.6%	-2.6%	0.069	82.2%	17.8%	-0.009	23.5%	76.5%
Firm	Raw	0.407	55.5%	44.5%	0.397	50.8%	49.2%	-0.005	-102.3%	202.3%
$N \geq 10$	Resid.	0.039	111.0%	-11.0%	0.055	79.1%	20.9%	-0.008	6.0%	94.0%
Occ.	Raw	0.236	-8.7%	108.7%	0.222	-9.3%	109.3%	-0.040	95.0%	5.0%
	Resid.	-0.055	76.5%	23.5%	0.004	45.7%	54.3%	-0.002	16.0%	84.0%

Note: Firm components are calculated with a lower bound of peers (N) of one, five or ten, this was not necessary for the between occupation components as the minimum number of peers was 24. We use the log of earnings and the log of log of family liquid wealth plus one when calculating the covariances.

5.2 Parental connections

In this subsection, we explore one plausible mechanism for the observed sorting of individuals from wealthier background into higher-paying firms: parental networks. Specifically, wealthier parents may leverage their professional connections to help their children to secure better jobs.[12] Using matched employer-employee data for whole population of Sweden, we can 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.

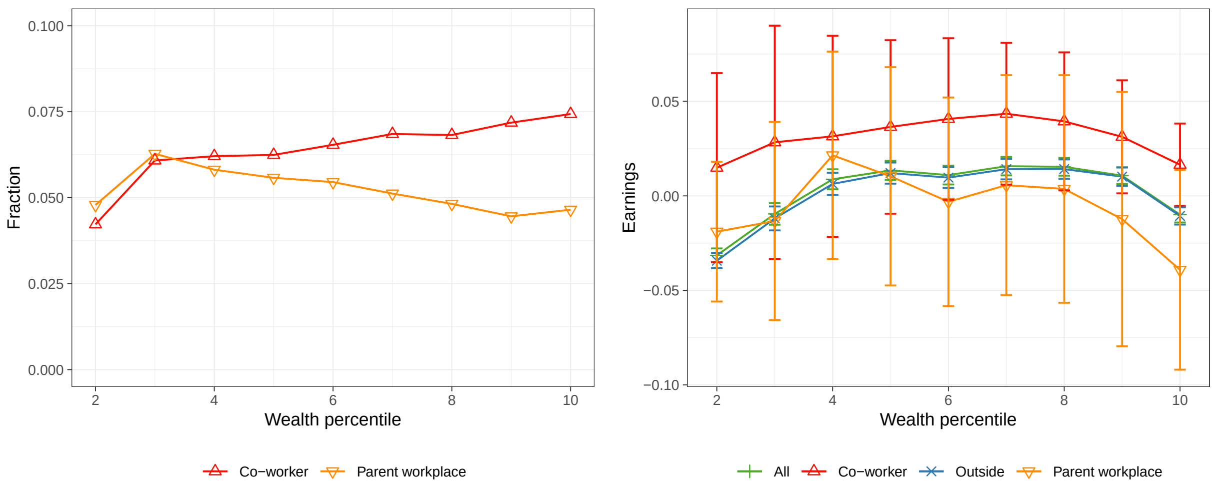
The left panel of Figure 11 presents the proportion of young adults employed in either a current or former firm of one of their parents within the first five years of entering the labor market ("Parent workplace" line). It also displays the proportion working with any former co-worker of their parents 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 11 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

[12]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.

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 11: 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.

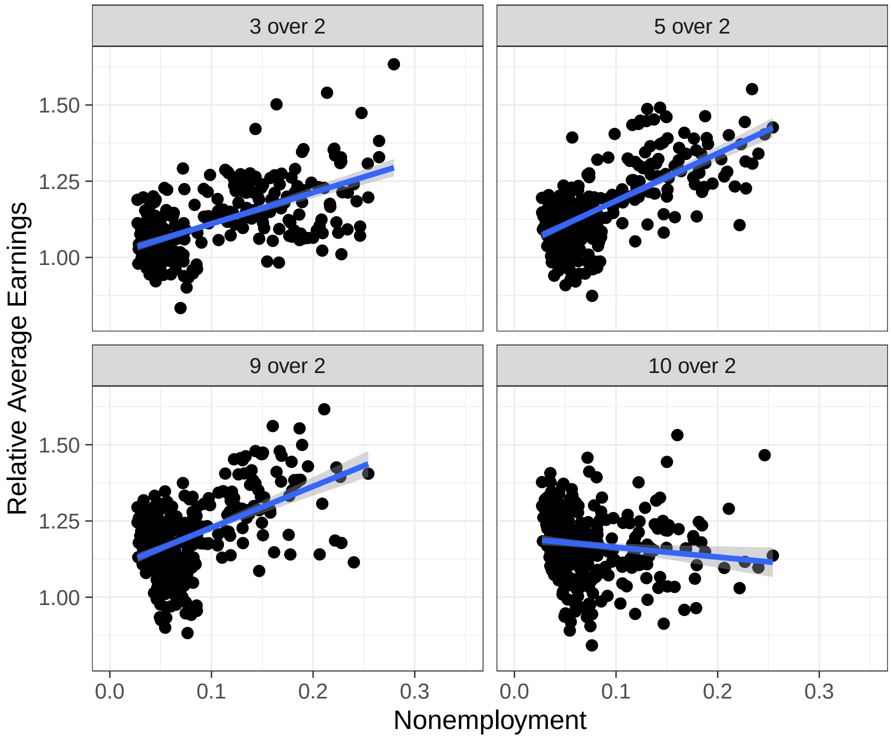
5.3 Local labor markets

An alternative mechanism that can explain the selection of wealthier individuals into higher-paying (and more stable) jobs is the safety net that family wealth provides for unemployed workers. That is, higher parental wealth enables workers to extend their search period and hold out for better matches. The role of parental wealth as insurance is likely to be more important during the periods (or in localities) of high unemployment when jobs are scarce. To test this hypothesis, 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.[13] 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 12 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 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.[14]

Figure 12: 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.

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

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

6 Model

In this section, we develop a parsimonious partial equilibrium on-the-job search model with assets, heterogeneous job destruction rates and wages, and stochastic disutility of working to explain the empirical relationships we observe over the early years in the labor market.[15] The model builds on Lise (2013) and is similar to Clymo et al. (2022) but includes on-the-job search.

We use the model for three purposes. First, we assess whether a relatively simple model can replicate the patterns documented above. Second, we use the model to appraise 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.

Environment

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 d, 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 the non-pecuniary cost of working, which is positive only if a worker receives a disutility shock in their job and is equal to zero otherwise.

The per period utility function is:

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

where α determines the relative risk aversion. The worker chooses how much to consume or to 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

[15]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.

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.[16] 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.

Workers receive job offers at rate λ_0 when unemployed and at rate 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 the rate $\delta(w)$, upon which they transition into unemployment. We allow for the job destruction rate to depend on the wage, which is key to generating the decline in job separations over the lower levels of the initial asset distribution.[17]

When workers are in a match, they are subject to non-pecuniary disutility shock, u^d, that arrives at rate ϕ^E. The worker continues to experience disutility from the match until they leave their job. This shock captures other non-wage factors that can induce workers to switch jobs, such as job amenities, changes in commuting distance due moving to a different residence, job changes of their spouses or partners, etc. The non-pecuniary disutility of the match always begins at 0. This stochastic disutility is key for generating an increase in job separations over the top part of the initial asset distribution.

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 $\phi^U = 1/12$ (implying an average duration 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 for two values of non-pecuniary costs of working. Let $U(w, a)$ and $U^L(w, a)$ denote the value of

[16] 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.

[17] 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.

unemployment, and unemployment at the lower unemployment benefit level, respectively.[18] Let $W(w,a)$ and $W^D(w,a)$ denote the value of employment with zero and positive disutility level, respectively. Beyond a worker's optimal consumption level, there are four reservation strategies that the worker must determine.

First, the two reservation wages associated with accepting job offers for unemployed workers with asset level a, previous wage w, and higher or lower level of benefits, respectively, $w^U(w,a)$ and $w^L(w,a)$, are defined as solving:

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

Second, upon receiving a disutility shock workers may choose to transition into unemployment, instead of bearing the non-pecuniary costs of work. The associated reservation strategy solves:

$$W^D(w^{uD}(a),a) \coloneqq U(w^{uD}(a),a). \tag{5}$$

Finally, workers who remain in the employment state after receiving a disutility shock accept all job offers above the reservation wage $w^{eD}(w,a)$, which is defined as solving:

$$W(w^{eD}(w,a),a) \coloneqq W^D(w,a). \tag{6}$$

Recall that disutility in the new job goes back to zero. We discuss these in more detail below. Those in employment without disutility accept offers that are greater than their current wage since $W_w > 0$, which also entails a unique solution for (4).

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

$$\rho U(w,a) = \max_c \Bigg\{ u(c) + \lambda_0 \int_{w^U(w,a)} \big(W(x,a) - U(w,a)\big) dF(x) \\ + \phi^U[U^L(w,a) - U(w,a)] + U_a(w,a)\dot{a} \Bigg\}, \tag{7}$$

where assets evolve according to:

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

and

$$\rho U^L(w,a) = \max_c \Bigg\{ u(c) + \lambda_0 \int_{w^L(w,a)} \big(W(x,a) - U^L(w,a)\big) dF(x) + U^L_a(w,a)\dot{a} \Bigg\}, \tag{8}$$

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

where assets evolve according to:

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

The HJB equations for a worker with assets a and wage w in employment with zero and positive disutility of work are, respectively, written as:

$$\rho W(w,a) = \max_c \Bigg\{ u(c) + \lambda_1 \int_w \big(W(x,a) - W(w,a)\big) dF(x) + \delta(w)[U(w,a) - W(w,a)] \\ + \phi^E[\max\{W^D(w,a), U(a)\} - W(w,a)] + W_a(w,a)\dot{a} \Bigg\} \tag{9}$$

and

$$\rho W^D(w,a) = \max_c \Bigg\{ u(c) - u^d + \lambda_1 \int_{w^{eD}(w,a)} \big(W(x,a) - W^D(w,a)\big) dF(x) \\ + \delta(w)[U(w,a) - W(w,a)] + W_a^D(w,a)\dot{a} \Bigg\}, \tag{10}$$

where assets evolve according to:

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

Finally, we impose a zero borrowing constraint:

$$a \geq 0. \tag{11}$$

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:

$$u'(c^U(w,a)) = U_a(w,a) \quad \text{and} \quad u'(c^E(w,a)) = W_a(w,a). \tag{12}$$

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 savings 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 only by differences in the job search behavior of individuals. For the purposes of our discussion, we will focus on two reservation wages: $w^U(w,a)$ — the minimum accepted wage to exit unemployment, and $w^{uD}(a)$ — the minimum wage at which workers are willing to stay in the job with non-pecuniary disutility of work. These two objects are key to generating the observed dynamics of wages and job flows. The results we show below are well known in the literature (especially the first), but we describe them here for clarity and completeness, as well as 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:

$$w_a^U(w,a) = \frac{U_a(w,a) - W_a(w^U(w,a),a)}{W_w(w^U(w,a),a)} = \frac{u'(c^U(w,a)) - u'(c^E(w^U(w,a),a))}{W_w(w^U(w,a),a)}. \tag{13}$$

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 ensuring that the offer arrival rate when unemployed is higher than when employed, so that the reservation wage $w^U(w,a)$ is higher than $b(w)$, the benefit level a worker receives whilst unemployed.

Considering the choice of quitting into unemployment versus staying in the same job following a disutility shock, we find a similar expression for the derivative of the associated reservation wage, written as:

$$w_a^{uD}(a) = \frac{U_a(w^{uD}(a),a) - W_a^D(w^{uD}(a),a)}{W_w^D(w^{uD}(a),a) - U_w(w^{uD}(a),a)} = \frac{u'(c^U(w^{uD}(a),a)) - u'(c^E(w^{uD}(a),a))}{W_w^D(w^{uD}(a),a) - U_w(w^{uD}(a),a)}. \tag{14}$$

Again, since the denominator is positive, the numerator determines the sign of the derivative. Since for a given wage, workers in unemployment receive less flow payments than those in employment, the sign of (14) is, unlike (13), unambiguously positive.

These two rules highlight that job acceptance and job separation rules are determined by the level of assets a worker has access to. Workers with lower assets, provided that search efficiency is lower in unemployment than in employment, accept lower paying jobs, and are also more willing to endure jobs with non-pecuniary disutility, than those with higher assets.

6.1 Calibration

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'. Indeed, recovering this parameter is one of the primary goals of our quantitative model.

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 $\tilde{\rho} = 1.05^{1/12}$, considering a model period to be a month, and assume that workers are in the labor market for 40 years on average implying a social discount rate $\rho = \tilde{\rho} + \frac{1}{d}$. We currently set $r = 0.5\rho$, and choose $\alpha = 5$.

This leaves us with the remaining 12 parameters to calibrate, $\theta = \{\eta_w^1, \eta_w^2, b, \lambda_0, \lambda_1, \lambda^r, \delta_H, \delta_L, \delta_i, u^d, \phi^E, \psi\}$. Next we turn to identification.

Identification

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

Unemployment insurance and job finding rates: As stated above, we chose the unemployment benefit to replicate an 80% replacement rate, which expires at a rate of $\phi^U = 1/12$. When unemployment insurance (UI) expires, it is replaced by a basic benefit with a replacement rate of 50%. We calibrate λ_0 and λ_1 by matching job transition rates for both unemployed and employed individuals.

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

Disutility shock, its arrival rate, and the fraction of available parental wealth: The reason for why the model can generate the increase in the E-NE transition rate at the top of the wealth distribution is the disutility shock. The reservation wage for staying in a job with non-pecuniary costs is increasing in assets, $w_a^{uD}(a) > 0$, which means that workers with higher assets are more likely to quit into unemployment upon receiving the disutility shock. This derivative is larger the higher is the value of available parental wealth, ψ. We argue that the level and the slope of the increase in the E-NE rate, as well as the decline in earnings for workers at the top of the asset distribution pin down values for u^d, ϕ^E and ψ.

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:

$$\hat{\theta} = argmin_{\theta}\Big\{\big[m - m^s(\theta)\big]W\big[m - m^s(\theta)\big]\Big\}.^{19} \tag{15}$$

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

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

6.2 Results

Calibrated parameters

Table 3 shows the pre-determined and internally calibrated parameters from the model. In the previous subsection, we showed that to generate the precautionary motive for search required that a higher efficiency of search in unemployment than in employment. Indeed, we find that unemployed workers face an almost 4 times higher offer arrival rate than their employed counterparts.[20] We also observe an extremely skewed job destruction distribution, where workers in low wage jobs undergo extreme levels of unemployment risk, but this decreases dramatically with wages. Finally, the model implies that workers receive a non-pecuniary cost of working around once every 17 months.

Table 3: Parameter values

Parameters	Name	Value	Reason/moments
		Pre-determined	
ρ	social discount rate	$1.05^{1/12} + \frac{1}{40\times 12}$	5% annual and 40 years
r	interest rate	0.5ρ	
α	CRRA	5	literature
		Internally calibrated	
η_w^1	w distribution	0.68	$var(w)$ and $skew(w)$
η_w^2	w distribution	5.47	$var(w)$ and $skew(w)$
λ_0	offer arrival rate in NE	0.61	NE-E schedule
λ_1	offer arrival rate in E	0.14	J2J schedule
δ_H	highest job destruction	0.89	E-NE schedule at low assets
δ_L	lowest job destruction	0.00	E-NE schedule at low assets
δ^i	interpolation parameter	0.003	E-NE schedule at low assets
u^d	work disutility	0.44	wages and E-NE schedule at the top
ϕ^E	disutility arrival rate	0.06	wages and E-NE schedule at the top
ψ	scale parameter	0.39	wages and E-NE schedule at the top

Moments

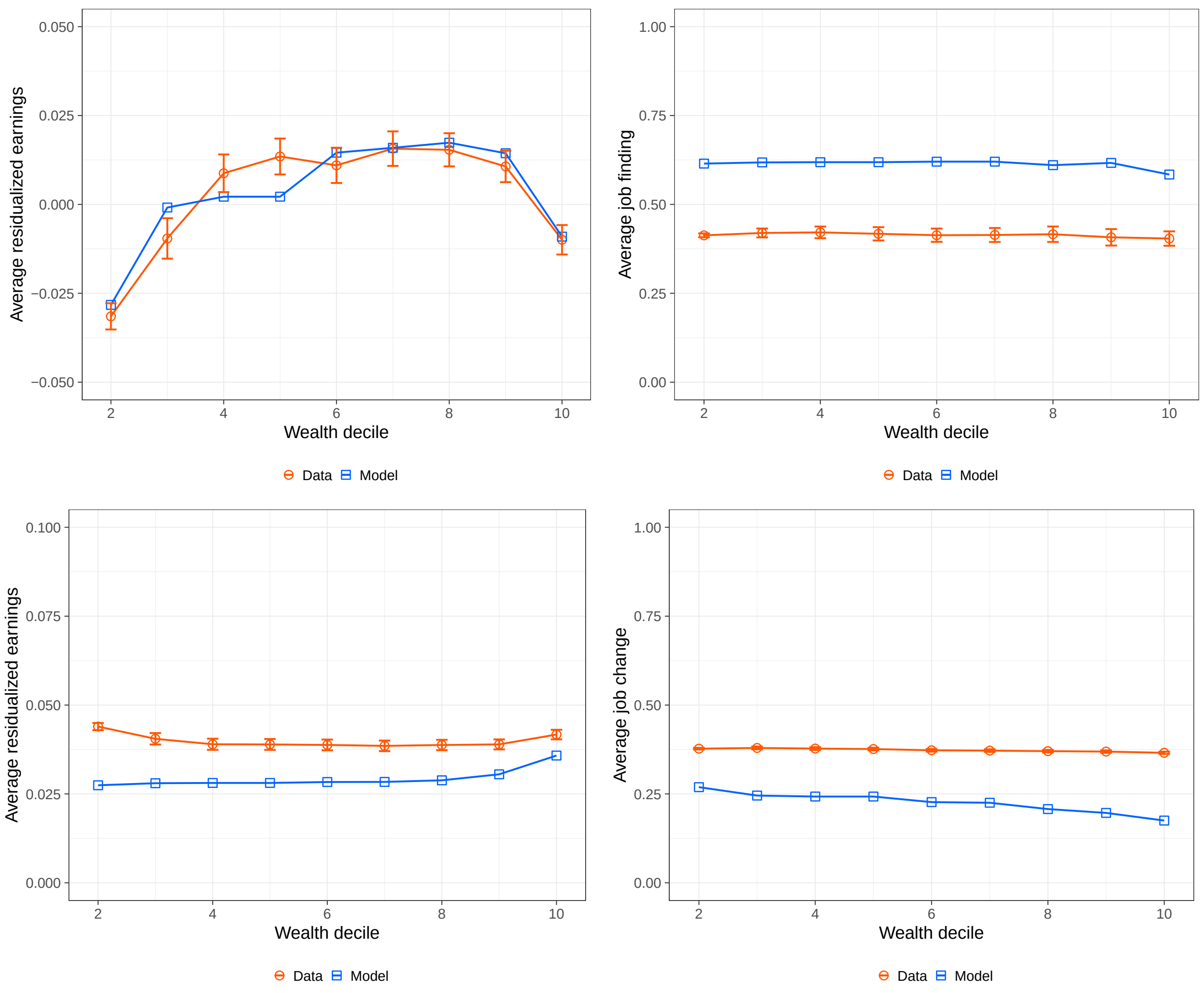
Table 4 shows the empirical variance and skewness of the wage distribution during the first five years, and the corresponding moments in the model. Figure 13, shows the residualized wages, job separation, job finding, and job change rates across the initial wealth distribution against the data counterparts. 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 low wages, and fit slightly higher levels for the job finding probability, and lower levels for the job change probability.

[20] 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. The offer yield may still be significantly higher among the employed

Table 4: Targeted moments

Moments	Data	Model
$var(w)$	0.62	0.65
$skew(w)$	-1.92	-1.98

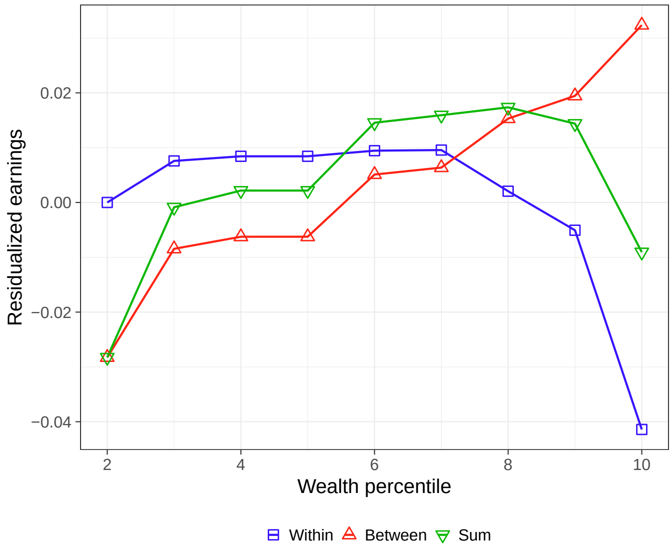
Figure 13: Empirical and simulated moments: wages and job transitions



Firms

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. In Figure 14 plots the non-targeted within- and between-firm wage components across the initial wealth spectrum generated by the model.

Figure 14: Simulated within- and between-firm components of log-earnings



The model delivers very similar patterns to those observed in the data (see Figure 9). As discussed in Section 6, 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 and 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, largely due to a higher incidence of quits following disutility shocks. 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.

7 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

(Faberman et al., 2022), even if the resulting arrival rate is lower.

steady-state distribution of wages.[21] Thus, we impose the following budget constraint:

$$E(b_{min}) = \tau E(w), \tag{16}$$

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

The model interprets the changes in wages for individuals with access to lower levels of assets as being due to changes in acceptance behavior for the unemployed. This acceptance margin becomes less important as we move up the initial asset grid. At the top of the asset distribution, changes in acceptance decisions for those already employed following shocks to the non-pecuniary utility of the job is more important. Thus, through the lens of the model, liquidity will distort acceptance decisions for the unemployed far more for low-asset individuals than those at the top. It is well understood that the benefit level a worker receives may impact future job quality of the unemployed (Nekoei and Weber, 2017).[22] Our results suggest that small changes in benefit levels could have a large impact on earnings outcomes.

Upon entering the labor market, workers receive minimal benefits b_{min}. In line with the Swedish UI system, we assume a benefit level equal to 670 SEK (around 60 US dollars) per week, in the baseline. The benefit level amounts to about 16% of the average weekly earnings during the first five years after labor market entry. Below, we consider policies that increase the amount of income that workers receive upon entry, b_{min}. Note that after the first job, the benefits revert back to standard income-based UI benefits, $b(w)$.

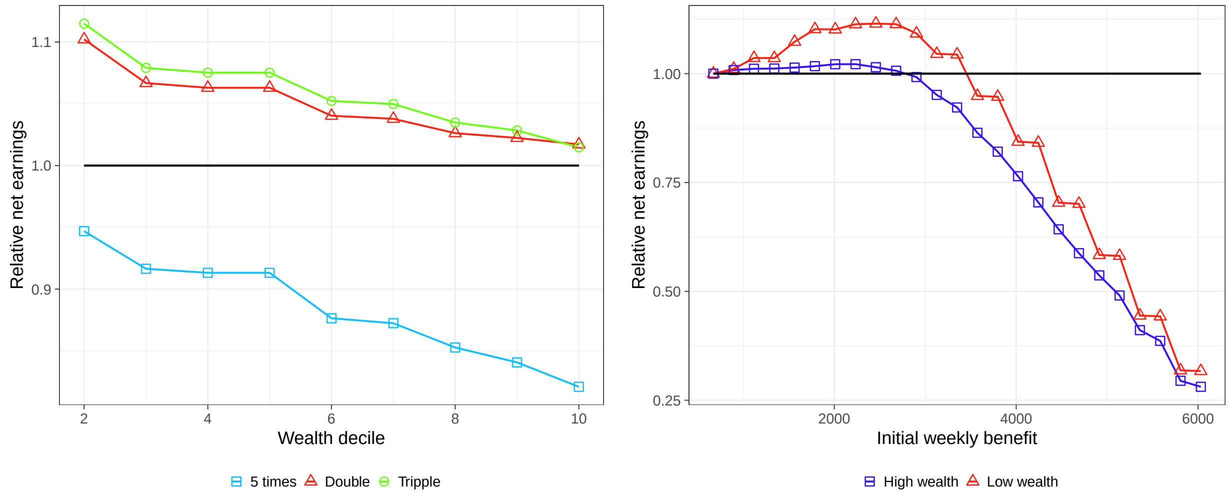
The left panel of Figure 15 depicts the resulting increase in earnings relative to the baseline when the minimal benefits are multiplied by 2, 3, and 5. First, this policy has a larger effect on the earnings of low-asset workers. For example, doubling benefits increases early career average earnings for the lowest two deciles by over 10% and has only a minimal impact on those in the highest decile. Second, raising benefits too much (e.g. five times), can lead to an overall decline in average wages due to a higher tax burden. We show this latter point more clearly in the right panel of Figure 15, where we present the percentage change in earnings over different levels of benefits for individuals in the bottom 20 and top 10 percentiles of wealth. Overall, the model suggests that a higher benefit level upon initial labor market entry can increase average early career earnings for all workers.

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

[21] 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.

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

Figure 15: Simulated increase in benefits upon entry



equivalent variation (CEV), γ, that solves:

$$\mathbb{E}_0\left[\int_{t=0}^{\infty} e^{-\rho t}\big(u(c_t(1+\gamma)) - u^d\big)dt\right] = \mathbb{E}_0\left[\int_{t=0}^{\infty} e^{-\rho t}\big(u(\tilde{c}_t) - \tilde{u}^d\big)dt\right], \tag{17}$$

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

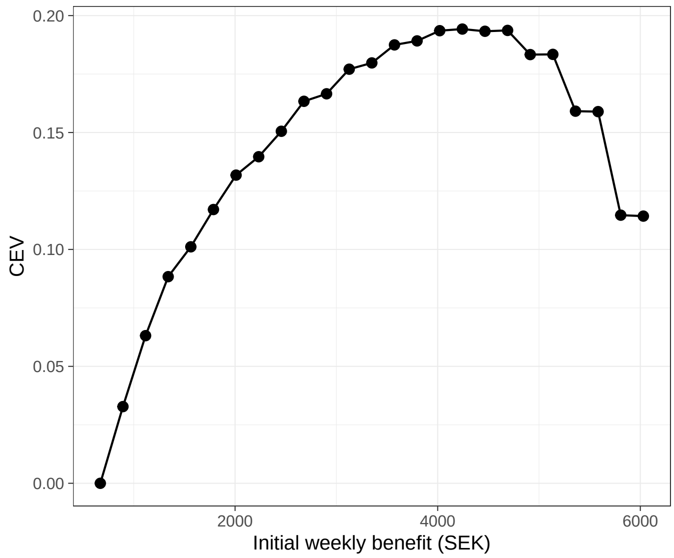
Figure 16 shows the resulting CEV across different levels of initial unemployment benefits. We observe strikingly large welfare gains from providing higher benefits upon entry, doubling the benefit level results in a CEV increase of around 7.5%. This takes into account that the higher benefit level results in an increase in the tax rate, it is just that this increase is small (see Figure C.3). This small increase in the tax rate is in part due to average earnings increasing for workers following changes in acceptance behavior as just discussed in 15. It turns out that the optimal policy is to increase benefits upon entry to around 4000 SEK per week, or about six times the benefit level that workers receive in the baseline. As well as being relatively cheap, providing extra liquidity to those entering the labor market improves welfare significantly since these are on average wealth poor.

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.

8 Conclusion

In this paper, we present a comprehensive picture of the relationship between parental wealth and the early labor market outcomes of children. First, we document an intergenerational correlation between parents' wealth and their children's earnings that is similar in magnitude to the correlation between parents' and children's earnings. However, we find that the positive link between parental wealth and children's earnings persists even within parental income percentiles. We also find that parents' wealth is strongly correlated with a

Figure 16: Consumption equivalent variation



child's wealth at the age of 18. These features suggest that family wealth enhances children's earnings outcomes beyond the effect captured through parental earnings, and that parents, perhaps unsurprisingly, provide financial transfers to their children.

Next, 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 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.

Finally, we interpret our results through a search model with savings, search on and off the job, and stochastic disutility of work. Our results suggest that parents provide substantial wealth to their children, which enables them to search longer for higher-paying and more stable jobs. 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 earnings.

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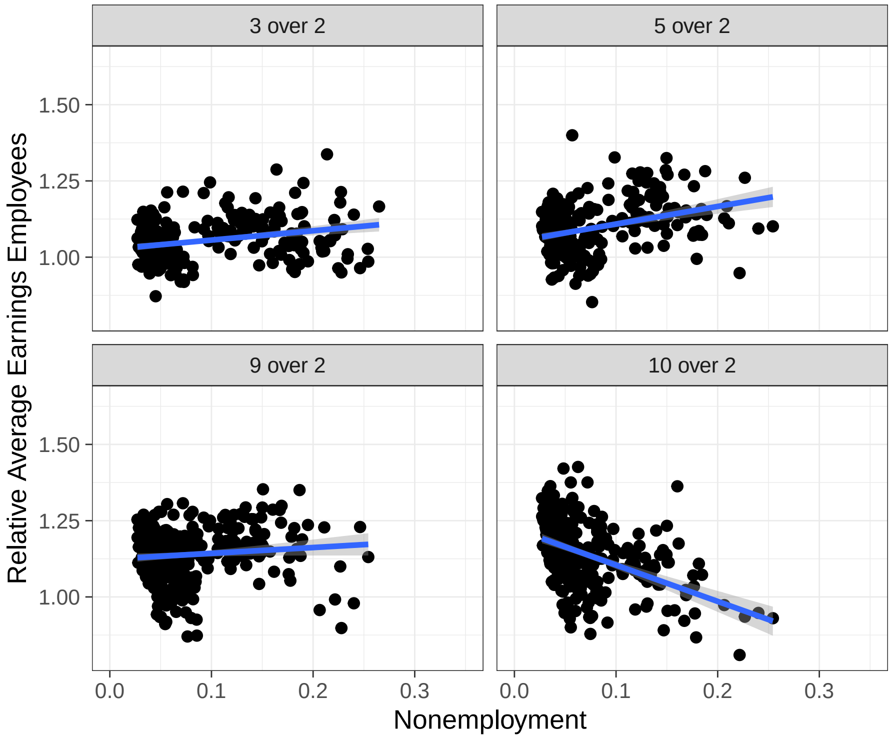
Appendix A. Local labor markets and parental wealth

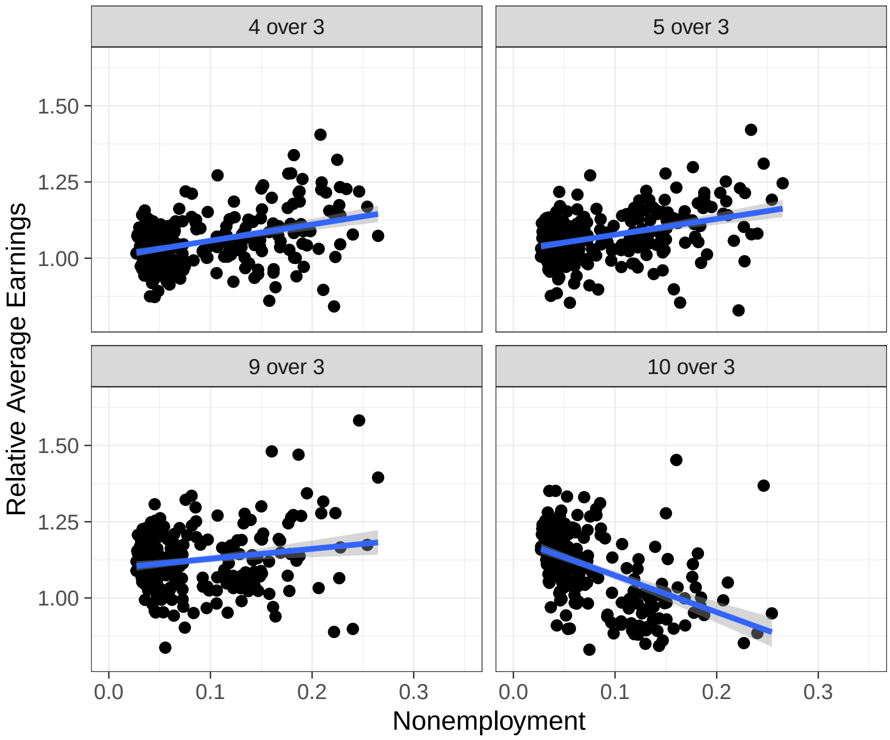
This appendix provides some additional figures related to the analysis in Section 5.3.

Figure A.1: 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.2: 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.

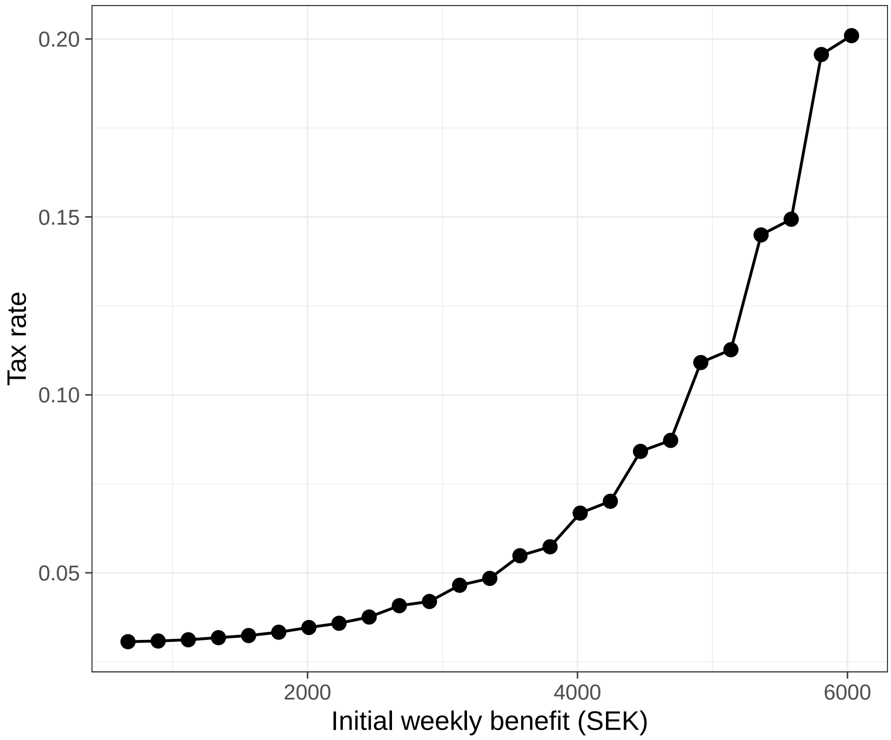
Unemployment insurance (UI) is voluntary in Sweden and administered by trade union-linked funds with publicly subsidized fees following a Ghent system (Clasen and Viebrock, 2008). For the period 2000–2020, the initial replacement rate has been 80% of the previous wage up to a nominal ceiling of 2900–4550 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. Further model figures

Figure C.3 shows the tax rate that balances the budget that is required to finance changes in benefit levels upon entry.

Figure C.3: The implied tax rate, as the function of benefits upon entry



Appendix D. 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, which 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 6, 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.