Intergenerational Mobility in Welfare: Wages and Amenities*

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December 27, 2025

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Abstract

Measures of intergenerational mobility primarily focus on earnings and often overlook substantial heterogeneity in job amenities. We propose a novel measure of intergenerational welfare mobility, "value-value" slope, including both pecuniary and non-pecuniary value of a job. We apply a revealed preference approach to construct common rankings of jobs based on worker flows. Using Danish administrative data, we document that there is 31% more intergenerational mobility than earnings-based mobility measures alone would suggest: the value-value slope is 0.105 and the wage-premia slope is 0.151. Importantly, this aggregate pattern masks striking gender differences: comparing within each gender, daughters exhibit 38% greater mobility in total welfare than in wages; for sons, the two measures nearly align. Gender differences trace to how family background shapes educational and occupational paths. Daughters pursue academic tracks and enter white-collar jobs with similar amenities at high rates regardless of background. Sons' paths are more stratified: those from disadvantaged families disproportionately follow vocational routes into blue-collar work, where both wages and amenities differ sharply from the professional jobs that advantaged sons obtain.

Keywords: Intergenerational mobility, earnings inequality, amenities

JEL Codes: J62, D31, J30

*First draft: November 16, 2025. We are grateful to Peter Arcidiacono, Patrick Bayer, Rafael Dix Carneiro, Michael Dinerstein, Gregor Jarosch, Arnaud Maurel, and Laura Pilossoph for patient advising and support. We thank Jason Baron, Matthias Kehrig, Andrea Lanteri, Marjorie McElroy, and Isaac Sorkin for helpful suggestions and comments. We also thank all participants at Duke for their valuable comments and suggestions. This paper has greatly benefited from conversations with Flavio Cunha, Juanna Joensen, Nirav Mehta, Chris Moser, Sharon Traiberman, Xincheng Qiu, and many others. All remaining errors are our own.

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1 Introduction

"[T]he wages of labour vary with the ease or hardship, the cleanliness or dirtiness, the honourableness or dishonourableness of the employment. A . . . blacksmith . . . seldom earns so much . . . as a [coal miner] . . . . His work is not quite so dirty, is less dangerous, and is carried on in daylight, and above ground. . . ."

— The Wealth of Nations (Book X, Part I), Adam Smith (1776)

The transmission of well-being across generations is a central concern of the social sciences. To the extent that someone's fortune in life is strongly associated with the fortune of their parents, this may suggest that the opportunities available to one generation are unequally distributed, dependent on a lottery of birth. For this reason, a large literature in the social sciences measures how labor market outcomes in one generation are associated with parental outcomes, quantifying the degree of intergenerational persistence.[1] This literature primarily focuses on *income*, which is central to the well-being of workers, with labor earnings as its main component.[2] Yet, large differences in non-wage aspects of jobs—workplace safety, scheduling flexibility, and job security—also shape the well-being of workers. Furthermore, non-pecuniary aspects of jobs may influence pay directly, generating pay differentials that compensate workers for their exposure to risk or unpleasant conditions, resulting in workers receiving higher pay in unpleasant jobs and lower pay in pleasant jobs (Rosen, 1986).

Consequently, using an earnings-based mobility measure may understate or overstate the degree to which the labor market outcomes of children are related to the labor market outcomes of their parents. For instance, children from low-income families might move "up" in the earnings distribution by working in unpleasant jobs with higher pay (e.g., barista to sanitation worker), while children from high-income families might move "down" the earnings ladder by working in pleasant jobs with lower pay (e.g., corporate lawyer to art history professor). In this instance, earnings-based mobility measures will overstate the degree of intergenerational mobility in welfare. Conversely, it may be the case that children experience more mobility in non-wage aspects of jobs than in earnings alone, in which case, earnings-based mobility measures will understate the degree of intergenerational mobility in welfare. While existing work has extensively examined how earnings persist across generations, scant attention has been paid to intergenerational persistence in non-wage attributes of jobs.[3] Non-pecuniary aspects of a job may be accessible to

[1] Some canonical papers in this literature include Becker and Tomes (1979), Black and Devereux (2011), and Chetty et al. (2014).

[2] There are additional related studies that focus on other dimensions of intergenerational persistence, such as wealth (Charles and Hurst, 2003), consumption expenditures (Charles et al., 2014), and occupations and employment (Corak and Piraino, 2011).

[3] To the best of our knowledge, only Boar and Lashkari (2025) considers this subject, using different methods based on survey measures.

certain groups of workers but not others, potentially reinforcing inequalities across generations.[4]

In this paper, we propose a novel measure of *intergenerational mobility in job welfare*, capturing both pecuniary and non-pecuniary elements of a job. Our central question is: to what extent do parents with good jobs have children with good jobs? Our key innovation is the *value-value slope*: we regress the rank of children's average job value on the rank of the parents' average job value, directly assessing the degree to which parents with good jobs (high pay, good amenities, or both) have children with good jobs.[5] Building on earnings-based mobility measures, the value-value slope captures intergenerational persistence in utility space, encompassing both monetary compensation and amenities. We also examine a supplementary measure, the *value-earnings slope*, which measures how parental earnings rank predicts children's job value rank, thereby assessing how parental economic status shapes children's access to high-value jobs.

To construct this measure, we conceptualize that each job's value comprises a *common* value component—combining a monetary job wage premium and an amenity component that all workers collectively value (or dislike)—and an idiosyncratic component that varies across individual workers and time. The focus of this paper is to identify the component of job welfare that is common across workers, recovering a single market-wide ranking. The key challenge is that many important factors that make some jobs more desirable than others are unobserved: such factors include the quality of supervisors, the degree of autonomy offered in decision-making, and workplace safety; furthermore, the common valuation of these factors is unobserved.

To address this challenge, we build on Sorkin (2018) in ranking all jobs in the labor market using a revealed preference approach. Notably, we extend his approach from the *firm* level to the *job* level, where we define each job as an establishment-occupation pair.[6] This refinement is crucial: different occupations within the same establishment can vary significantly in both pay and access to amenities. Our method leverages aggregate worker flows to extract a single market-wide ranking (up to an i.i.d. draw in utility), a "consensus job ladder". The approach rests on revealed preference logic: the volume and direction of worker flows between jobs reveal relative desirability. Concretely, if workers systematically move from Job A to Job B, we infer

[4]There are multiple reasons we care about the amenity value of a job. Seminal work by Rosen (1986) and Mortensen (2003) highlights two opposing forces of how wages are affected by differences in non-pay amenities. In a frictional market, two distinct motives generate differences in non-pay job attributes. The "Mortensen" motive reflects variations in the utility provided by the firm, producing augmenting wage variation, whereas the "Rosen" motive arises from firms' marginal cost of providing amenities, resulting in compensating wage differentials. Sorkin (2018) demonstrates that worker transitions between jobs reveal preferences over a broad set of non-wage attributes—preferences that significantly shape both individual welfare and aggregate labor market outcomes.

[5]Our methodology produces ordinal rankings due to normalizations in the procedure, necessitating the rank-rank approach.

[6]In our preferred approach, we group establishments into establishment types using a k-means algorithm to reduce measurement errors.

that Job B is collectively more attractive, whether due to higher pay, better amenities, or both.[7]

We construct two complementary rankings of jobs using this revealed preference logic. First, we implement a PageRank algorithm based on voluntary job-to-job transitions in the labor market, where voluntary mobility patterns reveal workers' preferences over jobs through a static discrete choice framework. Second, we derive forward-looking job values ("job prospects") from a dynamic search model that accounts for both the instantaneous flow value of a job and continuation value. This forward-looking measure differs from the PageRank approach in three key ways. First, PageRank assumes homogeneous job size and equal hiring intensity across jobs; the search model adjusts for these differences using observed employment levels and estimated offer intensities from nonemployment-to-employment flows. Second, the search model allows us decompose job value into flow payoffs (current wages and amenities) versus continuation values (job security and future opportunities), enabling us to separately analyze each component's role in intergenerational persistence. Third, the search model addresses an identification problem: if involuntary separation rates vary across jobs, PageRank will misidentify job rankings. The search model solves this through an exogenous reallocation shock that captures involuntary transitions, identified by comparing observed separation rates to predicted endogenous separation rate at contracting versus expanding jobs. We map out all job-to-job transitions across the labor market and assign each job pair a single "score", with jobs that draw more net inflows receiving higher scores. Both approaches produce a combined measure, V_j, that captures the total value of a job under a single index without separately identifying individual amenity components.[8]

We implement our approach using full-population Danish administrative records spanning nearly four decades. For native Danes born in 1980-1981, we measure children's average job value at ages 30-39 (2010-2019) and parents' average job value at the ages 36-45 (1991-2000). The matched employer-employee structure of Danish data allows us to construct job rankings using millions of voluntary job-to-job transitions from the prime-age working population across these two time horizons. We rank these average job values nationally and regress child's job value rank on their parents' job value rank. The value-value slope measures relative mobility: how much the expected job-value rank of a child changes when the parent's job-value rank increases by one percentile. We also calculate upward mobility as the expected job-value rank of children whose parents are at the 25th percentile of the job-value distribution. Together,

[7] It is important to note that we are assuming a common notion of desirability: while we allow that individual workers have idiosyncratic tastes, we do not allow for different workers to have systematically different job ladders, a potential limitation that we assess empirically by extending our method to heterogeneous preference in Section 5.

[8] While we emphasize a common notion of desirability, we also allow for heterogeneous valuations by splitting our sample and constructing rankings of jobs separately for different subgroups defined by family background and gender.

these measures capture both the relative persistence across the distribution and the absolute prospects for children from disadvantaged backgrounds.

Our empirical analysis produces four main findings. First, intergenerational mobility is higher once amenities are incorporated: the value-value slope is 0.105 and the wage-premia slope is 0.151. This 31% difference is statistically significant and economically meaningful, highlighting that earnings-based measures may understate the degree of welfare mobility across generations. Put different, children from lower-income backgrounds appear to experience meaningful mobility into jobs with better non-wage attributes even though wage mobility is more limited. Second, while the value-value slope reveals greater mobility, parental earnings remain a strong predictor of children's total job welfare: parental earnings rank predicts children's job value rank similarly to the wage component alone. This indicates that parental economic status shapes children's access to good jobs (high pay, good amenities, or both) about as much as it shapes access to high wages alone. Children from lower-income backgrounds appear to experience meaningful mobility into jobs with better non-wage attributes even when wage mobility is more limited. Taken together, earnings-based mobility measures capture an important part of how economic status relates to the second generation's job welfare, but they understate the true degree of welfare mobility because children move along both job amenities and job wage premia.

Third, and most critically, earnings-based measures do not reliably track welfare mobility — even in the aggregate — and they can be especially misleading when considering mobility outcomes of sons and daughters separately. For daughters, the value-value slope, measuring total job welfare transmission, is 38% lower than the wage-premia slope, indicating substantially greater mobility in total job welfare than wages alone would suggest. For sons, the value-value and wage-premia slopes yield more similar estimates of intergenerational persistence. This stark gender difference reveals that how we measure intergenerational mobility fundamentally shapes our conclusions about equality of opportunity across generations—a finding of particular importance given that much of the intergenerational mobility literature focuses on sons.

We demonstrate robustness of our conclusions along four dimensions. First, we address measurement error in job value ranks. We prove that measurement errors attenuate our slope estimates toward zero and apply a three-step empirical Bayes correction to both children's and parents' job value ranks in our primary specifications, yielding bias-corrected estimates. Second, we validate our rankings using the poaching index proposed by Bagger and Lentz (2019), an alternative measure outside our framework that captures the fraction of hires poached from other firms. This independent measure yields strikingly similar conclusions: both aggregate and gender-specific results hold. Third, within our framework, our results remain quantitatively similar across various specifications: different numbers of establishment clusters and inclusion or exclusion of within-firm promotions. Fourth, our common value assumption appears reasonable:

separate job rankings constructed using only male transitions versus only female transitions correlate at 0.82, indicating that men and women rank jobs quite similarly.

Finally, we investigate the underlying mechanisms driving both our aggregate results and gender differences. We find that parental wealth exerts limited direct effects on children's labor market outcomes. Using an unexpected inheritance design exploiting sudden parental deaths, we show that large wealth shocks, even exceeding annual permanent income, fail to alter children's labor market trajectories, even for younger heirs. Rather, education emerges as a key mediator: children from wealthier backgrounds disproportionately pursue college degrees, which subsequently provide pathways to jobs with higher earnings and better amenities.

The centrality of education further explains observed gender differences in mobility in Denmark. As established above, these differences do not reflect preference heterogeneity. Instead, the patterns arise from how family background differentially shapes educational pathways for sons and daughters. In Denmark's secondary education system, daughters pursue academic tracks more uniformly across family backgrounds, leading to widespread college attendance and subsequent employment in white-collar jobs with relatively similar amenities. Sons from disadvantaged families more commonly pursue a vocational education involving an apprenticeship, generating stronger stratification in both wages and job amenities. This generates a striking contrast: for daughters, strong intergenerational transmission of wages combines with weak transmission of amenities, yielding substantially greater welfare mobility than earnings mobility alone would suggest. For sons, family background shapes wages and amenities more similarly than for daughters, resulting in more similar persistence across both measures.

Our findings provide both encouraging news and important caution for researchers and policymakers. In Denmark, earnings-based measures understate welfare mobility by approximately 31% in the aggregate—a difference that is both statistically significant and economically meaningful. This reveals that children experience substantially greater mobility in total job welfare than earnings alone would suggest. However, this aggregate pattern masks substantial heterogeneity: earnings-based measures can overstate or understate mobility in welfare depending on the subgroup, as we demonstrate in our analysis of differences in mobility for sons and daughters. Whether Denmark's patterns hold elsewhere remains an open empirical question. We view our methodological framework as a template that researchers can apply globally; the approach requires parent-child linkages and longitudinal employer-employee data, both increasingly available across developed and developing countries. Applying our methods to diverse settings would not only test the external validity of our findings but also, more importantly, shed light on how labor market institutions, social insurance systems, and education policies jointly shape the relationship between wages and welfare across generations.

Related Literature. This paper extends several strands of the literature. First, we contribute to the literature on intergenerational mobility and its measurement. Canonical intergenerational mobility analysis often focuses on earnings-based measures, whether in the form of intergenerational elasticity (IGE) motivated by theoretical work (Becker and Tomes, 1979, 1986; Solon, 2004) or rank-rank measures (Dahl et al., 2008; Chetty et al., 2014; Chetty and Hendren, 2018a,b; Chetty et al., 2020). While these two measures provide valuable insights into how economic status is transmitted across generations, they remain limited to pecuniary outcomes. Our contribution to this literature is twofold. First, we develop a measure of intergenerational mobility in job welfare. We adopt a state-of-the-art revealed preference approach to measure it, extending the discussion of intergenerational transmission of economic status from money space to utility space. Second, using Danish administrative data, we empirically document the intergenerational transmission of total job value and compare our estimates with earnings-based measures.[9]

Second, we extend the literature that studies how non-pecuniary amenities contribute to overall inequality. Seminal works by Rosen (1979) and Mortensen (2003) show that non-wage characteristics can be both compensating and augmenting; thus, interpreting non-wage characteristics of a job in terms of compensating differentials is subtle. Recently, a growing body of literature has used revealed preference approaches, grounded in discrete choice and search models, to leverage worker-flow data and quantify the total value of a job, with a particular focus on the role of non-pecuniary amenities in shaping inequality, whether in the context of aggregate inequality (Sorkin, 2018) or gender inequality (Morchio and Moser, 2024). Our paper makes two key contributions to this literature. First, we extend Sorkin (2018)'s firm-level approach to the job level, where we define each job as an establishment-occupation pair. This refinement is crucial: different occupations within the same establishment can vary significantly in both pay and access to amenities, allowing us to capture heterogeneity that firm-level analysis may miss. Second, we apply this revealed preference approach to study an underexplored dimension of inequality: how total job value transmits across generations in Denmark.

Third, our paper bridges the economics literature and sociology literature on intergenerational occupational mobility, which have traditionally compared children's occupations with those of their parents using three main approaches: (1) average income within an occupation (Abramitzky et al., 2014; Collins and Wanamaker, 2022); (2) average education level within an occupation (Song et al., 2020; Ward, 2023); and (3) Altham statistics, which measure oc-

[9]Both our value-based measures and existing earnings-based measures are subject to biases discussed in the literature (e.g., measurement error, transitory fluctuations, life-cycle bias), as summarized by Deutscher and Mazumder (2023). We acknowledge that our rank-rank measure may face similar criticisms. However, Mazumder (2016) and Nybom and Stuhler (2017) suggest that these biases are considerably reduced when using rank-rank rather than IGE. Chetty et al. (2014) found that rank-rank correlation is highly linear in the United States, compared to IGE. Similarly, Deutscher and Mazumder (2020) found linearity is a reasonable approximation for Australia. However, some studies have documented pronounced nonlinearities in other countries, such as Denmark (Landersø and Heckman, 2017; Heckman and Landersø, 2022; Eshaghnia et al., 2024).

cupational associations across generations (Long and Ferrie, 2013; Feigenbaum, 2018). While each approach has its merits (Abramitzky et al., 2025), they all focus on occupation level. We build on this literature by studying intergenerational *job* mobility, where we define each job as an occupation-establishment pair. This granular approach recognizes that wage and amenity bundles in an occupation may vary across establishments. Our contribution is that we apply an economic framework, a revealed preference approach, to this interdisciplinary question. By ranking jobs based on workers' actual transition behavior, we extend an existing approach that does not rely on proxy-based or survey-based measures to a novel setting, offering a distinct measure of how economic status is transmitted across generations.

Lastly, we note one contemporaneous paper that shares our perspective on incorporating non-pecuniary job attributes into the measurement of intergenerational mobility. Boar and Lashkari (2025) examines how parental income shapes children's access to occupations with desirable non-monetary qualities. Using the General Social Survey, they construct an index of occupational attributes such as respect, learning opportunities, and work hazards, and show that children of higher-income US parents are more likely to enter occupations scoring higher on this index. Our contribution is novel along three key dimensions. First, our more granular job-level data allow us to capture within-occupation, across-establishment heterogeneity that analyses based on occupation-only information might miss. Second, we employ a revealed preference approach, rather than survey-based indices, to capture the non-pecuniary component of job value. We apply the PageRank algorithm and estimate a dynamic search model using millions of job-to-job transitions observed in highly accurate administrative data. Third, we go beyond how parental earnings affect children's access to occupations with desirable non-pecuniary qualities, by focusing on the full bundle of job value, including both pecuniary and non-pecuniary components, and study the intergenerational transmission of job value in utility space, which provides a welfare-based measure of intergenerational mobility.

Road Map. Section 2 and 3 lay out our conceptual framework and revealed preference approach to rank jobs. Section 4 describes our Danish administrative data and sample construction. Section 5 presents our main results on intergenerational mobility in earnings and total welfare. Section 6 demonstrates when earnings-based measures can mislead. Section 7 examines underlying mechanisms using an unexpected inheritance design and mediation analysis. Section 8 presents additional results and robustness. Section 9 concludes.

2 Framework: From Earnings Mobility to Welfare Mobility

In this section, we develop a framework to measure intergenerational mobility in job welfare rather than earnings alone. We begin by reviewing canonical earnings-based mobility measures and then introduce our conceptual framework, where jobs are bundles of wages and amenities. Finally, we formalize our main empirical specification, which regresses children's job value ranks on parents' job value ranks to measure intergenerational transmission in job welfare.

2.1 Earnings-based Intergenerational Mobility

The conventional approach to measuring social mobility consists of summary measures of the joint distribution of earnings between parents and children such as the intergenerational elasticities (IGE) (Becker and Tomes, 1979) and intergenerational rank-rank slope (Dahl et al., 2008; Chetty et al., 2014; Chetty and Hendren, 2018a,b).[10] Our focus in this paper is the rank-rank specification. We rank children based on their incomes relative to other children in the same birth cohort and rank parents based on their incomes relative to other parents with children in these birth cohorts.[11] We characterize mobility by regressing the national rank of children in the pre-tax earnings distribution R_i^c on the national rank of parents in the pre-tax earnings distribution R_i^p:

$$\underbrace{R_i^c}_{\text{Child's Earnings Rank}} = \alpha^R + \beta^{Rank-Rank} \underbrace{R_i^p}_{\text{Parent's Earnings Rank}} + \epsilon_i \tag{1}$$

This regression gives rise to two canonical measures of intergenerational earnings mobility: rank-rank slope $\beta^{Rank-Rank}$, which captures relative earnings mobility, and absolute upward mobility $\alpha^R + 0.25\beta^{Rank-Rank}$, the expected national rank of children born to families at the 25th percentile of income distribution.

We focus on the rank-rank framework for several reasons. First, our PageRank algorithm and dynamic search model produce ordinal rankings rather than cardinal income values due to normalizations, naturally aligning with the rank-rank approach.[12] Second, the rank-rank estimates are robust to different treatments of zero earnings, which poses significant challenges for IGE estimates that rely on log transformations. However, we acknowledge important limitations: the rank-rank slope is a purely ordinal measure that does not capture changes in absolute income inequality across generations and compresses information at the tails of the distribution.

[10]The IGE characterizes the joint distribution by regression the log of child earnings on the log of parent earnings, excluding children with zero earnings. However, this canonical log-log specification sometimes yields unstable estimates of mobility in certain contexts due to the nonlinearity of the joint distribution and sensitivity to the treatment with zero earnings. Chetty et al. (2014) find that alternative specifications for the United States yield IGE estimates ranging from 0.26 to 0.70. The treatment of zero incomes is particularly consequential: assigning those with zero income a value of \$1 yields an IGE of 0.618, while treating them as having \$1,000 yields an IGE of 0.413.

[11]Following standard practice in the literature, parental earnings are measured as the sum of earnings across fathers and mothers when both can be linked, or the single parent's earnings otherwise.

[12]We provide more details on normalization in Section 3.

2.2 Jobs as Bundles of Wages and Amenities

We conceptualize jobs as bundles that provide both pecuniary and non-pecuniary value. Formally, we define the total value of a job j as

$$\mathcal{V}(\Psi_j, a_j) \tag{2}$$

where j indexes jobs at the occupation-establishment level, Ψ_j represents the pecuniary component (wage premium), and a_j captures non-pecuniary attributes such as workplace conditions, schedule flexibility, and job security. The challenge is that amenities a_j are typically unobserved. Moreover, we cannot simply survey workers about job quality because reported satisfaction may reflect selection: workers who value certain amenities sort into jobs that provide them.

Instead, we adopt the revealed preference approach developed by Sorkin (2018). The key insight is that workers "vote with their feet" during a voluntary job-to-job transition: when workers move from job k to job j, they reveal that j offers higher total value than k.[13] By aggregating these revealed preferences across millions of job transitions, we recover a market-wide ranking of jobs that reflects both observed wages and unobserved amenities. Section 3 details the methodology for constructing these rankings from observed job transition patterns.

Having estimated the total value $\mathcal{V}(\Psi_j, a_j)$ for each job, we transform these values into percentile rankings. We define the rank of job j as $V_j = \text{Rank}\left(\mathcal{V}(\Psi_j, a_j)\right)$, where ranks are uniformly distributed on [0,1], with $V_j = 0$ representing the lowest-value job and $V_j = 1$ representing the highest-value job. We interpret the ordinal ranking of V_j across all jobs as the "consensus job ladder". Highly ranked jobs offer substantial wage premia and/or highly valued amenities, whereas low-ranked jobs offer lower pay and/or poorer non-wage conditions. We emphasize that this approach assumes a common notion of desirability across workers. We later relax this assumption by allowing for heterogeneous job rankings.

To understand the relative importance of different channels of intergenerational transmission, we compare mobility patterns based on pecuniary components versus total job value. We construct rankings based solely on the pecuniary component Ψ_j by estimating job wage premia using an Abowd et al. (1999)-style (hereafter, AKM) regression where we define jobs as occupation-establishment pairs.[14] Comparing intergenerational persistence in job wage premia versus total job value allows us to assess whether family background primarily shapes access to high-paying jobs or whether it also determines access to the full bundle of pecuniary and

[13] Voluntary transitions of workers between jobs are required. We discuss how our matched employer-employee data accurately identifies voluntary moves in Section 4.

[14] Following the AKM literature, we impose a log-linear structure on earnings: $Y_{it} = \alpha_i + \Psi_{J(i,t)} + \xi X_{it} + r_{it}$, where Y_{it} denotes log earnings, α_i is a worker fixed effect, $\Psi_{J(i,t)}$ represents job fixed effects, and X_{it} includes time-varying covariates (age-gender interactions and year fixed effects).

non-pecuniary job attributes.

2.3 Intergenerational Transmission of Welfare

Finally, to study intergenerational mobility, we compute for each individual (parent or child) the average value of the jobs held during their respective 10-year window and rank these average values within their generation. Our primary specification regresses children's job value rank on parents' job value rank:

$$\underbrace{V_i^c}_{\text{Child's Value Rank}} = \alpha^{VV} + \beta^{Value-Value} \underbrace{V_i^p}_{\text{Parent's Value Rank}} + \epsilon_i \tag{3}$$

where V_i^c denotes the rank of the child's average job value over 2010–2019 and V_i^p denotes the rank of the parent's average job value over 1991-2000.[15] This *value-value specification* is the welfare analog to the canonical earnings-based rank-rank regression in Equation (1). This regression yields our primary measure of intergenerational welfare mobility: the *value-value slope* ($\beta^{Value-Value}$). We report both relative mobility ($\beta^{Value-Value}$) and absolute upward mobility ($\alpha^{VV} + 0.25\beta^{Value-Value}$). The value-value slope measures relative mobility, i.e., how much the expected job-value rank of a child changes when the parent's job-value rank increases by one percentile. Absolute upward mobility measures the expected job-value rank of children whose parents are at the 25th percentile of the job-value distribution. Together, these measures provide insight into both the relative disparity between children of parents at different points on the job ladder via the rank-rank slope and the absolute job prospects for children of lower-ranked parents via absolute upward mobility.

As a supplementary measure, we also examine how parents' *earnings* affect children's job value:

$$\underbrace{V_i^c}_{\text{Child's Value Rank}} = \alpha^{VE} + \beta^{Value-Earnings} \underbrace{R_i^p}_{\text{Parent's Earnings Rank}} + \epsilon_i \tag{4}$$

This value-earnings slope allows us to connect our welfare-based approach back to canonical mobility studies and assess whether high-earning parents transmit advantages in overall job quality beyond just earnings. Our main focus, however, remains the value-value specification in equation (3), as it provides the most comprehensive measure of welfare mobility by capturing

[15] We describe the construction of parental measures in Section 4. Parental job value is the average of father's and mother's job values when both parents can be linked, or the single parent's job value otherwise. We also present additional results using alternative aggregation methods, including the sum and maximum of parental job values.

the full bundle of job attributes on both sides.[16]

3 Measuring Job Values

This section details the methodology we employ to estimate the total value of jobs, inclusive of both wages and amenities, which extends the approach of Sorkin (2018) to consider the value of jobs rather than establishments or firms.

3.1 Revealed Preference Approach

We use a PageRank approach, in which the volume and direction of worker flows between jobs reveal relative desirability. The key insight is that workers "vote with their feet." Concretely, if workers systematically move from Job A to Job B, we infer that Job B is collectively more attractive—whether due to higher pay, better amenities, or both. By observing millions of job-to-job transitions across the labor market, we can aggregate these individual revealed preferences to extract a single market-wide ranking of jobs (up to an i.i.d. draw in utility) that reflects the collective preferences of all workers in the economy.

Crucially, we extend this approach from the *firm* level to the *job* level, where we define each job as an occupation-establishment-type pair. This refinement is crucial because different occupations within the same firm can vary significantly in both pay and access to amenities. A manager and a production worker at the same establishment face different wage schedules, working conditions, autonomy, and career trajectories. By defining jobs at the establishment-occupation level, we capture within-establishment heterogeneity in total job value.

The key distinction between our approach and the original approach is that we need to make assumptions about the information revealed from *promotions*: situations where a worker transitions from working in one occupation to another occupation while remaining at the same establishment. In our preferred approach, we treat transitions between jobs induced by promotions in the same way that we treat transitions between jobs induced by mobility across employers. If a worker is observed to be employed in one occupation before working at another at the same establishment, we assume that this transition is voluntary. As this assumption is strong, ruling out the possibility that some occupation transitions within employers are *involuntary*, we consider an alternative approach that considers job-to-job transitions induced by

[16]The value-earnings specification highlights a key difference between our framework and Boar and Lashkari (2025). They use survey-based measures to examine how parental earnings affect children's access to occupations with desirable non-pecuniary qualities. In contrast, we measure the full bundle of job value using revealed preferences, capturing both pecuniary and non-pecuniary components simultaneously. Our value-value specification (equation (3)) then examines how this total job value transmits across generations.

mobility across employers alone as a source of information.

We illustrate the revealed preference approach from a static discrete choice problem. When worker i makes a voluntary job-to-job transition and chooses between job j and k, the worker compares the total value of each job. We model the worker's utility from job j as

$$U_{ij} = \underbrace{\mathcal{V}_j}_{\text{common value}} + \epsilon_{ij} \tag{5}$$

where $\mathcal{V}_j$ represents common value of job j, the component shared across all workers, and ϵ_{ij} captures idiosyncratic match-specific preferences. We assume ϵ_{ij} is an i.i.d. type I extreme value with scale parameter normalized to 1.[17]

By the logit structure, the probability that any worker i chooses job k over job j is

$$P(\text{choose } k \text{ over } j) = \frac{\exp(\mathcal{V}_k)}{\exp(\mathcal{V}_k) + \exp(\mathcal{V}_j)} = \frac{M_{kj}}{N} \tag{6}$$

where N denotes the total number of workers who face a choice between jobs k and j, and M_{kj} is the number who choose k over j, while M_{jk} is the number who choose j over k. Abstracting from firm size, the relative value of two jobs can be expressed through observed bilateral flows:

$$\mathcal{V}_k - \mathcal{V}_j = \ln\left(\frac{M_{kj}}{M_{jk}}\right). \tag{7}$$

Given all bilateral endogenous worker flows, the recursive structure in principle gives the value of all jobs j, $\mathcal{V}_j$. In the context of the labor market, however, we could run into two practical problems. First, for pairs of jobs, there are no flows in both directions or no flows at all; this approach would not yield well-defined values of jobs. Second, even when bilateral flows exist, there is no guarantee that pairwise comparisons would yield a consistent valuation of jobs. For instance, cycles may emerge where $\mathcal{V}_A > \mathcal{V}_B$, $\mathcal{V}_B > \mathcal{V}_C$, but $\mathcal{V}_C > \mathcal{V}_A$, preventing us from constructing a consistent ranking of jobs.

Sorkin (2018) resolves both problems by collapsing all pairwise conditions into one equation per job. Rather than solving equation (7) pairwise, we impose it simultaneously for all jobs j in the economy:

$$\frac{M_{kj}}{M_{jk}} = \frac{\exp(\mathcal{V}_k)}{\exp(\mathcal{V}_j)}, \forall j \in \mathscr{E} \tag{8}$$

where $\mathscr{E}$ is the set of all jobs. If we rearrange and cross-multiply, we can identify $\mathcal{V}_j$ as the fixed

[17] A limitation of this approach is that everyone has essentially the same rankings of jobs up to an EV1 error. Additionally, the scale parameter normalization means that cardinal values are not identified; only ordinal rankings are meaningful. This is why we work with job value ranks rather than absolute values in our intergenerational mobility analysis.

point of the recursion below:

$$\exp\left(\mathcal{V}_k\right) = \frac{\overbrace{\sum_{j\in\mathscr{E}} M_{kj}\exp\left(\mathcal{V}_j\right)}^{\text{value weighted entry}}}{\underbrace{\sum_{j\in\mathscr{E}} M_{jk}}_{\text{exits}}} \tag{9}$$

This equation generates a recursive definition of total job value: a good job attracts workers from other good jobs and experiences few departures. The numerator aggregates the value-weighted inflow of workers into job k: jobs that attract workers from high-value positions receive higher scores. The denominator counts total outflows: jobs with many departures are penalized.

3.2 Forward-Looking Job Value

As an alternative to the PageRank algorithm, we also consider the ranking over jobs recovered from a Burdett and Mortensen (1998) model, which is detailed in Appendix A. We estimate a job ladder model for several reasons.

First, the PageRank algorithm implicitly assumes that all jobs employ the same number of workers and make the same number of offers—an implausible assumption. In reality, jobs that employ many workers have more workers leaving them than jobs that only employ some workers, but this does not imply they are less desirable. Similarly, jobs that make many offers will hire many workers, but this does not necessarily signal desirability. The search model addresses this issue by adjusting for the number of workers employed in a job and offer intensity.

Second, the job ladder model allows us to distinguish the ranking workers have over *flow payoffs* from the ranking workers have over *jobs*, which may be driven by differences in *job security* across jobs as well as flow payoffs. This decomposition enables us to speak to the importance of rankings over job security or wage premia, which may be measured directly, separately from other non-pecuniary aspects of jobs that are unobserved and included in flow payoffs. We can thus decompose job value into a component explained by differences in flow payoffs and a component explained by differences in continuation values.

Third, the job ladder model is to address an important identification problem that may bias the PageRank algorithm. To the extent that the share of job-to-job transitions that are *involuntary* varies across jobs, the PageRank algorithm will fail to identify the common ranking that workers have over jobs. The job ladder model addresses this problem by allowing for the risk of an involuntary transition to vary across jobs.

The search model nests the PageRank approach. In the model, jobs are differentiated in three key dimensions: flow utility, job destruction risk, and the risk of exogenous shocks. Workers receive offers from jobs at a common rate that varies based on their employment status. In each period, workers draw Gumbel-distributed shocks associated with different options that are available to them.

In steady state, the number of workers transitioning from job k to job j can be expressed as:

$$M_{jk} = \underbrace{g_k W \left(1-\delta_k\right)\left(1-\rho_k\right)}_{\text{\# workers staying at } k} \times \underbrace{\lambda_1 f_j}_{\text{prob. of receiving an offer from } j} \times \underbrace{\frac{\exp\left(\mathcal{V}_j\right)}{\exp\left(\mathcal{V}_j\right)+\exp\left(\mathcal{V}_k\right)}}_{\text{prob. of accepting } j} \tag{10}$$

where g_k is the share of all workers employed at k, W is the total number of workers, δ_k and ρ_k are exogenous separation rates (job destruction and reallocation, respectively), and $\lambda_1 f_j$ is the probability an employed worker at k gets an offer from j. Taking the ratio of transitions from j to k versus k to j yields:

$$\frac{M_{kj}}{M_{jk}} = \underbrace{\frac{f_k}{f_j}}_{\text{relative offers}} \times \underbrace{\frac{g_j\left(1-\delta_j\right)\left(1-\rho_j\right)}{g_k\left(1-\delta_k\right)\left(1-\rho_k\right)}}_{\text{effective sizes}} \times \underbrace{\frac{\exp\left(\mathcal{V}_k\right)}{\exp\left(\mathcal{V}_j\right)}}_{\text{relative values}} \tag{11}$$

where the three terms capture relative offer rates, effective firm sizes (accounting for employment levels and separation rates), and relative values. Sorkin (2018) defines the "flow-relevant" utility $\exp\left(\hat{\mathcal{V}}_j\right) \equiv \frac{f_j \exp(\mathcal{V}_j)}{g_j(1-\delta_j)(1-\rho_j)}$, this simplifies to:

$$\frac{M_{jk}}{M_{kj}} = \frac{\exp\left(\hat{\mathcal{V}}_j\right)}{\exp\left(\hat{\mathcal{V}}_k\right)} \tag{12}$$

This expression has the same functional form as equation (8), but with important differences. The search model incorporates three elements that PageRank omits: first, it adjusts for differences in firm size g_j; second, it accounts for variation in layoff rates δ_j and exogenous separation risks ρ_j, and third, it distinguishes offer rates by employment status, using hires out of non-employment to identify relative offer intensities f_j. These adjustments address the key limitations of the PageRank approach outlined above, particularly the unrealistic assumption that all jobs employ equal numbers of workers and make equal numbers of offers.

Therefore, we have our two primary rankings of jobs: the forward-looking value from the dynamic search model and the PageRank value.[18]

[18]Due to data limitations for the parental sample, we only estimate this forward-looking job value for children.

3.3 Alternative Rankings and Validation

To validate our primary rankings of jobs, we compare them to alternative measures and test sensitivity to specification choices.[19]

Poaching Index. Following Bagger and Lentz (2019), we construct a poaching index defined as the ratio of employer-to-employer hires to all hires. The intuition is that high-value jobs can selectively recruit ("poach") workers from other employers, whereas low-value jobs must rely more heavily on hiring from non-employment. The poaching index provides an independent validation of our revealed-preference rankings: jobs that rank highly according to both our forward-looking value and PageRank measures should also exhibit high poaching rates.

Robustness to Preference Heterogeneity. Our baseline estimates assume a common valuation of jobs across all workers. We test this assumption by constructing separate job rankings by gender. We construct our primary job rankings using male transitions only and female transitions only to capture potential differences in how men and women value both the pay and non-pay components of a job.

3.4 Addressing Measurement Error

A key concern for our intergenerational mobility welfare analysis is that measurement errors in job value ranks exist on both sides of the regression. Measurement error in job value rank, V_j, can arise for three reasons. First, job-to-job transitions are rare events, even though we use all voluntary transitions of prime-age native Danes over a 10-year window. Second, our 10-year average may not fully capture lifetime permanent job value ranks, as jobs some workers held in their 30s may not represent the lifetime job welfare.[20] Third, our job value estimates contain estimation errors from both the PageRank algorithm and the dynamic search model.

Following Nybom and Stuhler (2017), we show that measurement errors attenuate our estimates of both $\beta^{Value-Earnings}$ and $\beta^{Value-Value}$ toward zero. The direction of bias is unambiguous: our raw estimates provide a lower bound on the true intergenerational persistence of welfare. Appendix B.1 provides a formal proof of attenuation bias in our context.

To alleviate this attenuation bias, we apply a three-step empirical Bayes correction following Walters (2024).[21] The procedure shrinks raw job value estimates toward their conditional mean,

[19] Table A-3 provides a comprehensive list of job rankings used in the paper.

[20] For instance, family background may affect early-career jobs (ages 20s) that precede our measurement window.

[21] To the best of our knowledge, addressing measurement error in the rank-rank regression represents a frontier in the econometrics literature. Unlike classical measurement error problems, rank-rank regressions introduce extra challenges because the ranking transformation is nonlinear and depends on the joint distribution of the variables (Chetverikov and Wilhelm, 2023; Mogstad et al., 2024). While empirical Bayes shrinkage has been

with the degree of shrinkage determined by each observation's signal-to-noise ratio. We apply this correction to both children's and parents' job value ranks, yielding bias-corrected estimates $V_i^c(EB)$ and $V_i^p(EB)$ that we use in our primary specifications. Appendix B.2 provides detailed implementation steps, including estimation of signal and noise variances, construction of shrinkage factors, and validation of the correction procedure.

4 The Danish Laboratory: Context and Data

This section describes our empirical setting and sample construction. We begin by discussing why Denmark provides a useful laboratory for studying intergenerational mobility in total job value, highlighting institutional features that make non-wage job attributes particularly salient. We then describe our administrative data and outline our sample construction.

4.1 Modern Danish Welfare State

Reducing inequality and promoting social mobility is a central objective of the modern Danish welfare state. After tax and transfers, income inequality is substantially lower and intergenerational income mobility is higher in Denmark than in the U.S. One distinctive feature of Denmark is the high level of social services: universal health-care, free college tuition, equality of per pupil expenditures across all neighborhoods, and generous childcare and maternity leave policies. However, equality in provision is not the same as equality in use. For instance, while college is free for all, children from higher-income families attend and complete university at substantially higher rates than their lower-income peers (Landersø and Heckman, 2017). Thus, intergenerational persistence in other outcomes, including net wealth, educational attainment, and more, is substantially higher than intergenerational persistence in income in Denmark (Boserup et al., 2014; Karlson and Landersø, 2024).

The Danish labor market further motivates examining the total compensation of a job beyond just earnings. Progressive taxation (40-55%) largely compresses take-home pay differentials across the earnings distribution. Meanwhile, collective bargaining agreements covering 84% of workers establish minimum standards for wages, working hours, and workplace conditions (Dansk Industri, 2024). Employers retain significant discretion to offer terms exceeding these minimums, facilitated by both firm-level negotiations with union assistance and individual

widely used to correct for measurement error in levels, recent work by Chen et al. (2025) demonstrates that such methods do not necessarily correct measurement error in regression contexts, particularly when error structures are complex. Recent advances have also developed methods for handling two-sided measurement error in distributional and mobility analyses (Callaway et al., 2025; Nybom et al., 2018), though the application of these methods to our specific context of job ranking-based mobility measures remains an open question for future research.

negotiations, particularly for high-skilled workers (Dahl et al., 2013; Kreiner and Svarer, 2022; Humlum et al., 2025). Critically, while monetary compensation faces high marginal tax rates that compress pay differentials, non-wage amenities remain largely untaxed, creating incentives for both employers and workers to shift compensation toward non-pecuniary job attributes (Bagger et al., 2021). This institutional asymmetry—where taxes compress one dimension of compensation but leave another unconstrained—makes Denmark a particularly informative setting for studying the intergenerational transmission of total job value.

4.2 Data

We use administrative register data covering the full population of Denmark between 1985 and 2022. The data contain unique individual identifiers, which enable us to link children with their parents and link families to a wide range of characteristics across time. The matched employer-employee structure provides detailed labor market histories, including information on occupation, employers, and earnings. In addition to information on income, assets, and liabilities for both parents and children, we also add information on completed education, household structure, and demographic characteristics.[22]

We supplement these records with weekly employment spell data from the Labour Market Dynamics Group at Aarhus University (1985-2014). This dataset specifies the starting and ending dates for each employment spell. This granular information allows us to identify voluntary job-to-job transitions, instances where workers move directly between employers without intervening non-employment periods.

4.3 Main Sample

We study the intergenerational transmission of job welfare for native Danes born in 1980-1981. To rank jobs, we use millions of employment spell records from the prime-age working population of native Danes. We construct three interconnected samples: the Intergenerational Mobility (IGM) sample links parents and children using the population register (Befolkningen, BEF); the Job sample draws on millions of job-to-job transitions to measure the total value of primary jobs;[23] the IGM-Job sample combines the first two samples, enabling us to analyze intergenerational transmission of job values and compare it with canonical earnings-based mobility measures.

IGM Sample. Our base dataset includes all native Danes born in 1980-1981 who can be

[22] Appendix C provides a detailed description of all of the data sources and variable definitions.

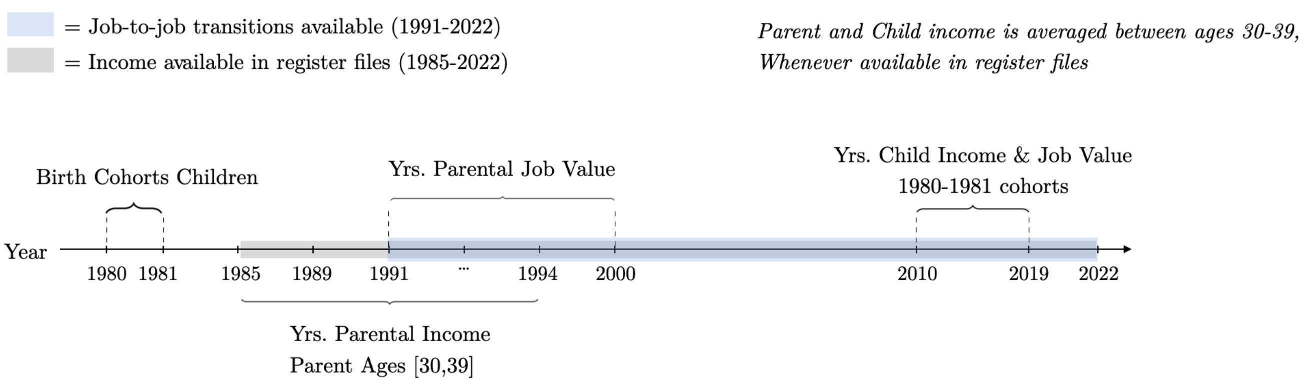
[23] A worker's primary job is defined as the most important job a worker held in a given year.

linked to at least one parent in the administrative records.[24] We follow these children until ages 38-39 (observed in 2019) and track parental information annually from 1985 to 2019. We impose earnings restrictions to ensure adequate measurement of economic outcomes for both generations.[25] Starting with 101,347 native Danes born in 1980-1981 who link to parents, the sample reduces to 87,709 individuals once we verify earnings observations for both children and at least one parent.

Job Sample. Tracking job-to-job flows is central to measuring rankings of jobs. For children, we use the Employer-Employee Register (Detaljeret lønmodtagerdata fra e-Indkomst, BFL, 2008 onwards) to identify voluntary job-to-job transitions. For parents, we use weekly employment spell data from the Labour Market Dynamics Group at Aarhus University (1985-2014), which specifies the starting and ending dates for each job spell. We restrict the sample to prime-age native Danish workers and focus on each individual's primary job, excluding self-employment.

IGM-Job Sample. The IGM-Job sample merges the IGM sample with estimated job values, allowing us to study intergenerational transmission of job values and compare it to the intergenerational transmission of earnings.

Figure 1: Data Availability and Our Sample of Parents and Children



Notes: This figure illustrates data availability and measurement windows for our IGM-Job sample. All parental income measures are observed when parents were aged 30–39 (1985–1994), while parental job value is measured over 1991–2000 due to the availability of consistent occupation codes only from 1991. Children's income and job value are both measured at ages 30–39 (2010–2019). All measures are averaged over available years within their respective windows.

Figure 1 illustrates the data availability and measurement windows for our IGM-Job sample. All parental income measures, including earnings, pre-tax income, and disposable income, are measured when parents were aged 30–39 (1985–1994); children's income measures are measured

[24] The native Dane restriction ensures we focus on children who did not migrate and whose parents did not migrate.

[25] We drop children for whom we observe fewer than four parental earnings observations when parents were aged 30-39.

at ages 30–39 (2010–2019). Child's job value is also measured over the same period (2010–2019). However, due to the availability of consistent occupation codes only from 1991 onward, we measure parental job value during 1991–2000 rather than 1985–1994.[26] Throughout the analysis, all monetary variables are converted to 2022 Danish Kroner (DKK).[27]

Table 1: Summary Statistics

	IGM Sample	IGM-Job Sample
Panel (a) Number of Counts		
Number of Parent-Child Pairs	87,709	66,992
Panel (b) Earnings		
Child Average Log Earnings	12.50	12.81
Family Average Log Earnings	12.82	12.93
Father Average Log Earnings	12.57	12.65
Mother Average Log Earnings	12.07	12.16
Panel (c) Age		
Father Average Age at Birth (years)	28.70	28.67
Mother Average Age at Birth (years)	25.83	25.91

Notes: This table presents summary statistics for the IGM sample and IGM-Job sample. Child average earnings are measured at ages 30-39 (2010-2019), and parent average earnings at ages 30-39 (1985-1994). All earnings are average log earnings over the respective periods, expressed in 2022 Danish Kroner.

For parental earnings, we first sum earnings across both parents in each year, then average this sum over the 10-year window (1985-1994), and rank families by this average. This measure captures the average family-level economic resources available to children during the ages 5-14. We apply the same aggregation procedure to all other parental income measures. For parental job value, we compute the average job value across both parents over the 10-year window (1991-2000) and rank families by this average.[28] Whether we observe one or two parents depends on whether parental links can be established in the administrative records; in practice, the vast majority of children are linked to both parents. For children, we measure individual earnings and job value rather than household-level measures, as differential timing of household formation across children could confound comparisons.

Table 1 presents summary statistics for our samples. The IGM-Job sample contains 66,992 parent-child pairs, approximately 77% of the IGM sample. The reduction occurs because some parents or children do not have well-defined measurable job values from the Job sample.[29]

[26]Detailed sample construction procedures are provided in Appendix C.

[27]We adjust for inflation using the consumer price index (CPI) from Statistics Denmark (2025)

[28]In the Appendix D, we present additional results using alternative aggregation methods, including the sum and maximum of parental job values.

[29]This includes individuals, either parents or children, who hold jobs in self-employment, or agriculture

The two samples are highly comparable. Children in the IGM-Job sample have slightly higher average log earnings (12.81 versus 12.50), but family, father, and mother earnings are nearly identical across samples. Parental ages at birth are also virtually the same (within 0.03-0.08 years), indicating that the IGM-Job sample captures a similar population to the broader IGM sample.

4.4 Job Definition and Descriptive Patterns

We define a job as an occupation-establishment-type pair. Rather than using individual establishments, we apply k-means clustering to group establishments into 12 types based on their within-establishment earnings distributions.[30] Specifically, for each establishment, we calculate moments of the within-establishment wage distribution (mean, standard deviation, and percentiles). The k-means algorithm then groups establishments with similar wage profile characteristics by minimizing the sum of squared distances between each establishment's wage profile and its assigned cluster centroid.[31] Our occupation codes are six-digit DISCO-08 codes. DISCO-08 is the official Danish version of the International Standard Classification of Occupations (ISCO-08) developed by the International Labour Organization (ILO).[32]

This definition reflects several considerations. First, defining jobs directly as occupation-establishment pairs would lead to excessive sparsity and more severe measurement errors for jobs in small establishments compared to large ones. Clustering establishments mitigates this issue while preserving meaningful variation across establishments. Furthermore, we prioritize the occupational dimension because hierarchical occupations within establishments reflect differential access to both pay and non-wage amenities. The six-digit granularity captures detailed job characteristics, distinguishing workers, employees, managers, senior managers, and directors within the same establishment type, while maintaining adequate sample sizes for reliable job value estimation.

Table 2 presents correlations between our job ranking measures and job wage premia for the children's sample. Two key patterns emerge. First, our different job ranking approaches are highly correlated with each other: the forward-looking job value and PageRank measures correlate at 0.61, while both measures correlate positively with the poaching index (0.72 and 0.49,

industries, as well as those whose jobs lack sufficient job-to-job transitions for us to estimate job values during the observation period.

[30]We assess the robustness of our results to alternative clustering specifications. Using 30 establishment clusters yields quantitatively similar findings.

[31]Formally, the algorithm solves $\min_{C_1,\ldots,C_{12}} \sum_{j=1}^{12} \sum_{i \in C_j} \|x_i - \mu_j\|^2$, where x_i represents the wage distribution moments for establishment i, C_j denotes cluster j, and μ_j is the centroid of cluster j.

[32]DISCO-08 is a six-digit, five-level classification for occupations. The first digit generally identifies major occupational groups (e.g., workers, employees, managers, and directors), while subsequent digits provide finer distinctions within these categories.

Table 2: Correlation Matrix, Children's Sample

Variables	(1) PageRank	(2) Job Value	(3) Poaching	(4) Job FE	(5) Resid Earnings
(1) PageRank	1.00				
(2) Job Value	0.61	1.00			
(3) Poaching Index	0.49	0.72	1.00		
(4) Job FE (AKM)	0.58	0.58	0.33	1.00	
(5) Residualized Log Earnings	0.47	0.52	0.34	0.70	1.00

Notes: This table presents correlations between job ranking measures for the children's sample (2010-2019, N=2,134,436 observations). PageRank and Job Value are our primary measures of total job value derived from revealed preferences in job-to-job transitions. Poaching Index by Bagger and Lentz (2019) measures the ratio of employer-to-employer hires to total hires. Job FE (AKM) represents the job earnings premium estimated from an AKM regression with job defined as an occupation-establishment-type pair. Residualized Log Wage is log earnings net of year fixed effects.

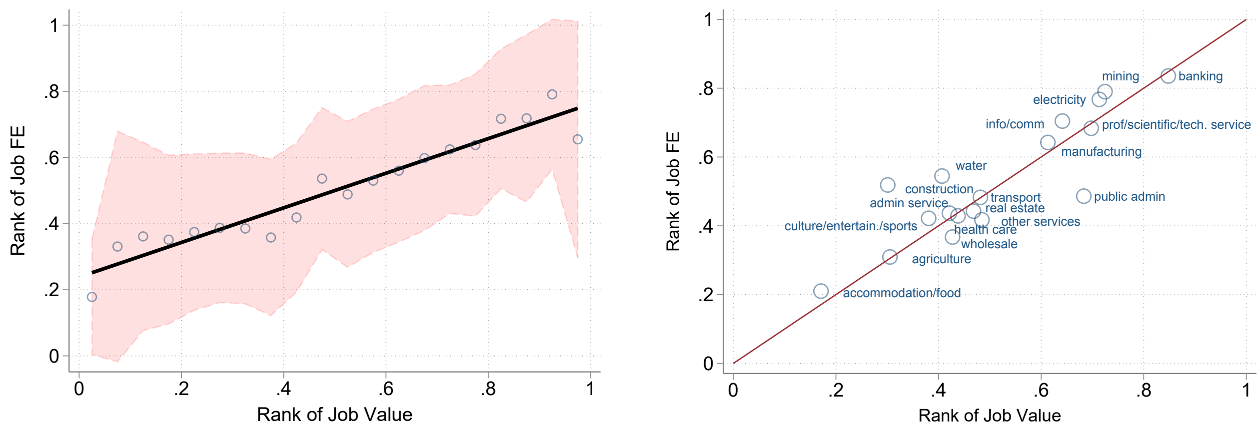
respectively). This consistency across independent measurement approaches validates our revealed preference framework. Second, these rankings capture meaningful job quality dimensions beyond monetary compensation. While our total job value measures correlate positively with the AKM job fixed effect (0.58 for both) and residualized log wages (0.47-0.52), the imperfect correlations indicate that total job value incorporates dimensions beyond wage premia alone.

Figure 2 illustrates the relationship between job earnings premia and total job value for the children's sample. Panel (a) sorts jobs on the basis of job value rank. The circles plot a binscatter with 20 bins, while the solid line shows the linear regression fit estimated on the job-level data. The shaded region shows plus and minus one standard deviation of job-level wage premium rank within each value bin. Panel (b) plots the sector-level means, weighted by the number of person-years represented by each sector. The solid line shows the 45-degree line for reference. Notably, construction ranks highly in earnings premia but substantially lower in overall job value, falling well below the 45-degree line. Public administration exhibits the reverse pattern: it ranks highly in overall job value but lower in earnings premia, consistent with the presence of significant non-wage amenities in the public sector.

5 The Welfare Mobility vs. Earnings Mobility

This section presents our main empirical findings on intergenerational welfare mobility in Denmark. We begin by documenting earnings-based mobility using canonical income measures, then turn to our primary contribution: estimating intergenerational transmission of total job value.

Figure 2: Relationship between Job FE and Job Value



(a) Overall (b) Sector

Notes: This figure plots the relationship between job earnings premia and total job value for the children's sample (2010-2019). Panel (a) presents a binscatter with a solid line as the linear fit, and the shaded region indicates plus and minus one standard deviation of job-level wage premium rank within each value bin. Panel (b) plots the sector-level means, weighted by the number of person-years represented by each sector. The solid line shows the 45-degree line for reference.

5.1 Earnings Mobility in Denmark

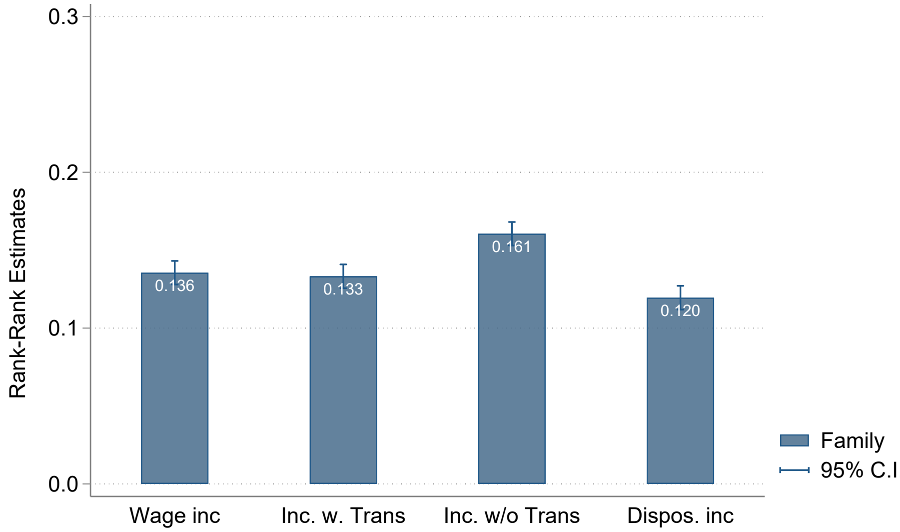
Figure 3 presents rank-rank slope estimates for four income measures: wage income (pre-tax earnings), income with transfers, income without transfers, and disposable income.[33] Each bar represents the rank-rank slope estimate from regressing the child's average income rank on the family's average income rank, where both generations' incomes are measured at ages 30-39. Family outcomes are the percentile rank of the sum of the mother's and father's outcomes.

The estimates are remarkably consistent across income definitions, ranging from 0.120 (disposable income) to 0.161 (income without transfers). The baseline estimate using wage income is 0.136, indicating that a 10-percentile increase in family earnings rank is associated with a 1.36-percentile increase in child earnings rank. These estimates confirm Denmark's position as a high-mobility society: the intergenerational persistence in income with some transfers is substantially lower than the 0.34 estimate for the United States reported by Chetty et al. (2014).[34]

[33]Complete definitions of these income measures are provided in Appendix Table A-1.

[34]Their income measures include labor earnings, capital income, as well as unemployment insurance, Social Security, and disability benefits.

Figure 3: Rank-Rank Slope Estimates



Notes: This figure depicts rank-rank estimates for different income measures. Each bar shows the coefficient β from the regression: $R_i^c = \alpha^R + \beta R_i^p + \epsilon_i$, where R_i^c denotes the average percentile rank of child at ages 30 and 39 (2010-2019), and R_i^p denotes the average percentile rank of family for each measure averaged over ages 30 and 39 (1985-1994). Family outcomes are the percentile rank of the sum of the mother's and father's outcomes. Error bars represent 95% confidence intervals. Appendix Table A-4 presents the full regression results.

5.2 Intergenerational Welfare Mobility

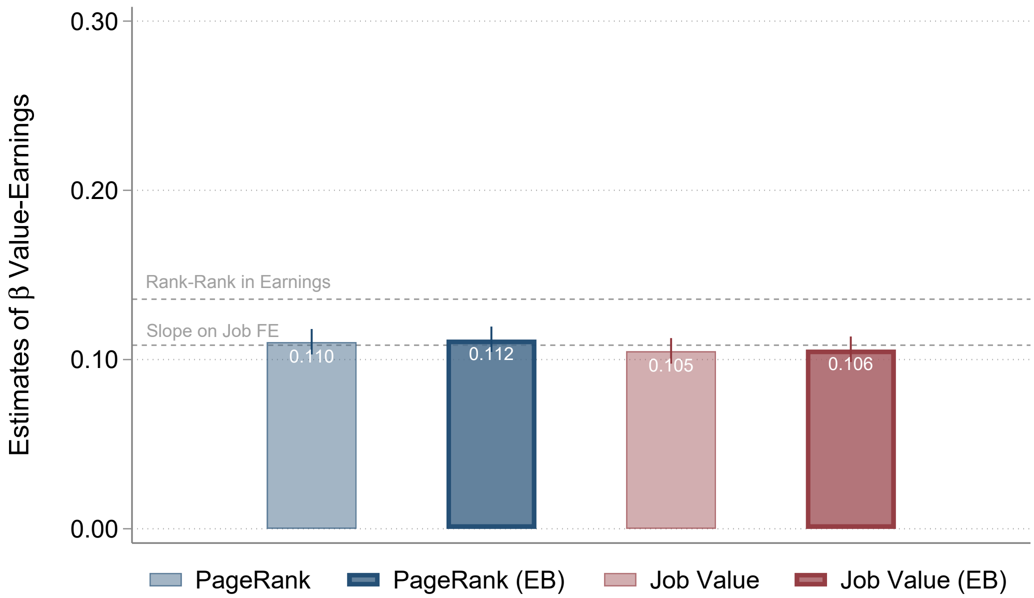
We now turn to our primary question: how does the measure of intergenerational mobility change when we measure total job welfare rather than the earning component alone? To study intergenerational welfare mobility, we compute for each individual the average value of jobs held during their 10-year measurement window and rank these average values within their generation. We estimate two specifications that capture different aspects of intergenerational transmission.

5.2.1 Value-Earnings Transmission ($\beta^{Value-Earnings}$)

We begin by examining how parental earnings predict children's job value. Figure 4 presents estimates from regressing children's job value on parents' earnings rank. This value-earnings slope connects our welfare-based approach to earnings-based mobility studies, revealing whether high-earning parents transmit advantages in overall job quality beyond just earnings.

Our first finding of this paper: *parental earnings predict children's job value (0.106-0.112) nearly identically to the wage component alone (0.108).* The horizontal reference line labeled "Slope on Job FE" (0.108) represents our key comparison: the intergenerational persistence when

Figure 4: Intergenerational Welfare Mobility ($\beta^{Value-Earnings}$) Estimates



Notes: This figure presents estimates of intergenerational transmission from parental earnings to children's job value. Each bar shows the coefficient $\beta^{Value-Earnings}$ from the regression $V_i^c = \alpha^{VE} + \beta^{Value-Earnings} R_i^p + \epsilon_i$,where V_i^c is the child's job value rank and R_i^p is the family earnings rank. PageRank and Job Value refer to different methods for constructing job rankings (see Section 3). EB denotes estimates with empirical Bayes correction for measurement error. Two reference lines provide comparison benchmarks: "Slope on Job FE" (0.108) isolates pecuniary transmission through job wage premia, while "Rank-Rank in Earnings" (0.136) shows the wage income rank-rank slope. Appendix Table A-5 presents the full regression results.

we regress children's job wage premium on parental earnings rank.[35] This job FE-earnings slope isolates the pecuniary transmission channel—how parental earnings translate into children's access to high-wage jobs. When we instead use our comprehensive job value measures that incorporate both pecuniary and non-pecuniary components, we observe virtually no change: the value-earnings slopes (0.106-0.112) are statistically indistinguishable from the job FE-earnings benchmark. Our comprehensive job value measures, which incorporate both pecuniary and non-pecuniary components, yield slopes statistically indistinguishable from this benchmark. This finding does not necessarily imply that non-pecuniary transmission is absent, but it suggests that such transmission does not substantially alter the aggregate mobility pattern beyond what we observe through wages.

Two additional observations deserve emphasis. First, measurement error does not appear to substantially bias our estimates: the empirical Bayes corrected slopes are very close to the uncorrected estimates. Second, readers may wonder how our value-earnings slopes compare to the more canonical rank-rank slope in wage income. The figure includes a second reference line labeled, "Rank-Rank in Krones" (0.136), which shows the wage-income rank–rank slope from Figure 3. Our value-earnings slopes are slightly lower.[36]

5.2.2 Value-Value Transmission ($\beta^{Value-Value}$)

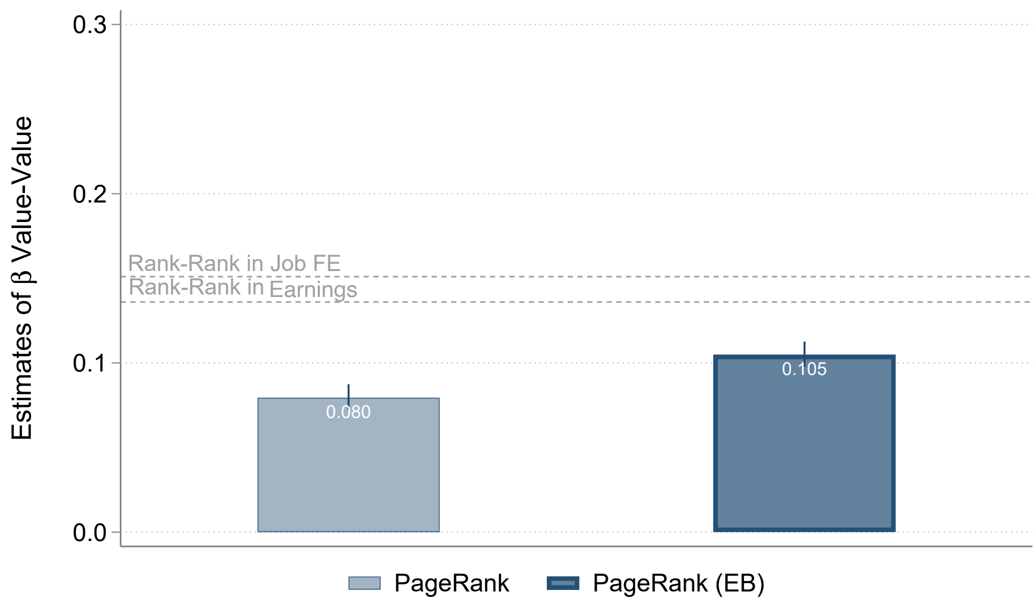
We now turn to our primary specification, which provides the welfare analog to canonical earnings-based rank-rank regressions. Figure 5 presents estimates from regressing children's job value rank on parents' job value rank. This value-value slope measures relative positional mobility: how much the expected job value rank of a child changes when the parent's job value rank increases by one percentile. By capturing the full bundle of job attributes—both pecuniary and non-pecuniary—on both sides of the equation, this specification provides a comprehensive measure of welfare mobility.

The second key finding of the paper: there is lower intergenerational persistence in total job value (0.105) compared to wage premia alone (0.151)–a 31% difference that is both statistically significant and economically important. The reference line labeled "Rank-Rank in job FE" denotes the slope from regressing children's job wage premium on parental job wage premium, which captures intergenerational transmission purely through the pecuniary dimension of jobs. Our value-value estimate of 0.105 falls substantially below this job FE-to-job FE slope of 0.151, indicating that earnings-based measures understate the true degree of welfare mobility across

[35] Appendix Table A-5 presents the full regression results.

[36] This difference reflects that these two measures capture different aspects of intergenerational transmission: individual wage earnings incorporate both the job wage premium and individual worker fixed effects, whereas our job value measures capture the common pecuniary and non-pecuniary components of jobs that any worker at that job would receive, regardless of worker identity.

Figure 5: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) Estimates



Notes: This figure presents estimates of intergenerational transmission from parental job value to children's job value. Each bar shows the coefficient $\beta^{Value-Value}$ from the regression $V_i^c = \alpha^{VV} + \beta^{Value-Value} V_i^p + \epsilon_i$, where both parent and child outcomes are measured as job value ranks. EB denotes estimates with empirical Bayes correction for measurement error. The gray dashed lines show two comparison benchmarks: the wage income rank-rank slope and the job FE-to-job FE slope. Appendix Table A-6 and A-7 present the full regression results.

generations.[37]

Two additional points are worth noting. First, measurement error plays a non-trivial role in this specification. When both parent and child outcomes are measured with noise, the empirical Bayes correction substantially increases the estimate from 0.080 to 0.105, highlighting the importance of accounting for measurement error when job values appear on both sides of the regression. Second, the reference line also displays the canonical rank-rank slope for wage income (0.136). Our value-value slope remains below this benchmark as well, further confirming greater mobility when measuring total welfare compared to earnings.

However, these conclusions warrant important caveats. While we find that earnings-based measures understate the welfare mobility by 31% in aggregate, does this pattern hold uniformly across different groups? As we demonstrate in Section 6, the aggregate correspondence between earnings and welfare mobility masks substantial heterogeneity across gender groups.

Our analysis also raises questions about other mobility dimensions. Do we observe similar patterns for absolute mobility—whether children achieve better welfare outcomes than their parents in absolute terms? More specifically, how does the gap between expected welfare and expected earnings vary across the parental distribution? Do earnings-based measures understate or overstate the absolute mobility outcomes for children from disadvantaged backgrounds? We address this question with additional robustness checks in Section 8.

6 When Earnings-Based Measures Can Mislead: The Case of Gender

So far, we have established that earnings-based mobility measures understate true welfare mobility by about one third in aggregate. However, this aggregate pattern masks important heterogeneity. In Section 6.1, we show that canonical measures can substantially mislead when we examine sons and daughters separately. Section 6.2 then traces these gender differences to their roots in Denmark's educational system, where family background leads sons and daughters into divergent pathways that ultimately shape not just their wages but also the amenities their jobs provide.

6.1 Gender Differences in Welfare vs. Earnings Mobility

Although earnings-based mobility measures track welfare mobility closely in aggregate, as we demonstrate in this section, it can be quite misleading when we perform the analysis separately

[37] Appendix Table A-6, and A-7 present the full regression results.

by the gender of the child.

6.1.1 Value-Earnings Transmission ($\beta^{Value-Earnings}$) By Gender

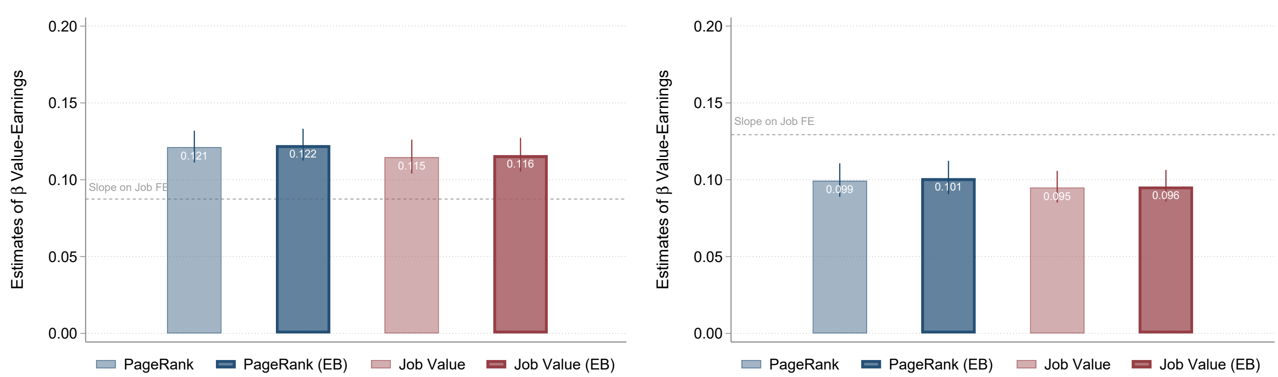
Our key finding that the aggregate pattern, where parental earnings rank predicts children's job value similarly to the wage component alone, breaks down completely once we split by gender. Figure 6 reveals sharply different patterns for sons and daughters.

For sons, panel (a), the $\beta^{Value-Earnings}$ estimates of (0.116) lie noticeably above the job FE-earnings benchmark (0.087, dashed line). This 33-percent gap indicates that sons from high-earning families maintain their advantage more strongly when we account for the total job value, inclusive of both pay and non-pay amenities, than earnings-based measures would suggest. Put differently, earnings-based measures make it appear that sons experience 33% more intergenerational mobility than they actually do when we measure outcomes using total job value.

For daughters, panel (b), the opposite holds: the $\beta^{Value-Earnings}$ estimates (0.096) fall noticeably below the earnings-based benchmark (0.129, dashed line), revealing that daughters' welfare outcomes depend less strongly on parental earnings than their wage outcomes do. Daughters from disadvantaged backgrounds achieve substantially higher ranks in overall job welfare than in the wage component alone. Earnings-based measures, therefore, understate the extent of welfare mobility that daughters experience by over 25%. These patterns hold consistently across both PageRank and Job Value, with and without empirical Bayes correction.

Figure 6: Intergenerational Welfare Mobility ($\beta^{Value-Earnings}$) by Gender

(a) Sons (b) Daughters



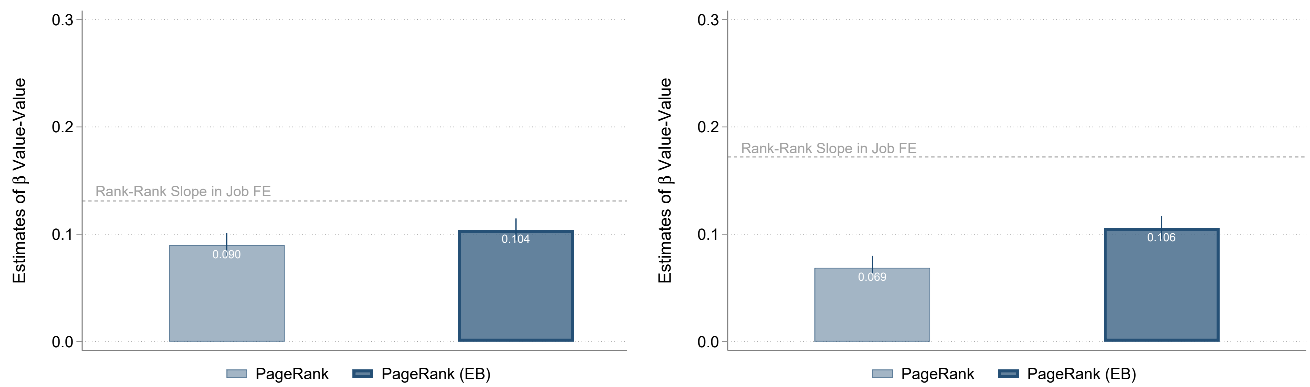
Notes: This figure presents estimates of $\beta^{Value-Earnings}$ by gender of child. PageRank and Job Value refer to different methods for constructing job rankings. EB denotes estimates with empirical Bayes correction for measurement error. The gray dashed line labeled "Slope on Job FE" shows intergenerational persistence when regressing children's job wage premium (from an AKM regression) on parental earnings rank, isolating the pecuniary transmission channel. Appendix Table A-8 presents the full regression results.

6.1.2 Value-Value Transmission ($\beta^{Value-Value}$) By Gender

The aggregate understatement of mobility does not hold uniformly across gender groups: daughters account for the majority of the effect, while for sons, welfare and wage mobility nearly align. Figure 7 reveals that this aggregate pattern masks stark gender differences.

Figure 7: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) by Gender

(a) Sons (b) Daughters



Notes: This figure presents estimates of $\beta^{Value-Value}$ by gender of child. EB denotes estimates with empirical Bayes correction for measurement error. The gray dashed line shows the comparison benchmark: the slope coefficient from regressing children's job wage premium (job FE) on parental job wage premium. Appendix Table A-10 presents the full regression results.

For sons, panel (a), welfare and wage mobility nearly align. The $\beta^{Value-Value}$ estimate (0.104) falls only slightly below the job FE benchmark (0.131, dashed line), by roughly 21 percent in point estimates; their confidence intervals are very close to overlapping.[38] This correspondence suggests that the degree of intergenerational persistence sons experience remains similar whether we measure outcomes through wage premia or through the overall welfare that a job brings. In other words, for sons, earnings-based measures provide a reasonably accurate picture of welfare mobility across generations—incorporating non-wage job attributes does not fundamentally alter our conclusions.

For daughters, panel (b), earnings-based measures understate mobility by 38 percent. The $\beta^{Value-Value}$ estimates (0.106) fall well below the job FE benchmark (0.172), suggesting that daughters experience substantially greater mobility in total job value than in the wage component alone. Daughters from disadvantaged backgrounds achieve much higher ranks in overall job welfare relative to their parents' job welfare than the wage component would suggest. This means earnings-based measures understate the true extent of welfare mobility that daughters

[38] In Appendix F.3, we display the gender results using the poaching index. For sons, the value-value and job FE slopes are statistically indistinguishable, while for daughters the value-value slope remains substantially and significantly below the job FE benchmark.

experience by 38 percent.

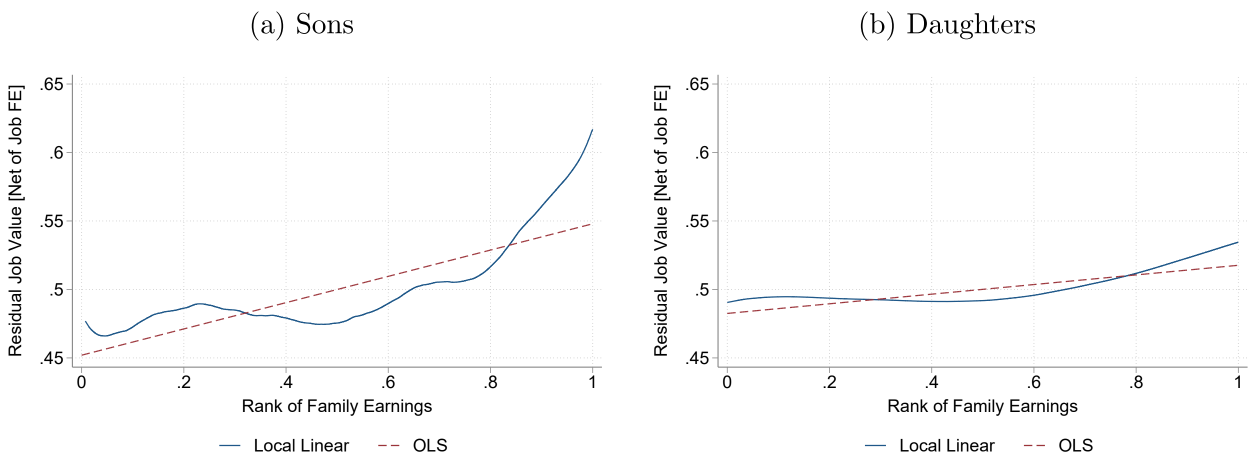
One might wonder whether these stark gender differences arise from men and women systematically valuing jobs differently. If men and women have fundamentally different preferences over the bundle of wages and amenities that a job offers, then our gender-specific mobility patterns might simply reflect preference heterogeneity rather than true differences in intergenerational mobility. To assess this possibility, we construct job rankings using male transitions only and female transitions only, allowing the revealed preference approach to capture any systematic differences in how each gender values jobs. We find the correlation between these gender-specific rankings to be 0.82 in the children's sample, indicating that male and female workers share largely common rankings of jobs. The divergent mobility patterns we document, therefore, do not appear to be driven by preference heterogeneity between men and women.

6.2 Tracing Family Influence on Education and Occupation by Gender

Where, then, do these gender differences originate? The patterns likely reflect a combination of forces operating in the Danish labor market. Women systematically sort into white-collar office jobs that offer decent pay and relatively uniform amenities, regardless of family background. Below, we provide evidence that women are substantially more likely to pursue the academic track in upper secondary schooling, leading to higher rates of college and university attendance. Critically, these educational pathways appear less stratified by family background for daughters than for sons. In contrast, sons from economically disadvantaged families are more likely than daughters to pursue a vocational education involving an apprenticeship. These divergent educational choices reinforce the types of jobs men and women ultimately hold in their thirties, which in turn generate the stark differences we observe between welfare mobility and earnings-based mobility. For sons, family background plays an equally important role in shaping both the wage component and total welfare. For daughters, however, educational and occupational choices lead them into jobs where amenities vary less systematically with parental income. These countervailing forces, strong intergenerational transmission of wages but weak transmission of amenities, generate substantially more welfare mobility than earnings mobility for daughters.

Figure 8 illustrates this mechanism by plotting the residual job value rank (net of the wage component) against parental earnings rank. The solid blue line shows the local linear regression estimate, which flexibly fits a weighted linear regression at each point using observations in a local neighborhood around that point. The dashed red line shows the OLS linear fit. Panel (a) shows that for sons, non-pecuniary job attributes rise sharply with parental earnings, particularly at the top of the distribution. Sons from high-earning families access jobs with substantially better amenities. Panel (b) reveals a strikingly different pattern for daughters:

Figure 8: Transmission of Non-Pecuniary Attributes by Gender



Notes: The figure plots the residual job value (net of the wage component) against parental earnings rank, estimated separately by the gender of the child. The solid blue line shows the local linear regression estimate, which flexibly fits a weighted linear regression at each point using observations in a local neighborhood around that point. The dashed red line shows the OLS linear fit.

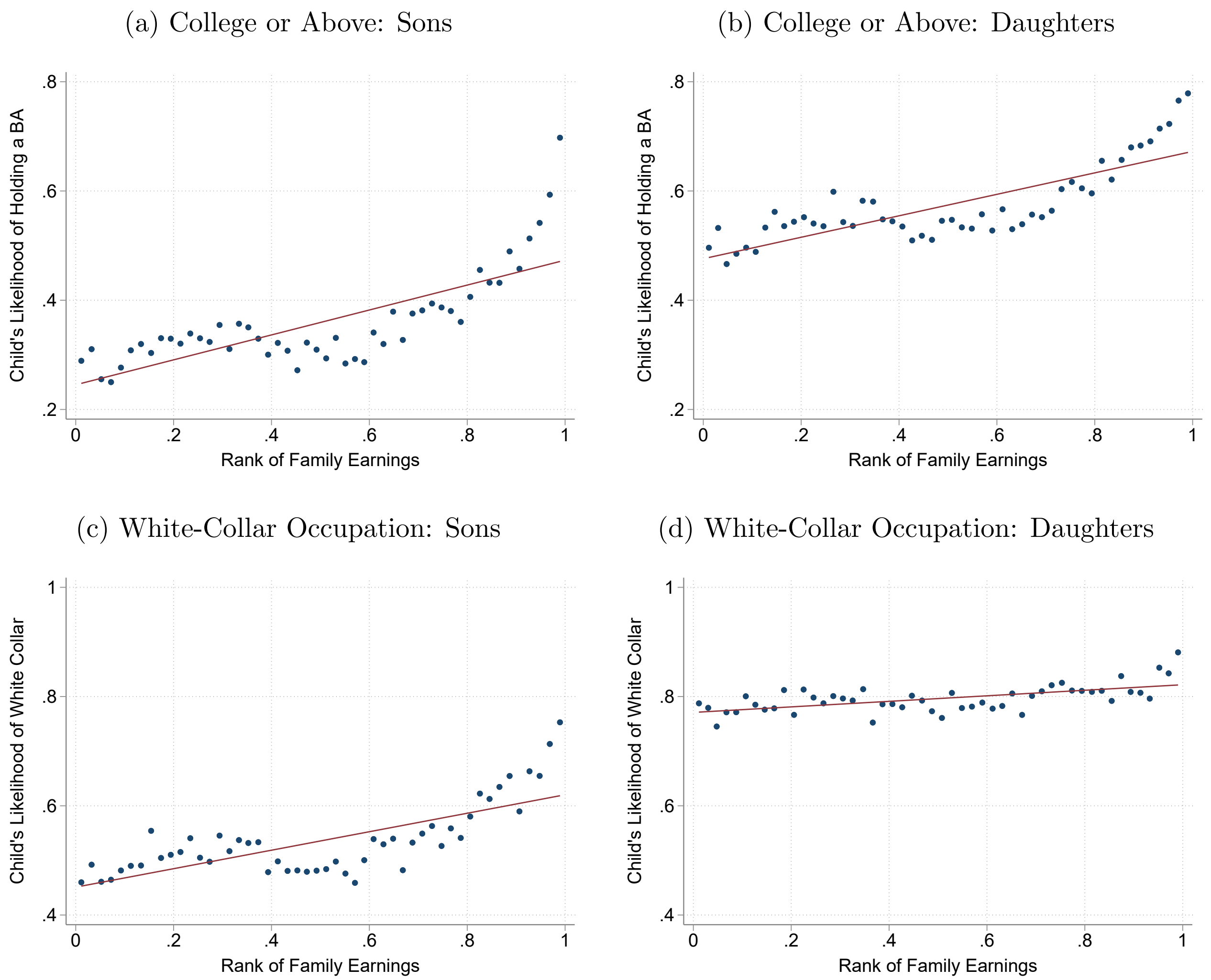
the relationship between parental earnings and non-pecuniary job attributes is nearly flat across the entire family earnings distribution. Daughters' access to job amenities appears largely independent of family background, further explaining why their welfare mobility substantially exceeds their earnings mobility.

These differential patterns in transmission of non-pecuniary components trace back to educational and occupational sorting by family background. Figure 9 demonstrates how family background shapes educational attainment and occupational choices differently by gender. Panels (a) and (b) show college and above (including BA, MA, and PhD) completion rates across the family earnings distribution. For sons, family background strongly predicts college completion: moving from the bottom to the top of the parental earnings distribution increases the likelihood of earning a BA degree from 25% to 70%. For daughters, while college completion also rises with family earnings, the gradient is slightly flatter, and the baseline rate is substantially higher. Forty-five percent of daughters from the most economically disadvantaged families hold a college degree.

The occupational patterns in panels (c) and (d) reveal even starker differences. Sons show a steep gradient in white-collar employment: those from the wealthiest families are 35 percentage points more likely to hold white-collar positions than their male peers from the poorest families.[39] In sharp contrast, daughters exhibit an essentially flat relationship—approximately 80% work in white-collar occupations regardless of family background. This limited sorting into white-collar work by family background among women, combined with their higher base-

[39]White-collar occupation includes management, professional, office, and service work.

Figure 9: Family Background Shapes Educational and Occupational Choices by Gender



Notes: Each panel plots the likelihood of educational or occupational outcomes against family earnings rank, estimated separately by the gender of the child. Panels (a) and (b) display the probability of completing at least a college degree (including BA, MA, and PhD); Panels (c) and (d) show the probability of holding a white-collar occupation, which includes management, professional, office and customer service work. Appendix F.2 provides the educational and occupational distribution for sons and daughters by family background.

line educational attainment, explains why non-pecuniary components of jobs transmit weakly across generations for daughters while remaining strongly stratified for sons.

7 Mechanisms: Is it About Parental Resources *per se*?

Thus far, we have documented substantial intergenerational transmission of total job value both in aggregate and by the gender of child: children from economically advantaged families, whether measured by parental position in the standard earnings distribution or by parental rank in the total job value distribution, systematically access higher-value jobs that offer higher wages or better amenities or both. An important question remains: *why* do children from more advantaged families have access to high-value jobs? Is it due to parental resources *per se*, the direct effects of parental wealth and income that can be deployed to secure better opportunities, or do parental resources operate indirectly through other channels such as educational choices?

This section investigates the mechanisms underlying intergenerational transmission of welfare. We first examine how different measures of parental resources relate to children's job value. We then employ an unexpected inheritance design to isolate the causal effect of parental wealth, and finally conduct a mediation analysis to quantify the role of education as a key mediator.

7.1 The Role of Parental Resources

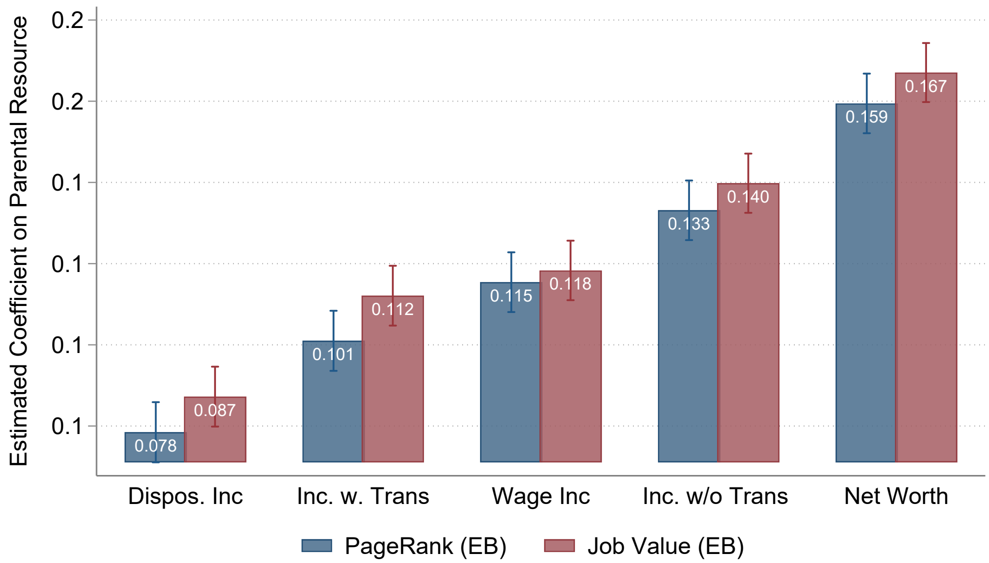
We start by examining how different measures of parental resources relate to children's job value rank. Figure 10 presents coefficient estimates from regressing children's job value rank on various measures of parental resource rank. We compare five measures: disposable income (accounting for taxes and transfers), income with public transfers, wage income (labor earnings only), income without transfers, and net worth (assets net of liabilities).[40]

Across different measures of parental resources, parental net worth (hereafter, wealth) emerges as the strongest predictor of children's job value, regardless of which job value measure we use. A one-percentile increase in parental net worth rank is associated with a 0.16-0.17 percentile increase in children's job value rank, substantially exceeding the associations with any income measures.

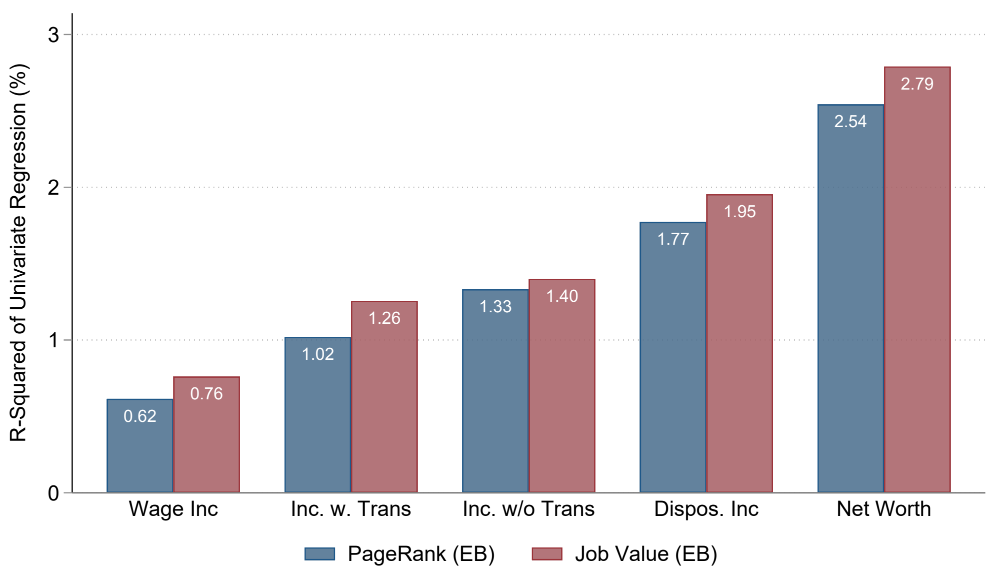
The strong association between parental wealth and children's job value raises a critical question: Does parental wealth causally improve children's job outcomes by relaxing financial constraints, or does wealth operate indirectly through intermediaries, such as children's educa-

[40]Complete definitions of these income measures are provided in Appendix Table A-1. Net worth is formally defined in Appendix Table A-2. Parental resources are measured at ages 30-39 (1985-1994). Each specification uses our two primary job value measures (PageRank and Job Value), both with empirical Bayes correction.

Figure 10: The Role of Parental Resources



(a) Coefficients



(b) R^2

Notes: This figure presents coefficients from regressing children's job value rank on different measures of parental resource rank (panel (a)) and the corresponding R^2 (panel (b)). Each pair of bars compares PageRank (navy) and Job Value (maroon), both with empirical Bayes correction. Parental resources are measured at ages 30–39 (1985–1994). Disposable income accounts for taxes and transfers; income with/without transfers captures the role of public benefits; wage income reflects labor earnings; net worth measures assets net of liabilities. All measures are ranked within their respective distributions.

tional choices, which subsequently provide pathways for children from economically advantaged backgrounds to access higher-value jobs? We address this question in the following subsection using quasi-experimental variation from wealth shocks.

7.2 Direct Wealth Effects: Unexpected Inheritance Design

The strong correlation between parental wealth and children's job values documented in the previous section raises an important question: through what channel does parental wealth shape labor market outcomes of children? A natural hypothesis emerges from models of job search with consumption-saving decisions.[41] In these frameworks, lower assets lead individuals to accept higher wage, lower amenity jobs. Once this constraint is relaxed through a change in their asset position, workers substitute toward low wage, high amenity jobs.

We test this prediction by exploiting quasi-experimental variation from unexpected inheritances induced by the sudden parental death of the last unmarried parent, following Druedahl and Martinello (2022). Large, unexpected inheritances provide a clean test: if the wages-amenities trade-off is governed by asset positions, substantial wealth shocks should induce workers to re-optimize their job choices, accepting positions with higher amenities at the cost of lower wages.

Estimating the causal effect of inheritance from parental death poses three challenges. First, individuals may anticipate receiving an inheritance at some time in their lives and adjust their behavior prior to the shock. Second, heirs might predict the timing of parental death (e.g., terminal illness) and react in advance. Third, parental death itself, independent of any wealth transfer, may affect child labor market outcomes.

Our approach addresses these concerns through three design features. First, our sample includes all heirs who are exposed to large potential inheritances between 2002 and 2015, differing only in the timing of parental death. Second, we restrict to sudden deaths from accidents (such as car crashes) or heart attacks with no precondition, minimizing anticipation of the timing. Third, we compare heirs receiving large potential inheritances (exceeding their yearly permanent income) to a placebo group whose parents died with little or no wealth to leave as a bequest.[42] This comparison isolates the wealth effect from any direct effects of parental death itself.

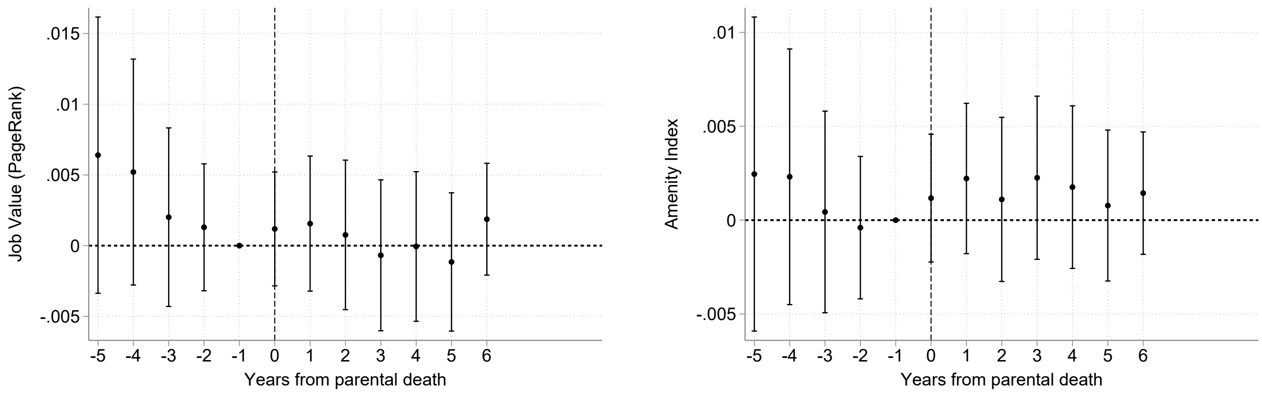
Figure 11 presents event-study estimates of large inheritance on job value (panel a) and amenity index (panel b). The vertical dashed line at year 0 marks the timing of parental death.

[41] Examples include Krusell et al. (2010); Lise (2013); Luo and Mongey (2019); Chaumont and Shi (2022).

[42] Details on the definition of permanent income, the calculation of potential inheritance in the Danish context, the event-study specification, sudden death timeline, data construction, and balance tests are provided in Appendix

Figure 11: The Effect of (Large) Inheritance on Labor Market Outcomes

(a) Job Value (PageRank) (b) Amenity Index



Notes: This figure presents event-study estimates of the effect of unexpected large inheritances on children's labor market outcomes. Panel (a) shows the percentile rank of job value; panel (b) shows the amenity index (residual job value net of job fixed effects). Complete specification details, balance tests, and robustness checks are provided in Appendix E.1.

Despite substantial increases in an heir's net worth following the parental death, we find no statistically significant effects on labor market outcomes.[43] The point estimates for both job value rank and amenity index remain close to zero up to six years after parental death, with tight confidence intervals ruling out economically meaningful effects.

The absence of direct wealth effects on labor market outcomes suggests that the strong correlation between parental wealth and children's job value does not primarily reflect the direct effect of wealth transfers *per se*. Large, unexpected wealth shocks, even those exceeding annual permanent income, fail to alter children's labor market trajectories. This conclusion holds, even when we separately perform the analysis by heir age, younger heirs (below age 30) and older heirs (above age 30).

7.3 Education as the Primary Mediator

If direct wealth effects are limited, how does parental wealth shape children's job outcomes? In this subsection, we identify education as the key mediator.

Our mediation analysis proceeds in two steps. First, we estimate the total effect of parental net worth on children's job value without controls. Second, we introduce high-dimensional child education fixed effects to isolate the direct effect of wealth conditional on educational attainment. The proportion mediated by education is calculated as $(1 - \beta_{\text{controlled}}/\beta_{\text{total}})$.[44]

[43] As shown in Appendix Figure A-6 and Figure A-7.

[44] This two-step comparison is a standard regression-based mediation approach: estimate the total association,

Table 3 presents the mediation analysis results. Columns (1) and (3) show the total effect of parental net worth rank on children's job value rank without controls. A one-percentile increase in parental wealth rank predicts a 0.16 percentile increase in children's PageRank and Job Value rank on average. Columns (2) and (4) include high-dimensional child education fixed effects based on four-digit educational attainment codes from the Danish education register. These codes capture detailed information on both the highest level of educational attainment and the specific field of study. The inclusion of child education fixed effects substantially reduces the wealth coefficient from 0.16 to 0.02-0.03. The proportion mediated by education, calculated as the share of the total effect that disappears when controlling for education, ranges from 81-86%. This result indicates that the vast majority of the wealth-job value gradient operates indirectly through children's educational pathways rather than through direct wealth effects.

Table 3: Parental Net Worth and Child Outcomes: Mediation via Education

	Child PageRank (EB)		Child Job Value (EB)	
	(1)	(2)	(3)	(4)
Parental Net Worth	0.164***	0.023***	0.155***	0.030***
	[0.004]	[0.003]	[0.004]	[0.003]
Proportion mediated by education		0.860		0.807
R^2	0.027	0.471	0.024	0.476
Observations	67,932	67,621	67,932	67,621
High-dimensional child education FE	No	Yes	No	Yes

Notes: This table examines child education as a mediator of the relationship between parental wealth and children's job values. Columns (1) and (3) show the total effect of parental net worth rank on children's job value rank without controls. Columns (2) and (4) include high-dimensional child education fixed effects, which include information on both the highest level of educational attainment and the specific field of study. The proportion mediated by education is calculated as $(1 - \beta_{\text{controlled}}/\beta_{\text{total}})$. Standard errors in parentheses. *** p<0.01.

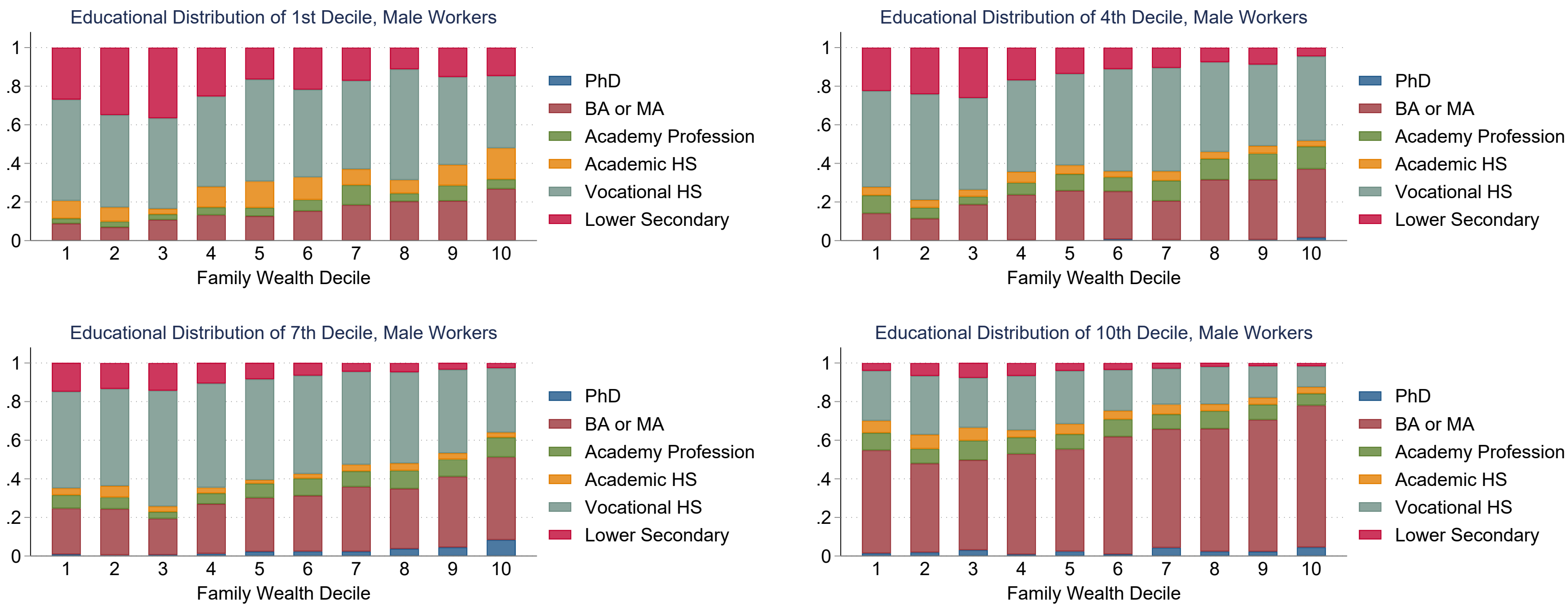
Figure 12 further illustrates the empirical relationship between parental wealth and child educational attainment across the earnings distribution. Each panel shows the educational composition of male workers at a specific earnings decile (1st, 4th, 7th, 10th), with bars representing the distribution across parental wealth deciles.[45] Within each panel, children from higher wealth deciles have substantially larger shares with college or university degrees (Academy Profession, BA or MA, and PhD) compared to children from lower wealth deciles. This pattern holds consistently across all four earnings deciles.[46]

then re-estimate conditional on the mediator, with the attenuation measuring the share explained (see, e.g., Heckman and Pinto (2015) and applied to intergenerational wealth by Fagereng et al. (2021)). Our contribution is applying this framework to children's job value, rather than earnings or wealth alone.

[45] We present results by earnings deciles here; results using job value deciles yield similar patterns.

[46] Why does education mediate such a large share of the job value-wealth relationship, particularly in a

Figure 12: Parental Wealth and Child Educational Attainment (By Wage Decile)



Notes: This figure shows the educational distribution of male workers by parental wealth decile, separately for workers at different positions in the earnings distribution. Each panel represents workers at a specific earnings decile (1st, 4th, 7th, 10th). Educational categories from bottom to top: Lower Secondary, Vocational HS, Academic HS, Academy Profession, BA or MA, and PhD.

A potential concern is that child education might simply proxy for parental education—highly educated parents both accumulate more wealth and transmit educational advantages directly to their children. To address this concern, we re-estimate our mediation analysis controlling for parental education. The results, presented in Appendix E.2 , show that the proportion mediated by child education remains high at 43% (of the total effect), even conditional on parental educational attainment.

8 Additional Results and Robustness

This section provides additional evidence on welfare mobility and demonstrates robustness to alternative specifications and heterogeneous job rankings.

8.1 Absolute Prospects and Nonlinear Rank–Rank Profiles

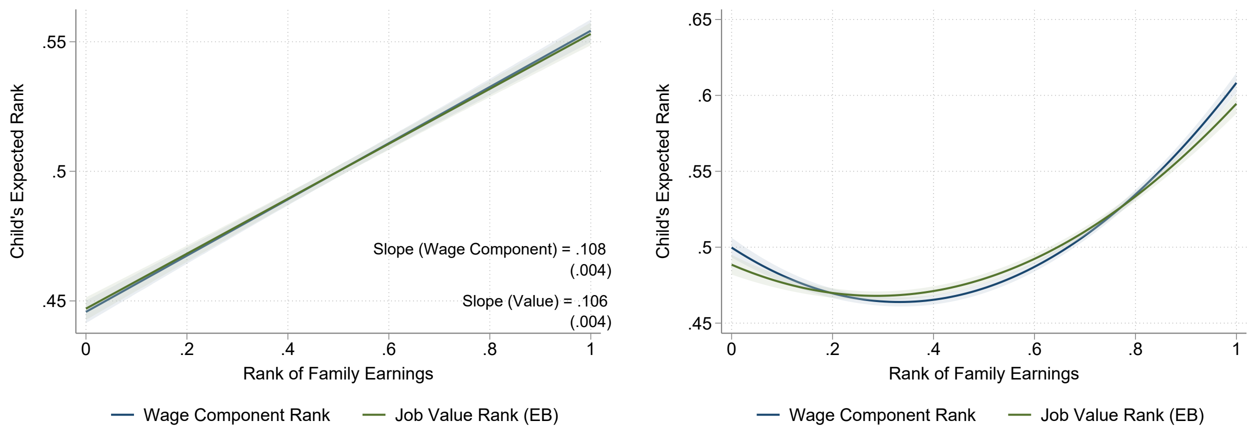
While rank–rank slopes summarize relative mobility, they do not describe children's absolute prospects across the parental distribution. Do children from economically disadvantaged families attain higher expected ranks when outcomes are measured by total job value rather than earnings? Moreover, a single linear rank–rank slope can mask important nonlinearities in the parent–child relationship; we therefore examine the implied rank–rank profile more flexibly below.

Figure 13 plots children's expected rank as a function of parental earnings position, comparing outcomes measured by total job value (green line) versus job wage premium (blue line). Panel (a) shows the linear comparison, where two lines lie nearly on top of each other throughout the parental distribution. Panel (b) presents a non-linear comparison using quadratic fits, with two curves tracking each other remarkably closely. Absolute mobility predicted from the value-earnings specification is statistically indistinguishable from predictions based on the job FE-earnings specification.

We now turn to the value-value specification. Figure 14 plots children's expected rank as a function of parental rank, comparing outcomes when both generations are measured by total job value (blue line) versus when both are measured by job wage premium (green line). Panel (a) presents the linear comparison; in the bottom half of the parental distribution, the blue line (job value) lies above the green line (job FE), indicating that children from lower-ranked families achieve higher expected ranks when measured by total job value than by wage premia

setting where college is free? Recent work by Landersø and Heckman (2017) and Heckman and Landersø (2022) offers one potential explanation: Denmark's compressed wage structure and generous social welfare benefits substantially weaken labor market incentives for educational investment. This is an important explanation for future research to investigate.

Figure 13: Absolute Mobility in Value-Earnings Specification



(a) Linear Comparison

(b) Non-linear Comparison

Notes: This figure plots children's expected rank by parental earnings rank in the value-earnings specification. The green line represents children's job value rank (with EB correction); the blue line represents children's job wage premium rank (job FE). Panel (a) shows linear fits; panel (b) shows quadratic fits.

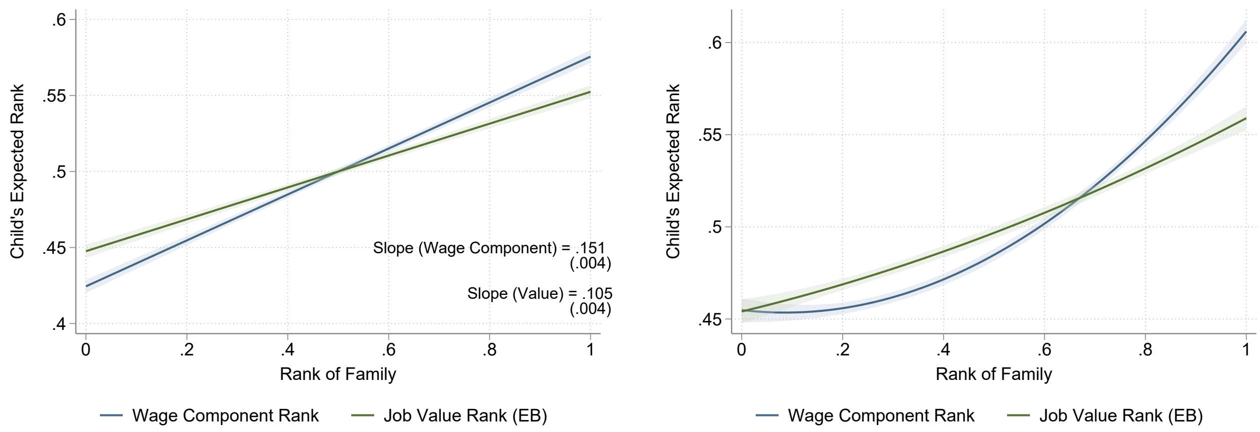
alone. The lines converge near the middle of the distribution, then diverge at the top: children from higher-ranked families achieve higher expected ranks when measured by earnings than by total job value. The steeper slope of the blue line, reflecting higher intergenerational persistence in wage premia, drives this pattern, suggesting that wage advantages are more strongly transmitted across generations than overall welfare. Panel (b) shows the non-linear comparison using quadratic fits. The gap between the two curves becomes more pronounced, particularly at the top of the parental distribution. Children from families in the top half of the parental distribution achieve higher expected ranks when outcomes are measured by wage premium than by total job value.

8.2 Components of Intergenerational Welfare Transmission

A key advantage of estimating the dynamic search model is that it allows us to examine how parental earnings transmit to individual components of forward-looking job value separately. By estimating each component of the value function, we gain additional insight into the specific channels through which parental earnings transmit to children's job quality. We highlight two key dimensions: job security and job flow value.

Figure 15 presents coefficient estimates from regressing the ranks of two components of forward-looking values of a job on parental earnings rank. First, children from families ranked higher in the earnings distribution hold jobs ranked higher in job security. The negative coefficients on job insecurity (-0.093) indicate that these children hold jobs with lower job de-

Figure 14: Absolute Mobility in Value-Value Specification



(a) Linear Comparison

(b) Non-linear Comparison

Notes: This figure plots children's expected rank by parental earnings rank in the value-value specification. The green line represents children's job value rank (with EB correction); the blue line represents children's job wage premium rank (job FE). Panel (a) shows linear fits; panel (b) shows quadratic fits.

struction rates—children at the 75th percentile of parental earnings hold jobs approximately 4.6 percentile points more secure (i.e., ranked lower in job destruction risk) than children at the 25th percentile. Second, children from higher-ranked families also hold jobs ranked higher in instantaneous flow payoffs (0.116), capturing the immediate utility from wages and job amenities. Both dimensions reinforce each other: parental position in the earnings distribution predicts children's access to jobs that rank higher in both flow payoffs and employment security.

8.3 Transmission of Non-Pecuniary Component

Lastly, we investigate the intergenerational transmission of the non-pecuniary component. Figure 16 plots the residual job value rank, the component of overall job value net of wage component, against parental earnings rank. The solid blue line shows a local linear regression estimate that flexibly fits a weighted linear regression at each point using observations in a local neighborhood, while the dashed red line shows the OLS linear fit. The figure shows a positive relationship between parental earnings and children's non-pecuniary job value, with the association strengthening considerably at the top of the parental earnings distribution. This pattern suggests that intergenerational transmission operates not only through wage outcomes but also through access to jobs with better amenities and working conditions.

Figure 15: Components of Intergenerational Welfare Transmission ($\beta^{Value-Earnings}$)

Notes: This figure presents estimated coefficients from two components of forward-looking values of a job on parental earnings rank. Each bar shows the coefficient from regressing the component's national rank on parental earnings rank. Job Insecurity measures the job destruction rate. Job Flow Value captures the instantaneous utility from being employed at the job. EB denotes estimates with empirical Bayes correction for measurement error. Appendix Table A-14 presents the full regression results.

Figure 16: Transmission of Non-Pecuniary Component

Notes: The figure plots the residual job value rank (net of the wage component, from the search model) against parental earnings rank. The solid blue line shows the local linear regression estimate, which flexibly fits a weighted linear regression at each point using observations in a local neighborhood around that point. The dashed red line shows the OLS linear fit. Appendix Table A-15 presents the OLS regression results.

8.4 Robustness and Heterogeneity

We examine the robustness of our findings along two key dimensions: alternative job ranking methods and heterogeneous rankings across gender.

8.4.1 Robustness Checks

Our main findings prove robust across alternative specifications and measurement approaches.

Alternative Job Rankings. The poaching index yields strikingly similar conclusions to our primary measures. Both key findings hold: (1) earnings-based mobility measures understate true welfare mobility by 31 percent in aggregate, and (2) daughters exhibit 38 percent greater mobility in total welfare than in wages, while sons show nearly aligned measures. This consistency across independent ranking methods—forward-looking value, PageRank, and poaching—provides strong validation of our results. See Appendix F.3.

Alternative Definition of a Job. We examine the sensitivity of our results to alternative definitions of jobs. Our findings remain quantitatively similar when we vary the number of establishment clusters. Using 30 clusters instead of 12 yields the same substantive conclusions. Second, we construct rankings that incorporate or exclude within-job promotions. Our baseline approach treats promotions and transitions between occupations within the same establishment as voluntary moves, revealing job preferences, similar to employer-to-employer transitions. As this assumption is strong, we also construct rankings using only employer-to-employer transitions, excluding promotions entirely. This alternative isolates mobility across employers from advancement within employers.

Establishment Value. We construct job rankings based purely on establishment value, removing the occupational dimension from our job definition. This alternative approach ranks jobs solely by the quality of the employer rather than the occupation-employer combination. Our qualitative results hold, but the magnitudes are dramatically lower, suggesting that measurement error issues become more severe.

8.4.2 Heterogeneous Rankings

Our baseline estimates assume a common ranking of jobs across all workers. We now relax this assumption by estimating separate job rankings for different demographic groups, allowing us to test whether preference heterogeneity affects our mobility estimates.

By gender. In Appendix F.4, we assess the extent to which men and women rank jobs differently. We construct our primary job rankings using male transitions only and female transitions only. We find a strong correlation (0.82) between male and female job rankings.

9 Conclusion

This paper develops a novel measure of intergenerational welfare mobility, including both pecuniary and non-pecuniary components of a job. By applying a revealed preference approach to rank jobs using observed voluntary worker transitions, we construct welfare-based mobility measures that reflect workers' common valuations of total job compensation.

In Denmark, we find 31% greater mobility in total job value than in wages alone, and parental earnings predict children's job values nearly as well as they predict wage components. These patterns suggest that earnings-based mobility measures accurately capture how economic status transmits to the second generation's job welfare, but they understate the true degree of welfare mobility across generations. However, this aggregate correspondence masks substantial heterogeneity: comparing within each gender, daughters exhibit 38% greater mobility in total welfare than in wages, while for sons the measures align more closely. Education emerges as the primary mechanism through which family background shapes the next generation's access to high-value jobs, with direct wealth playing a limited role. Children from wealthier backgrounds disproportionately pursue college degrees over vocational tracks, which subsequently provide pathways to jobs with higher earnings and better amenities.

Whether Denmark's patterns extend to other countries remains an open empirical question. We view our methodological framework as a template that researchers can apply globally; the approach requires parent-child linkages and longitudinal employer-employee data, both increasingly available across developed and developing countries. Applying our methods to diverse settings would not only test the external validity of our Danish findings but also, more importantly, shed light on how labor market institutions, social insurance systems, and education policies jointly shape the relationship between wages and welfare across generations.

Several limitations of our approach warrant acknowledgment and suggest productive directions for future research.

First, our revealed preference approach rests on the assumption that observed job transitions reveal workers' valuation of different positions. However, this assumption faces two interrelated challenges that become particularly salient when applied to intergenerational mobility. Valuation of jobs comes directly from observed worker voluntary transitions. Yet workers may value certain job attributes but cannot access them due to search frictions, information constraints, or a lack of suitable alternatives. A worker stuck in an undesirable job appears in our framework as if they value that position, when in reality, better options may be unavailable or unknown. This limitation reflects the fundamental challenge of distinguishing workers' true preferences from their constrained choice sets.

Second, our framework reveals an intriguing internal tension when moving from cross-sectional job transitions to intergenerational mobility. Our discrete choice model assumes individuals make choices subject to idiosyncratic preference shocks, random draws of utility that lead similar workers to different outcomes. Yet, our mobility analysis demonstrates that these "random" outcomes systematically correlate with family background. Children from advantaged families consistently draw better options or face choice sets tilted toward high-value jobs. What appears as luck in the choice model turns out to be a systematic advantage accumulated across generations. Reconciling this tension requires understanding how family background shapes not just preferences over jobs but the very structure of opportunities available, the choice sets themselves. Do advantaged families provide better information about job opportunities? Do they offer access to networks that unlock otherwise unavailable positions? Do they provide credentials that expand the feasible choice set? Do they cultivate their children into certain career paths or trajectories that they themselves value? Future work should develop methods to disentangle workers' actual choice sets from the universe of all jobs and to model how those choice sets vary systematically with family background.

Third, while we employ empirical Bayes corrections for measurement error, our job value rankings remain estimated objects with limitations. The measurement error in our context is non-classical—jobs with fewer observed transitions receive noisier estimates, and this noise correlates with true job values in ways that standard corrections cannot fully address. Developing more econometric tools to handle non-classical measurement errors represents an important methodological frontier.

Fourth, job quality presents only one dimension of overall welfare. Workers' well-being also depends on consumption possibilities, family relationships, and numerous other factors that extend beyond labor market positions. A truly comprehensive measure of intergenerational welfare mobility would incorporate these multiple dimensions, examining how family background shapes not just the jobs people hold but their broader life outcomes. Our focus on jobs reflects both data availability and the central role that employment plays in determining economic well-being, but it necessarily provides an incomplete picture. Integrating broad dimensions of welfare into the intergenerational mobility framework represents a fruitful path for future research.

Fifth, while we identify child education as a key mediator, we provide limited insight into the specific barriers that prevent economically disadvantaged families from fully utilizing Denmark's universal free tertiary education. Do children from lower-income families lack information about educational pathways and their returns? Do credit constraints bind at critical transitions, such as college enrollment? Would financial support for living expenses during higher education narrow mobility gaps, or would such policies primarily benefit families already on track for college? Understanding these questions requires a more detailed investigation of how family background translates into educational choices and subsequent labor market outcomes, and what policies can effectively alleviate educational gaps across the family background distribution.

Over two centuries ago, Adam Smith recognized that workers trade wages for working conditions. If we measure mobility solely through paychecks, we risk missing these tradeoffs entirely—mistaking lateral moves along the wage-amenity frontier for genuine improvements in welfare or failing to recognize when rising earnings come at the cost of deteriorating working conditions. By developing measures that capture both dimensions of job quality, we take a step toward understanding mobility in the space that ultimately matters: the opportunities for well-being that societies offer their members and the extent to which those opportunities depend on the lottery of birth.

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Online Appendix
Intergenerational Mobility in Welfare: Wages and Amenities

by Natalia Khorunzhina, Jesse Wedewer, Runling Wu

Contents

A Job Ladder Model

We follow Sorkin (2018) in estimating a job ladder model to rank jobs using revealed preference. The model extends his firm-level analysis to occupation-establishment pairs.

A.1 Model Structure

Jobs are characterized by three parameters: flow payoff v_j, exogenous job destruction rate δ_j, and exogenous reallocation rate ρ_j. Workers receive job offers at rate λ_1 when employed. Each period, workers draw i.i.d. Gumbel shocks ι over available options. The value of employment at job j satisfies:

$$
\begin{aligned}
\underbrace{V^e(v_j,\delta_j,\rho_j)}_{\text{value of being at } j} = \underbrace{v_j}_{\text{flow payoff}} + \underbrace{\beta}_{\text{discounter}} \mathbb{E}\Bigg\{ & \underbrace{\delta_j \int \{V^n + \iota_1\} dI}_{\text{exogenous job destruction}} \\
& + \underbrace{\rho_j(1-\delta_j)\sum_k \int \{V_k^e + \iota_2\} dI \tilde{f}_k}_{\text{exogenous job-to-job (reallocation)}} \\
& + \underbrace{(1-\rho_j)(1-\delta_j)}_{\text{no exogenous shocks}} \\
& \times \Bigg[\underbrace{\lambda_1}_{\text{offer}} \underbrace{\sum_k \int_{\iota_3}\int_{\iota_4} \max\{\underbrace{V_k^e + \iota_3}_{\text{accept}}, \underbrace{V_j^e + \iota_4}_{\text{reject}}\} dI dI f_k}_{\text{endogenous job-to-job}} \\
& + \underbrace{(1-\lambda_1)}_{\text{no offer}} \underbrace{\int_{\iota_5}\int_{\iota_6} \max\{\underbrace{V^n + \iota_5}_{\text{accept}}, \underbrace{V_j^e + \iota_6}_{\text{reject}}\} dI dI}_{\text{endogenous job destruction}} \Bigg] \Bigg\}.
\end{aligned} \tag{A1}
$$

With probability δ_j, the worker experiences job destruction and transitions to nonemployment. With probability $\rho_j(1-\delta_j)$, an exogenous reallocation shock forces the worker to draw from the offer distribution and accept a job-to-job transition. With probability $(1-\rho_j)(1-\delta_j)$, no exogenous shock occurs. The worker then either receives an offer (probability λ_1) or not (probability $1-\lambda_1$), making endogenous mobility decisions based on value comparisons and idiosyncratic utility draws.

A.2 Identification

Following Sorkin (2018), we identify model parameters from observed job-to-job transitions. The flow payoff v_j and value V_j^e are identified from the pattern of endogenous mobility: workers systematically move toward higher-value jobs. The job destruction rate δ_j is identified from employment-to-nonemployment transitions.

Identifying the Godfather Shock ρ_j. The exogenous reallocation parameter ρ_j captures involuntary employer-to-employer transitions driven by firm-level shocks rather than worker preferences. Sorkin (2018) identifies ρ_j by comparing observed separation rates to predicted endogenous separation rates at contracting versus expanding employers.

When an employer contracts, observed separations exceed the rate predicted by the model's endogenous mobility component. This excess is attributed to exogenous shocks: workers who would have stayed absent the firm-level disturbance. The approach computes the endogenous separation rate from expanding employers (the right side of the employer growth distribution) and uses this as the baseline. For contracting employers (the left side), separations exceeding this baseline are classified as exogenous, providing the exogenous weight $\frac{\text{excess}}{\text{excess+expected}}$ used to construct ρ_j.

In Sorkin (2018), the exogenous reallocation rate varies across 20 industry sectors. Our analysis differs in one key dimension: we define ρ_j at the occupation level rather than the industry level. This modification reflects our focus on occupation-establishment pairs as the unit of analysis. Each occupation may face different risks of involuntary reallocation due to occupation-specific demand shocks, technological change, or restructuring patterns. For example, production workers may face different exogenous mobility risks than managers within the same firm experiencing economic distress.

This occupation-level variation in ρ_j is identified using the same approach as Sorkin (2018), but applied to occupation-specific employer growth rates. We compute excess separations for each occupation separately, allowing the godfather shock to vary across occupations rather than industries. This captures heterogeneity in the extent to which different occupations experience involuntary versus voluntary mobility.

B Addressing Measurement error

B.1 Proof of Attenuation Bias

A1 (Rank Properities): Let $\widetilde{x}^*$, $\widetilde{y}^*$ denote true parent and child rank. True ranks are functions of observed ranks x^*, y^* as follows:

$$\widetilde{x}^* = F_x\left(x^*\right), \quad \widetilde{y}^* = F_y\left(y^*\right) \tag{A2}$$

where $F_x(\cdot)$ and $F_y(\cdot)$ are cumulative distribution functions. By construction, ranks are bounded: $\widetilde{x}^*, \widetilde{y}^*, \widetilde{x}, \widetilde{y} \in [0,1]$; ranks are uniformly distributed: $\widetilde{x}^*, \widetilde{y}^*, \widetilde{x}, \tilde{y} \sim U(0,1)$; all ranks have variance: $\mathrm{Var}(\cdot) = 1/12$.

A2 (Measurement Error in Ranks): Denote observed ranks as

$$\widetilde{x} = \widetilde{x}^* + \widetilde{u} \tag{A3}$$

$$\widetilde{y} = \widetilde{y}^* + \widetilde{v} \tag{A4}$$

where $\widetilde{u}, \widetilde{v}$ are the errors in ranks.

A3 (Generalized Error-in-Variables Model in Ranks): Following Nybom and Stuhler (2017), the relationship between observed and true ranks can be represented as a linear projection:

$$\widetilde{y} = \alpha + \lambda_y \widetilde{y}^* + \widetilde{w} \tag{A5}$$

where λ_y is the slope coefficient. By construction, $\widetilde{w}$ is uncorrelated with $\widetilde{y}^*$.

A4 (Exogeneity): Measurement errors are uncorrelated with the other generation's true rank:

$$\mathrm{Cov}(\widetilde{w}, \widetilde{x}^*) = 0, \qquad \mathrm{Cov}(\widetilde{v}, \widetilde{y}^*) = 0 \tag{A6}$$

Lemma 1: Under Assumptions A1-A2, measurement error in ranks is negatively correlated with true rank:

$$\mathrm{Cov}(\widetilde{v}, \widetilde{y}^*) = -\frac{1}{2}\mathrm{Var}(\widetilde{v}) < 0 \tag{A7}$$

Proof.

$$\begin{aligned}
\mathrm{Var}\left(\widetilde{y}^*\right) &= \mathrm{Var}(\widetilde{y}) \\
&= \mathrm{Var}\left(\widetilde{y}^*\right) + \mathrm{Var}(\widetilde{v}) + 2\,\mathrm{Cov}\left(\widetilde{y}^*, \widetilde{v}\right)
\end{aligned}$$

Thus, $\operatorname{Cov}(\widetilde{y}^*, \widetilde{v}) = (-1/2)\operatorname{Var}(\widetilde{v})$ $\square$

This negative correlation arises from the bounded support in A1: individuals at the top ($\widetilde{y}^* \approx 1$) cannot be overstated, so $\widetilde{v} \leq 0$; those at the bottom ($\widetilde{y}^* \approx 0$) cannot be understated, so $\widetilde{v} \geq 0$.

Lemma 2: Under Assumptions A1-A4, and Lemma 1:

$$\lambda_y = 1 - 6 \cdot \operatorname{Var}(\widetilde{v}) < 1 \tag{A8}$$

Proof.

$$\lambda_y = \frac{\operatorname{Cov}(\widetilde{y}, \widetilde{y}^*)}{\operatorname{Var}(\widetilde{y}^*)} = \frac{\operatorname{Cov}(\widetilde{y}^* + \widetilde{v}, \widetilde{y}^*)}{\operatorname{Var}(\widetilde{y}^*)} = 1 + 12 \underbrace{\operatorname{Cov}(\widetilde{v}, \widetilde{y}^*)}_{=-1/2\operatorname{Var}(\widetilde{v})} < 1$$

$\square$

Theorem (Attentuation Bias in Rank Correlation) Under Assumptions A1-A4 and Lemmas 1-2:

(i) Under left-side measurement error ($\widetilde{x} = \widetilde{x}^*$): $\rho^S_{(\widetilde{x}^*, \widetilde{y})} = \lambda_y \cdot \rho^S_{(\widetilde{x}^*, \widetilde{y}^*)}$

(ii) Under both-side measurement error: $\rho^S_{(\widetilde{x}, \widetilde{y})} = \lambda_x \lambda_y \cdot \rho^S_{(\widetilde{x}^*, \widetilde{y}^*)}$

where $\rho^S_{(a,b)} := \operatorname{Cov}(a,b)/\sqrt{\operatorname{Var}(a)\operatorname{Var}(b)}$ denotes the Spearman rank correlation.

Proof. Part (i): left-side measurement error

$$\begin{aligned}
\rho^S_{(\widetilde{x}^*, \widetilde{y})} = \frac{\operatorname{Cov}(\widetilde{x}^*, \widetilde{y})}{\sqrt{\operatorname{Var}(\widetilde{x}^*)\operatorname{Var}(\widetilde{y})}} &= \frac{\operatorname{Cov}(\widetilde{x}^*, \alpha + \lambda_y \widetilde{y}^* + \widetilde{w})}{\sqrt{\operatorname{Var}(\widetilde{x}^*)\operatorname{Var}(\widetilde{y})}} \\
&= \lambda_y \frac{\operatorname{Cov}(\widetilde{x}^*, \widetilde{y}^*) + \operatorname{Cov}(\widetilde{\mathrm{x}}^*, \widetilde{\mathrm{w}})}{1/12} \\
&= \lambda_y \frac{\operatorname{Cov}(\widetilde{x}^*, \widetilde{y}^*)}{1/12} \\
&= \lambda_y \rho^S_{(x^*, y^*)}
\end{aligned}$$

Part (ii): Both-side measurement error

$$\rho^S_{(\widetilde{x}, \widetilde{y})} = \frac{\operatorname{Cov}(\widetilde{x}, \widetilde{y})}{\sqrt{\operatorname{Var}(\widetilde{x})\operatorname{Var}(\widetilde{y})}} = \lambda_x \lambda_y \frac{\operatorname{Cov}(\widetilde{x}^*, \widetilde{y}^*)}{1/12} = \lambda_x \lambda_y \rho^S_{(x^*, y^*)}.$$

$\square$

B.2 Empirical Bayes

Following Sorkin (2018), we apply an empirical Bayes procedure to address measurement error in our job value estimates. The approach shrinks noisy estimates toward a conditional mean, with shrinkage inversely proportional to precision.

Let j index an occupation-establishment-type pair. Let $\hat{V}_j^e$ denote the estimated job value and $\hat{\pi}_j^2$ its estimated variance (computed via bootstrap). Let $\mathbf{x}_j$ be a vector of occupation fixed effects that serve as our shrinkage target. Unlike Sorkin (2018), who shrinks toward industry and location, we shrink toward occupation codes to capture occupation-specific means.

The shrinkage procedure solves for two unknowns: the true variance of job values $\hat{\sigma}^2$ and the occupation means $\hat{\boldsymbol{\lambda}}$. Define weights $w_j = n_j/(\hat{\pi}_j^2 + \hat{\sigma}^2)$ where n_j is the number of observations for job j. These satisfy:

$$\hat{\sigma}^2 = \max\left\{0, \frac{\sum_j w_j \left[\frac{n_J}{n_J - n_x}(\hat{V}_j^e - \mathbf{x}_j'\hat{\boldsymbol{\lambda}})^2 - \hat{\pi}_j^2\right]}{\sum_j w_j}\right\} \tag{A9}$$

$$\hat{\boldsymbol{\lambda}} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{V} \tag{A10}$$

where n_J is the number of jobs, n_x is the number of occupation categories, $\mathbf{W} = \text{diag}(w_j)$, $\mathbf{X}$ stacks the $\mathbf{x}_j'$, and $\mathbf{V}$ stacks the $\hat{V}_j^e$. We iterate until convergence: compute $\hat{\boldsymbol{\lambda}}$, update $\hat{\sigma}^2$, update weights, repeat.

The shrinkage estimator is:

$$\hat{V}_j^{EB} = (1 - \hat{b}_j)\hat{V}_j^e + \hat{b}_j \mathbf{x}_j'\hat{\boldsymbol{\lambda}} \tag{A11}$$

where the shrinkage factor is:

$$\hat{b}_j = \frac{n_J - n_x - 2}{n_J - n_x} \cdot \frac{\hat{\pi}_j^2}{\hat{\pi}_j^2 + \hat{\sigma}^2} \tag{A12}$$

This shrinks imprecise estimates (large $\hat{\pi}_j^2$) heavily toward the occupation mean, while leaving precise estimates largely unchanged.

C Data and Sample Construction

C.1 Sample Construction

C.1.1 IGM Sample

Our base dataset begins with all children who satisfy three criteria: (i) born in the 1980-1981 birth cohorts, (ii) native Danes, and (iii) linkable to at least one parent in the population register (BEF). The native Dane restriction ensures we focus on children and parents who did not migrate, avoiding complications from selective migration and incomplete earnings histories. We follow the 1980 cohort until age 39 and the 1981 cohort until age 38 (both observed in 2019). Parental information is available annually from 1985 to 2019, allowing us to construct comprehensive measures of parental economic status during the children's formative years. Our primary analysis sample imposes two additional restrictions to ensure adequate measurement of economic outcomes:

1. **Positive earnings requirement:** Parents must have strictly positive average earnings between 1985 and 1994, and children must have strictly positive average earnings between 2010 and 2019 (ages 30-39). This restriction excludes individuals with no labor market attachment during the measurement period.

2. **Minimum observation requirement:** We require at least four years of earnings data for both children (between ages 30 and 39) and parents (between 1985 and 1994, when parents are ages 30-39). This ensures our average earnings measures are not based on a small number of potentially unrepresentative years.

Starting with 101,347 native Danes born in 1980-1981 who link to parents, the sample reduces to 87,709 individuals once we verify earnings observations for both children and at least one parent.

C.1.2 Job Sample

The Job sample is constructed to measure job values using voluntary job-to-job transitions. The key requirement is tracking employment spells with sufficient granularity to identify direct job-to-job moves without intervening non-employment periods.

For children (2010-2019), we use the Employer-Employee Register (BFL), available from 2008 onwards. The BFL contains high-quality, comprehensive information on job spells, occupational codes, and hours worked in Denmark. For parents (1991-2000), we use spell data from the Labour Market Dynamics Group at Aarhus University (1985-2014), which specifies the starting and ending date for each employment record. Both data sources allow us to distinguish genuine job-to-job (EE) transitions, where workers move directly between employers, from transitions with intervening non-employment spells (ENE transitions). Only EE transitions are used to construct job rankings, as these reveal voluntary mobility decisions based on job preferences.

Importantly, while we measure parental earnings over 1985 to 1994 (when parents are aged 30-39), we measure parental job values over a different window: 1991-2000. This discrepancy arises because constructing comparable job rankings across generations requires consistent occupation codes. Consistent occupation codes start from 1991 and onward.

We impose several sample restrictions to ensure job values are evaluated by a representative prime-age working population. First, we truncate individual labor market histories to ages 19-55, as jobs should be ranked based on the revealed preferences of workers in their prime working years. Second, we exclude workers in self-employment, business ownership, as jobs in these sectors are difficult to compare with standard employment relationships. Third, we restrict our analysis to each individual's primary job, defined as the most important employment connection at the end of November of each survey year.

C.2 Variable Definitions

Table A-1: Definition of Income Measures

Variable	Definition
(1) Wage Income	Taxable wage earnings and fringes, labor portion of business income, non-taxable earnings, severance pay, and stock options.
(2) Income with Transfers	Total personal income (excluding rental value of own home). Total personal income is equal to the sum of wage income, business and self-employment income, capital income, public transfer income, property income, and other non-classifiable income that can be attributed directly to the individual person.
(3) Income without Transfers	Total personal income (as specified in item (2) above) minus public transfer income. The main items of public transfer income include: social assistance cash benefits, unemployment insurance benefits including leave, sickness benefits, pensions including disability pension and early retirement pay, housing allowance, and child allowance.
(4) Disposable Income	Total personal income including public transfers (as specified in item (2) above) and rental value of own home (for owner-occupied individuals) minus taxes, interest expenses, and child support.
(5) Family Measures (Father and Mother)	The sum of items (1)–(4) within households.

Table A-2: Definition of Net Worth (Druedahl and Martinello, 2022)

Variable	Definition
(1) Housing Equity	The value of real estate owned by the individual minus collateralized debts (valued at the market value of the associated bonds at the end of the year).
(2) Liquid Assets	The sum of all cash and savings account balances held by an individual in Denmark.
(3) Uncollateralized Debts	The sum of all debts not associated with a bond granted by banks in Denmark.
(4) Financial Wealth	The sum of the market value of stocks, bonds, and mutual funds directly owned by an individual via an investment account.
(5) Net Worth	The sum of items (1)–(4): Net Worth = Housing Equity + Liquid Assets + Debts + Financial Wealth, where debts enter with a negative sign. Includes wealth directly held by the individual; excludes pension funds and large durable goods (e.g., cars, boats).

D Main Results: Intergenerational Mobility

D.1 Tables for Main Mobility Analysis

Table A-3: A list of Rankings of Jobs

Ranking of Jobs Method	**Description**	**Reference**
1. Forward-looking value	Value of being at job j (V_j^e): consists instantaneous flow value and continuation value	Sorkin (2018)
2. PageRank algorithm	Sorkin PageRank ($V_j^{PageRank}$)	Page et al. (1998); Sorkin (2018)
3. Poaching index	Ratio of employer-to-employer hires to all hires	Bagger and Lentz (2019)
4. Robustness checks	Preference heterogeneity by (gender); number of establishment clusters; with/without promotion; establishment value	

Table A-4: Rank-Rank Slope Estimates

	Rank–Rank			
	(1)	(2)	(3)	(4)
Wage Income	0.136***			
	(0.004)			
Income w. Transfers		0.133***		
		(0.004)		
Income w/o Transfers			0.161***	
			(0.004)	
Disposable Income				0.120***
				(0.004)
Constant	0.437***	0.438***	0.424***	0.445***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	66,992	66,992	66,992	66,992
R^2	0.018	0.018	0.026	0.014

Notes: Each column reports a separate rank–rank regression using the indicated income measure. Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-5: Intergenerational Welfare Mobility ($\beta^{Value-Earnings}$) Estimates

	Dependent Variable: Child Outcome				
	Page Rank (1)	Page Rank (EB) (2)	Job Value (3)	Job Value (EB) (4)	Job FE (5)
Rank of Family Earnings	0.110*** (0.004)	0.112*** (0.004)	0.105*** (0.004)	0.106*** (0.004)	0.108*** (0.004)
Constant	0.445*** (0.002)	0.444*** (0.002)	0.448*** (0.002)	0.447*** (0.002)	0.446*** (0.002)
Observations	66,992	66,992	66,992	66,992	66,992
R^2	0.012	0.012	0.011	0.011	0.012

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-6: Intergenerational Transmission of Job FE

	Child Job FE
	(1)
Rank of Average Family Job FE	0.151***
	(0.004)
Constant	0.424***
	(0.002)
Observations	66,992
R^2	0.023

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-7: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) Estimates

	Dependent Variable: Child PageRank					
	PageRank			PageRank (EB)		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Family Job Value (EB)	0.089***			0.105***		
	(0.004)			(0.004)		
Sum Family Job Value (EB)		0.096***			0.109***	
		(0.004)			(0.004)	
Max Family Job Value (EB)			0.091***			0.105***
			(0.004)			(0.004)
Constant	0.456***	0.452***	0.454***	0.448***	0.445***	0.448***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	66,992	66,992	66,992	66,992	66,992	66,992
R^2	0.008	0.009	0.008	0.011	0.012	0.011

Notes: Standard errors in parentheses. Columns (1)–(3) use child PageRank; columns (4)–(6) use EB-corrected child PageRank. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

D.2 Tables for Gender Analysis

Table A-8: Intergenerational Welfare Mobility ($\beta^{Value-Earnings}$) Estimates, by Gender

	Dependent Variable: Child Outcome				
	(1) Page Rank	(2) Page Rank (EB)	(3) Job Value	(4) Job Value (EB)	(5) Job FE
Panel A: Women					
Rank of Family Earnings	0.099***	0.101***	0.095***	0.096***	0.129***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Constant	0.453***	0.452***	0.450***	0.450***	0.388***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	32,785	32,785	32,785	32,785	32,785
R^2	0.010	0.010	0.010	0.010	0.018
Panel B: Men					
Rank of Family Earnings	0.121***	0.122***	0.115***	0.116***	0.087***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Constant	0.437***	0.436***	0.445***	0.444***	0.502***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	34,207	34,207	34,207	34,207	34,207
R^2	0.015	0.016	0.012	0.012	0.007

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

D.3 Family Background and Gender-Specific Educational/Occupational Pathways

Table A-9: Intergenerational Transmission of Job FE, by Gender

	Child Job FE	
	(1) Men	(2) Women
Rank of Average Family Job FE	0.131***	0.172***
	(0.005)	(0.005)
Constant	0.480***	0.366***
	(0.003)	(0.003)
Observations	34,207	32,785
R^2	0.017	0.032
Adjusted R^2	0.017	0.032

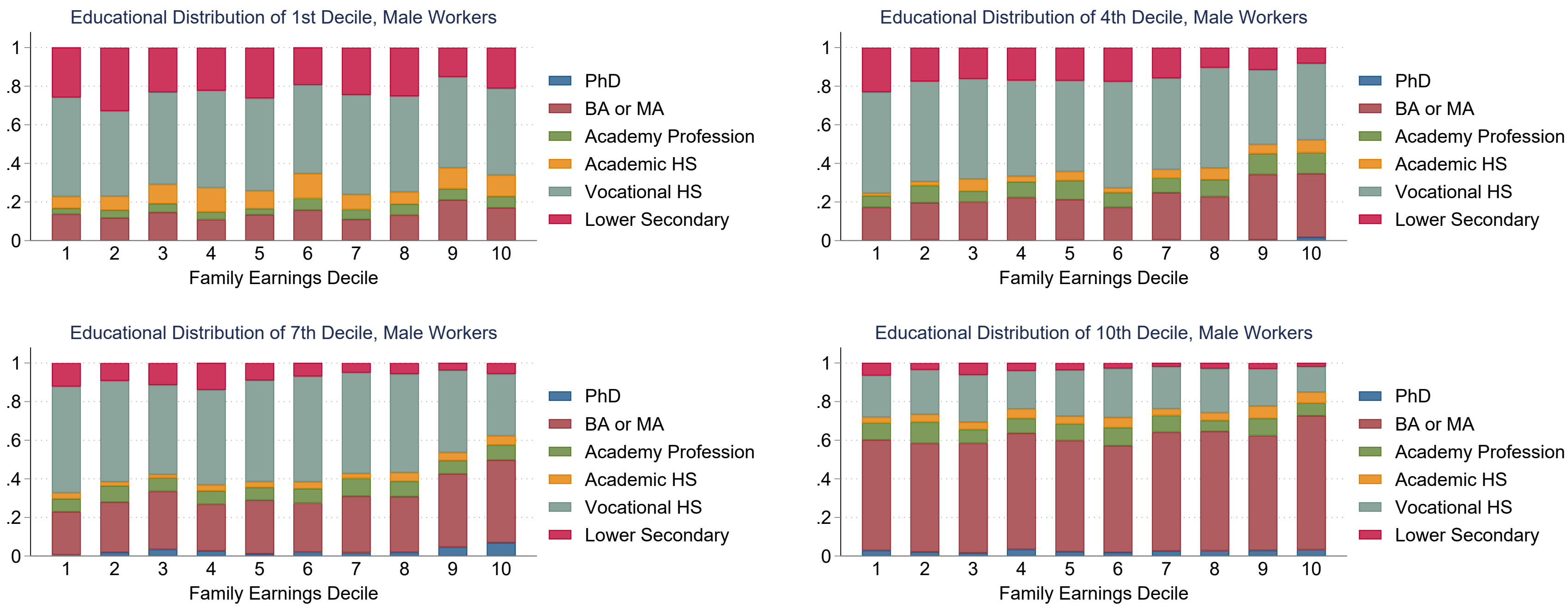
Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-10: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) Estimates, by Gender

	Dependent Variable: Child PageRank	
	(1) PageRank	(2) PageRank (EB)
Panel A: Women		
Rank of Average Family Job Value (EB)	0.089***	0.106***
	(0.005)	(0.006)
Constant	0.463***	0.450***
	(0.003)	(0.003)
Observations	32,785	32,785
R^2	0.005	0.011
Panel B: Men		
Rank of Average Family Job Value (EB)	0.089***	0.104***
	(0.006)	(0.005)
Constant	0.458***	0.446***
	(0.003)	(0.003)
Observations	34,207	34,207
R^2	0.008	0.011

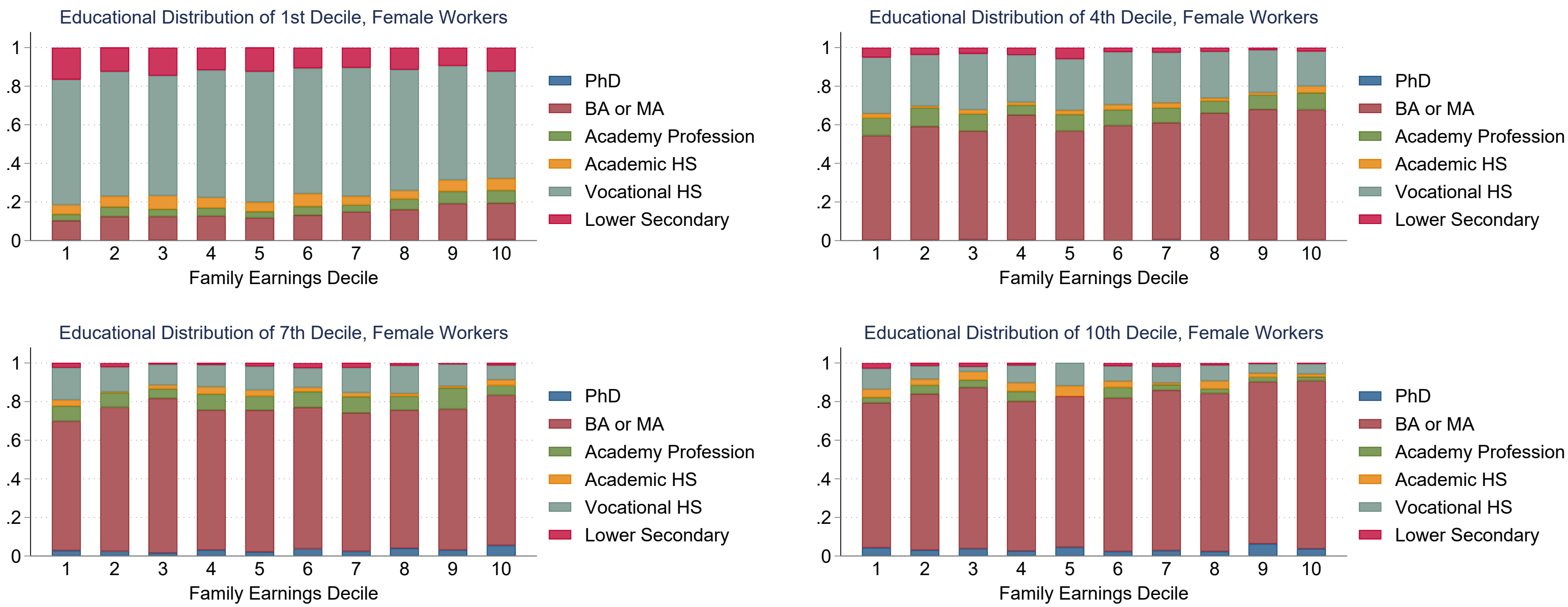
Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Figure A-1: Parental Earnings and Child Educational Attainment (Sons, By Wage Decile)



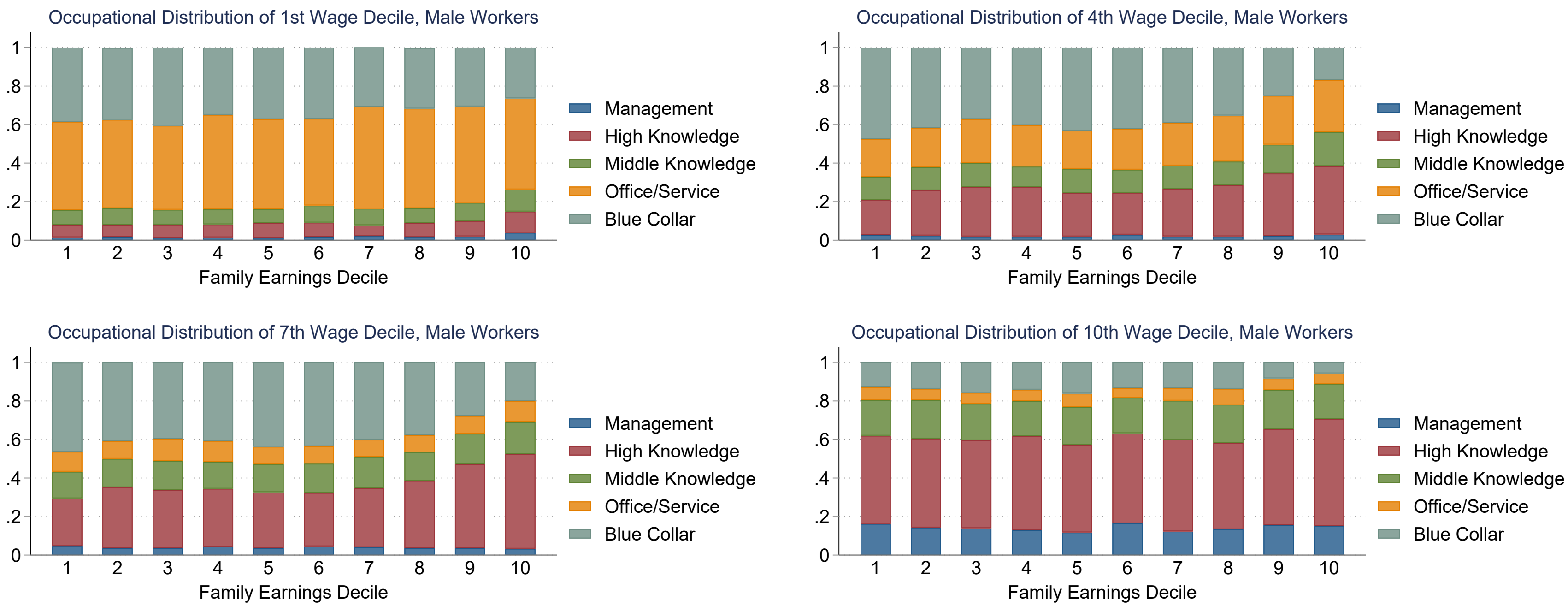
Notes: This figure shows the educational distribution of male workers by parental earnings decile, separately for workers at different positions in the earnings distribution. Each panel represents workers at a specific earnings decile (1st, 4th, 7th, 10th). Educational categories from bottom to top: Lower Secondary, Vocational HS, Academic HS, Academy Profession, BA or MA, and PhD.

Figure A-2: Parental Earnings and Child Educational Attainment (Daughters, By Wage Decile)



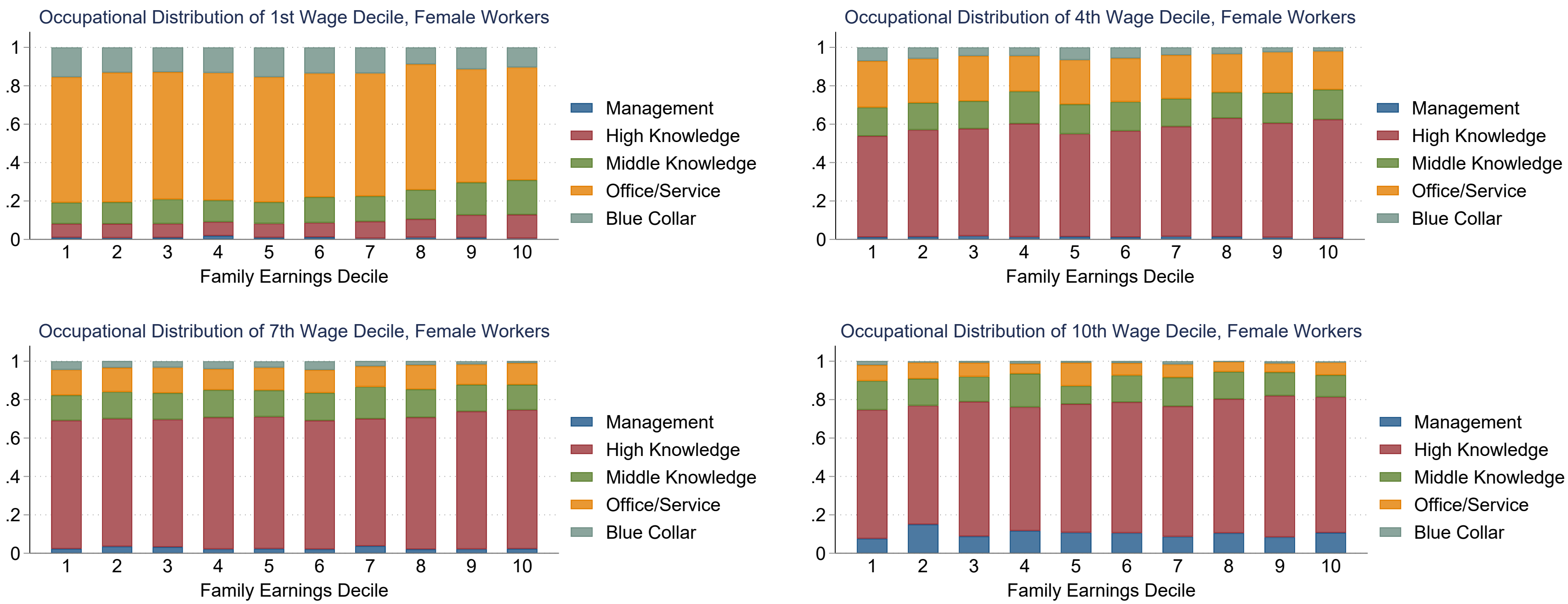
Notes: This figure shows the educational distribution of female workers by parental earnings decile, separately for workers at different positions in the earnings distribution. Each panel represents workers at a specific earnings decile (1st, 4th, 7th, 10th). Educational categories from bottom to top: Lower Secondary, Vocational HS, Academic HS, Academy Profession, BA or MA, and PhD.

Figure A-3: Parental Earnings and Child Occupational Distribution (Sons, By Wage Decile)



Notes: This figure shows the occupational distribution of male workers by parental earnings decile, separately for workers at different positions in the wage distribution. Each panel represents workers at a specific wage decile (1st, 4th, 7th, 10th). Occupational categories from bottom to top: Management, High Knowledge, Middle Knowledge, Office/Service, and Blue Collar.

Figure A-4: Parental Earnings and Child Occupational Distribution (Daughters, By Wage Decile)



Notes: This figure shows the occupational distribution of female workers by parental earnings decile, separately for workers at different positions in the wage distribution. Each panel represents workers at a specific wage decile (1st, 4th, 7th, 10th). Occupational categories from bottom to top: Management, High Knowledge, Middle Knowledge, Office/Service, and Blue Collar.

E Mechanisms

E.1 Unexpected Inheritance Design Details

We define permanent income as a weighted average of past five years of disposable income: $\text{perminc}_t = 0.45 \text{ dispinc}_t + 0.25 \text{ dispinc}_{t-1} + 0.15 \text{ dispinc}_{t-2} + 0.10 \text{ dispinc}_{t-3} + 0.05 \text{ dispinc}_{t-4}$.

Potential inheritance is defined by splitting the after-tax wealth equally among children (Andersen and Meisner Nielsen, 2011). In the Danish context, a minority of Danes draft a will (Andersen and Meisner Nielsen, 2011), and surviving children are always entitled to part of the inheritance even in the presence of a will (Danish Inheritance Act No. 515 of 06 June 2007, Section 5).

Our specification for individual i who experiences parental death at time τ_i is:

$$Y_{i,t} = \sum_{k<-2}^{-5} \delta_k \mathbf{1}[t - \tau_i = k] + \sum_{k\geq-2}^{7} \delta_k \mathbf{1}[t - \tau_i = k] + \alpha_i + \lambda_t + \theta_{a(i,t)} + \varepsilon_{i,t} \tag{A13}$$

The dependent variable $Y_{i,t}$ represents wealth holdings and labor market outcomes. For wealth, we examine net wealth and liquid assets. On the labor supply side, we analyze both the extensive margin (employment status) and the intensive margin (hours worked). Additionally, we investigate job turnover and mobility patterns through the following measures: the PageRank index, overall job value rank, an amenity index reflecting non-wage job characteristics, and indicators for switching occupation or employer.

δ_k coefficients trace out the dynamic treatment effects relative to $k = -1$. The specification includes a comprehensive set of fixed effects: individual fixed effects α_i, year fixed effects λ_t, and cohort fixed effects $\theta_{a(i,t)}$.

Figure A-5: Sudden Death Timeline

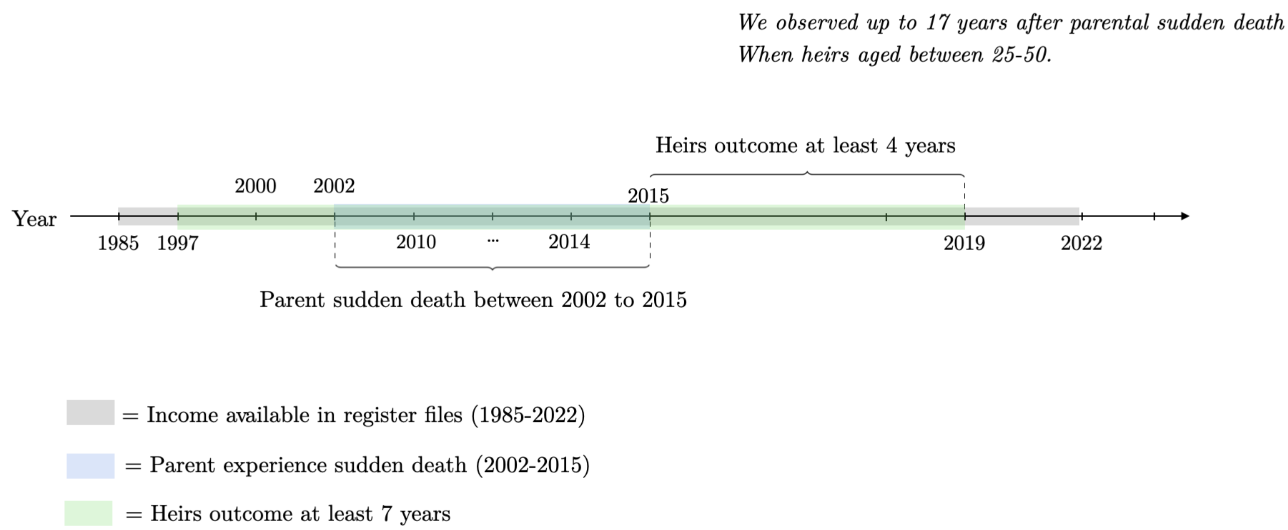


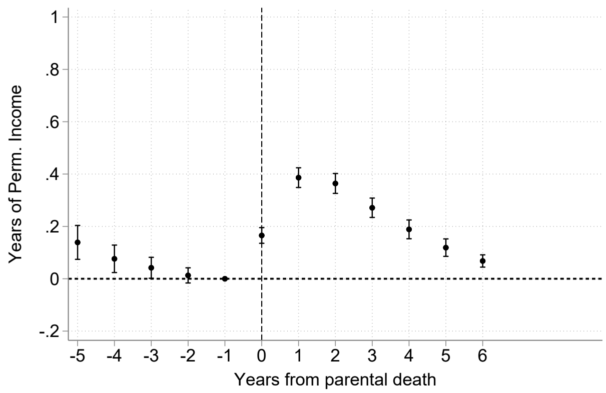
Table A-11: Inheritance and Heir Characterization, One Year before Parental Death

		Unexpected inheritance	
	All	All	Sizable pot. inheritance
Permanent income, 1,000 DKK	207.628	202.391	205.363
Net worth, normalized	0.250	0.195	0.636
Liquid assets, normalized	0.229	0.216	0.304
Uncollateralized debts, normalized	0.596	0.585	0.515
Financial investments, normalized	0.061	0.056	0.095
Housing equity, normalized	0.556	0.508	0.752
Disposable income, 1,000 DKK	212.878	207.583	210.379
Married	0.467	0.462	0.518
Year of inheritance	2003.669	2002.641	2002.609
Age at inheritance	39.890	39.307	40.615
Parental age at death	70.994	70.639	74.022
# individuals	223,355	21,750	6,286

Notes: Unexpected inheritances are those due to sudden parental death. Sizable potential inheritances are those larger than one year of the permanent income of the heir. Permanent and disposable income are in thousands DKK. In 2012 (as of December 31), 1 USD was equal to 5.64 DKK. All wealth measures are normalized by permanent income.

Figure A-6: The Effect of Inheritance on Net Worth

(a) Net Worth, Large Inheritance



(b) Net Worth, small or no inheritance (placebo)

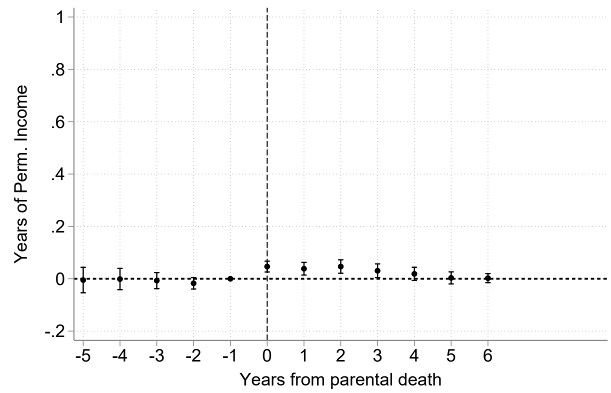
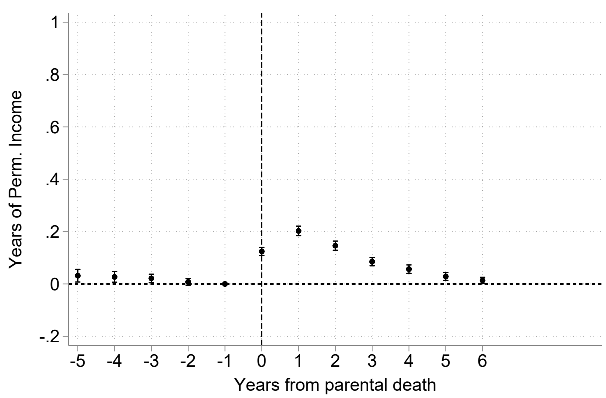
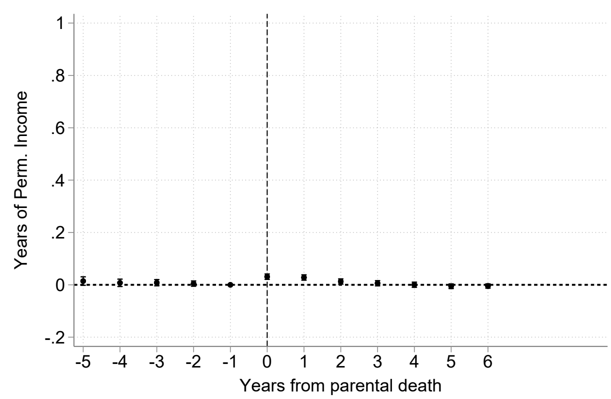


Figure A-7: The Effect of Inheritance on Liquid Assets

(a) Liquid Assets, Large Inheritance



(b) Liquid Assets, small or no inheritance (placebo)



E.2 Tables for Mediation Analysis

Table A-12: Parental Net Worth and Child Outcomes: Mediation via Education

	Child PageRank (EB)			Child Job Value (EB)		
	(1)	(2)	(3)	(4)	(5)	(6)
Parental Net Worth	0.164***	0.023***	0.015***	0.155***	0.030***	0.020***
	[0.004]	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]
Proportion mediated by child edu		0.860			0.807	
Proportion mediated by child, parental edu			0.909			0.871
R^2	0.027	0.471	0.482	0.024	0.476	0.488
Observations	67,932	67,621	67,125	67,932	67,621	67,125
High-dimensional child education FE	No	Yes	Yes	No	Yes	Yes
High-dimensional parental education FE	No	No	Yes	No	No	Yes

Notes: This table examines child and parental education as mediators of the relationship between parental net worth rank and children's labor market outcomes. Columns (1) and (4) show the total effect of parental net worth rank without education controls. Columns (2) and (5) include high-dimensional child education fixed effects (level and field of study). Columns (3) and (6) additionally include high-dimensional parental education fixed effects. Robust standard errors in parentheses. *** p<0.01.

Table A-13: Parental Net Worth and Child Outcomes: Mediation

	Child PageRank (EB)		Child Job Value (EB)	
	(1)	(2)	(3)	(4)
Parental Net Worth	0.086***	0.015***	0.090***	0.020***
	[0.004]	[0.003]	[0.004]	[0.003]
Proportion mediated by parental edu	0.476		0.419	
Proportion mediated by child, parental edu		0.909		0.871
R^2	0.102	0.482	0.081	0.488
Observations	67,442	67,125	67,442	67,125
High-dimensional child education FE	No	Yes	No	Yes
High-dimensional parental education FE	Yes	Yes	Yes	Yes

Notes: This table examines education as a mediator of the relationship between parental net worth rank and children's labor market outcomes. Columns (1) and (3) include high-dimensional parental education fixed effects. Columns (2) and (4) additionally include high-dimensional child education fixed effects (level and field of study). Robust standard errors in parentheses. *** p<0.01.

F Additional Results and Robustness

F.1 Tables for Additional Results

Table A-14: Components of Intergenerational Welfare Transmission ($\beta^{Value-Earnings}$)

	Child Job Insecurity		Child Job Flow Value	
	(1)	(2)	(3)	(4)
Rank of Family Earnings	-0.083***	-0.084***	0.104***	0.106***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.541***	0.542***	0.448***	0.447***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	66,992	66,992	66,991	66,992
R^2	0.007	0.007	0.011	0.011

Notes: Standard errors in parentheses. Columns (1)–(2) use child job insecurity (raw and EB-corrected); columns (3)–(4) use child job flow value (raw and EB-corrected). $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-15: Child Residual Job Value Rank on Family Earnings

	Dependent Variable: Child Residual Job Value	
	(1) Job Value	(2) Job Value (EB)
Rank of Family Earnings	0.067***	0.071***
	(0.004)	(0.004)
Constant	0.466***	0.465***
	(0.002)	(0.002)
Observations	66,992	66,992
R^2	0.005	0.005

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.2 Additional Results for Gender

Figure A-8: Absolute Mobility in Welfare and Earnings by Gender (Linear)

(a) Sons (b) Daughters

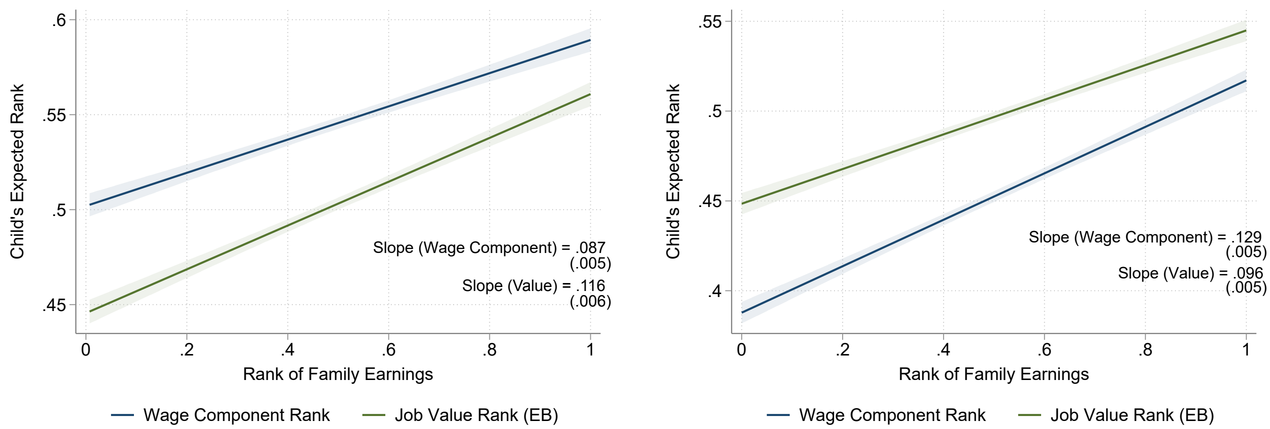
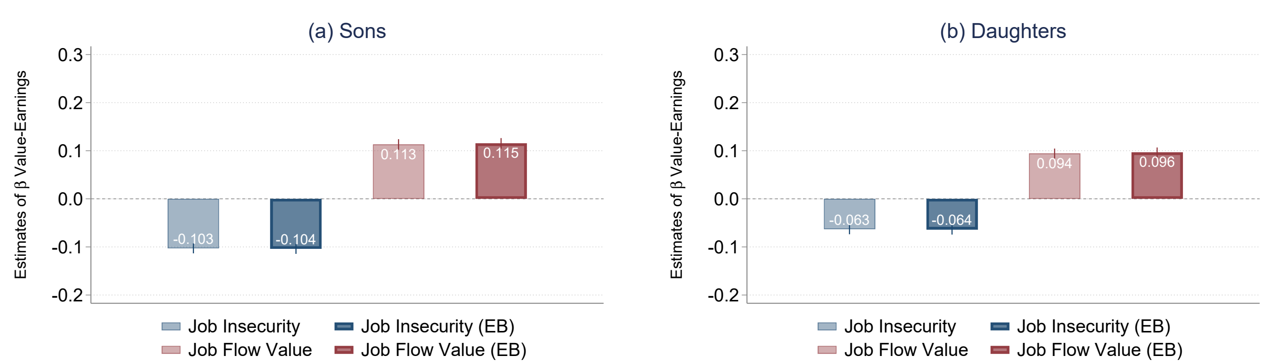


Figure A-9: Absolute Mobility in Welfare and Earnings by Gender (Non-linear)

(a) Sons (b) Daughters

Figure A-10: Components of Intergenerational Welfare Transmission ($\beta^{Value-Earnings}$)



F.3 Poaching Index

Figure A-11: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) Estimates - Poaching Index

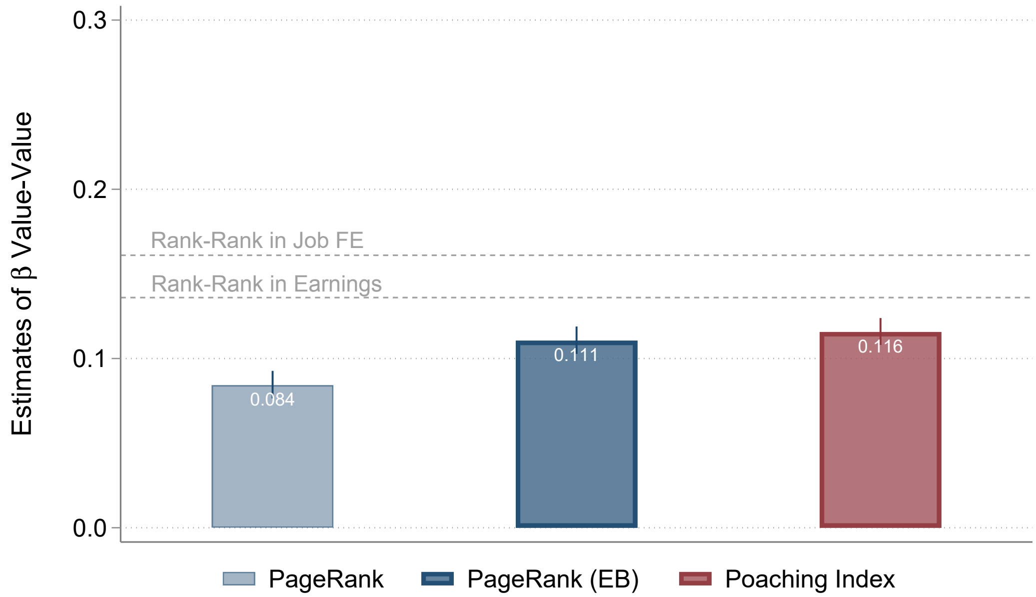


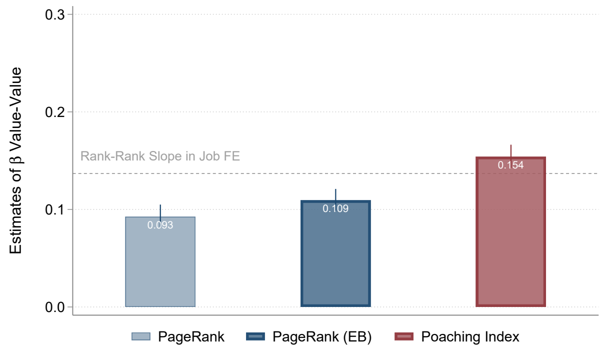
Table A-16: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) Estimates - Poaching Index

	Dependent Variable: Child Outcomes		
	(1) PageRank	(2) PageRank (EB)	(3) Poaching Index
Rank of Average Family Job Value	0.084***		
	(0.004)		
Rank of Average Family Job Value (EB)		0.111***	
		(0.004)	
Rank of Average Family Poaching Index			0.116***
			(0.004)
Constant	0.460***	0.447***	0.445***
	(0.002)	(0.002)	(0.002)
Observations	59,529	59,529	59,529
R^2	0.007	0.012	0.013
Adjusted R^2	0.007	0.012	0.013

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Figure A-12: Intergenerational Welfare Mobility ($\beta^{Value-Value}$) by Gender - Poaching Index

(a) Sons



(b) Daughters

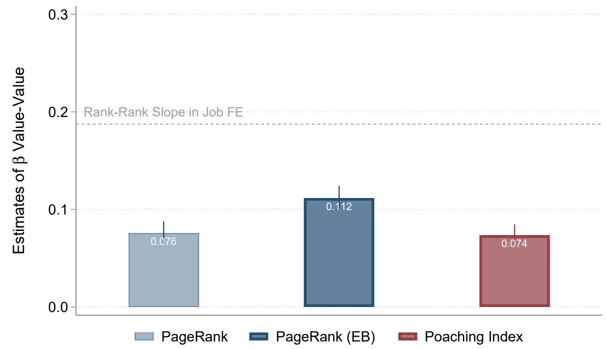


Table A-17: $\beta^{Value\text{-}Value}$ Estimates – Poaching Index, by Gender

	(1) PageRank	(2) PageRank (EB)	(3) Poaching Index
Panel A: Women			
Rank of Average Family Job Value	0.076***		
	(0.006)		
Rank of Average Family Job Value (EB)		0.112***	
		(0.006)	
Rank of Average Family Poaching Index			0.074***
			(0.005)
Constant	0.462***	0.448***	0.496***
	(0.003)	(0.004)	(0.003)
Observations	29,169	29,169	29,169
R^2	0.006	0.011	0.007
Panel B: Men			
Rank of Average Family Job Value	0.093***		
	(0.006)		
Rank of Average Family Job Value (EB)		0.109***	
		(0.006)	
Rank of Average Family Poaching Index			0.154***
			(0.006)
Constant	0.459***	0.446***	0.397***
	(0.003)	(0.003)	(0.003)
Observations	30,360	30,360	30,360
R^2	0.008	0.012	0.021

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

F.4 Heterogeneous Rankings

Table A-18: Correlation for Rankings Across Gender

Variables	(1) PageRank (women)	(2) PageRank (men)
(1) PageRank (women)	1.000	
(2) PageRank (men)	0.820	1.000

Note: $N = 66{,}992$ observations, 2010–2019 MEE.