Intergenerational Mobility in the Value of a Job*

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Abstract

Intergenerational mobility is usually measured in income, yet workers value job amenities as well as pay. We measure intergenerational mobility in the value of a job, which reflects both amenities and pay. Using a revealed preference approach, we infer the value of each job from voluntary moves in the labor market, including job-to-job transitions and quits into nonemployment. We embed this approach in a job ladder model in which workers differ in preferences and job opportunities. Weekly benefit records let us distinguish quits, which reveal preferences, from layoffs, which do not. Using Danish administrative data, we document that there is 37% less intergenerational persistence in job value than in earnings: the rank-rank slope is 0.11 in job value and 0.18 in earnings. A key reason behind this gap is that the children of high-earning parents tend to hold jobs that pay more but have worse amenities. Evidence from surveys suggests that these jobs are more demanding: they involve greater competition, longer hours, and greater time pressure.

Keywords: Intergenerational mobility, revealed preference, amenities
JEL Codes: J62, J32, J30

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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 I, Chapter X, Part I), Adam Smith (1776)

To the extent that the career outcomes of children are strongly associated with the career outcomes of their parents, this may suggest that the opportunities available to children 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] The standard approach in economics has been to measure intergenerational mobility in *income* or *earnings*. Yet, large differences in non-wage aspects of jobs, often described as amenities — such as workplace demands, autonomy and the intrinsic meaning of work — are also a central source of compensation. Furthermore, amenities may influence pay directly, generating pay differentials that compensate workers for their exposure to unpleasant conditions, resulting in workers receiving higher pay in unpleasant jobs and lower pay in pleasant jobs (Rosen, 1986).

Consequently, measures of intergenerational mobility in earnings may overstate or understate intergenerational mobility in the value of a job, which captures compensation in both pay and amenities. For instance, children from higher-earning families may move down the earnings distribution by working in jobs that pay less but offer better amenities, while children from lower-earning families move up by working in jobs that pay more but offer worse amenities. In this case, earnings-based mobility measures will overstate the degree of intergenerational mobility in the value of a job. Conversely, children from higher-earning families may be paid more in part because their jobs offer worse amenities, and children from lower-earning families may be paid less in part because their jobs offer better amenities. In this case, intergenerational mobility in earnings will understate intergenerational mobility in the value of a job. While existing work has extensively examined how earnings persist across generations, much less is known about intergenerational mobility in amenities or in the value of a job.

In this paper, we measure *intergenerational mobility in the value of a job*, which reflects both pay and amenities, in Denmark. This measure speaks to a broader question about intergenerational mobility in the labor market: to what extent do parents with good jobs have children with good jobs? To measure intergenerational mobility in the value of a job, we regress the

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

rank of children's average job value on the rank of their parents' average job value, assessing the degree to which parents with good jobs (high pay, good amenities, or both) have children with good jobs. As a natural complement to earnings-based mobility measures, the rank-rank slope in job value provides a more encompassing view of what a job offers workers.

The key challenge is that the value of a job is unobserved. While precise measures of pay are readily available, the non-pay attributes of jobs are typically unobserved by researchers. Furthermore, workers' valuations of the entire bundle of these attributes are almost never observed. Labor economics has only recently made progress on this challenge with a revealed preference approach (Sorkin, 2018; Taber and Vejlin, 2020; Arcidiacono et al., 2025). Its logic is simple: the volume and direction of worker flows between jobs reveal relative desirability. When a worker chooses between two jobs, the probability that she chooses one of them rises with the value of that job relative to the other. A job-to-job transition is a choice: the worker accepts an offer over the job that she holds. The flows of workers between two jobs are therefore informative about which of the two jobs workers value more, whether for its pay, for its amenities, or for both. Similarly, when workers decide to quit their jobs into nonemployment, they reveal how they value those jobs relative to nonemployment. Worker flows, however, reflect more than how workers value jobs. They also reflect recruiting intensity and layoff risk, which must be modeled.

To infer job values from these flows, we develop a search model: a partial-equilibrium Burdett–Mortensen model with taste shocks (Burdett, 1978; Burdett and Mortensen, 1998). The model accounts for three layers that lie between the moves we observe and the choices workers make. Each layer motivates one ingredient of our model. First, search frictions determine which jobs are available and how often offers arrive. As a result, a job that makes many offers will poach many workers, even if workers do not value it more than other jobs. To account for this, we model search frictions and capture *recruiting intensity* through the offer distribution. Second, not every separation into nonemployment is a choice. To account for *involuntary moves*, we distinguish exogenous job destruction from voluntary quits and job-to-job transitions, allowing the risk of job destruction to vary across jobs and worker types. Third, and most critically in the intergenerational mobility context, workers may not share a common ranking of jobs. To address this, we incorporate *preference heterogeneity*: we model workers as belonging to discrete types, defined by gender and education, allowing workers of different types to differ in how much they value utility from wages and in the amenity value they assign to the same job, so each type climbs its own job ladder. Our model is largely off the shelf, closely related to the frameworks of Sorkin (2018) and Arcidiacono et al. (2025).[2] What is new is how we bring the

[2]The model also captures the intergenerational transmission of worker types in the background: to the extent that children share their parents' type, for instance through education, their jobs are valued with the preferences, job-destruction risks, and offer arrival rates that we estimate for that type in their own generation.

model to the data.

The key to the revealed preference approach is that we must know *why* workers move. In our model, an employment-to-nonemployment (EN) transition occurs either because the worker is hit by a job-destruction shock or because she chooses nonemployment over remaining in her job. We refer to the first event as a layoff and to the second as a quit. Only a quit provides information about her preferences. A novelty of our approach is that we combine population-wide weekly benefit records and stated reasons for separation from the Danish Labour Force Survey (AKU) to distinguish layoffs from quits. The weekly benefit records provide the baseline classification for the full population in both generations. We classify each separation by the first benefit that the worker receives after the job ends. Workers who receive an unemployment-related benefit are classified as laid off. Workers who receive parental-leave benefits, student grants, or retirement benefits, or who receive no benefit within six months, are classified as having quit their job. We compare these labels with workers' stated reasons: around 70% of the separations that we classify as quits or layoffs match the reason stated in the AKU.

We show that the parameters of the model are identified from worker flows across jobs at different wages. First, we classify each transition from employment to nonemployment as a quit, which reflects a worker's choice, or a layoff, which reflects exogenous job destruction. We then use the endogenous moves, including quits and job-to-job transitions, to identify a PageRank score for each job–wage pair. Adjusting for how intensively each job recruits, we recover the value of each job at each wage. To identify the weight that workers place on wage utility, we assume that workers of the same type in the same job enjoy the same amenity, even though they may earn different wages. Under this assumption, the within-job quit-wage elasticity identifies this weight, because the more weight workers place on wage utility, the more strongly their quits respond to wage differences within a job. Last, we recover the amenity of each job as a residual.

We implement our approach using full-population Danish administrative records from 1985 to 2022. The population register links children to their parents, matched employer-employee records give the full labor market history of every worker, and weekly benefit records track every government transfer that an individual receives. We supplement these records with five additional sources. We use all five to measure job attributes at the occupation level. The Danish Labour Force Survey records workers' self-reported working hours, including unpaid overtime. The Work Environment and Health in Denmark survey measures workers' physical and psychosocial working conditions and their satisfaction with their jobs. Workers' compensation claims record workplace injuries and occupational diseases. The Occupational Information Network (O*NET) and the European Working Conditions Survey (EWCS), which are linked to the registers at the occupation level, measure the content of work and work activities in

each occupation. These occupation-level measures complement estimates from our revealed preference approach and help us interpret them.

We study native Danes born in 1980–1981 and their parents. We measure the value of the jobs that the children hold at ages 30–39 (2010–2019) and that their parents held in 1991–2000. To obtain these values, we estimate the model separately for the 1990s and the 2010s, each time on the prime-age working population of native Danes. The two estimation samples contain millions of voluntary moves, from which we infer the value of each job, at each wage, to each type of worker. For each generation, we define eight worker types by interacting gender with four education groups. A job is a three-digit occupation within one of twelve establishment types, which we obtain by clustering establishments on their within-establishment wage distributions, in the spirit of Bonhomme et al. (2019). We discretize wages into twelve bins.

We then use the estimated model to assign job values to the observed wage and employment histories of the parents and children. For each person, we average these values over the ten-year period. For parents, we then average over the mother and the father. We rank these averages within each generation and regress the child's job-value rank on the parents' job-value rank. The slope of this regression, the rank-rank slope in job value, provides a measure of relative mobility: how much the expected job value rank of a child changes when the parents' job value rank increases by one percentile. Local linear regressions allow the slope to differ across the parental distribution. Together, these measures provide insight into the persistence of a family's position in the distribution of job value across generations. We compute the same measures for earnings, using the same sample and the same years.

Our analysis produces three main findings. First, *there is 37% less intergenerational persistence in job value than in earnings*. The rank-rank slope is 0.111 for job value and 0.175 for earnings. The two slopes imply different gaps between the children of the highest-ranked and the lowest-ranked parents: 18 percentile points when parents and children are ranked by earnings, and 11 percentile points when they are ranked by job value.[3] The flatter slope in job value draws both tails toward the middle: children born to families at the bottom reach a higher position in the job value distribution than in the earnings distribution, while children born to families at the top reach a lower position in job value than in earnings. Put differently, a child born to parents in the bottom quintile reaches the top quintile with a probability of 13% when we rank by earnings and 16% when we rank by job value, compared with 20% under perfect mobility. Moreover, we reach a quantitatively similar conclusion when we rank workers by their utility from wages, which allows preferences for pay to differ across worker types. Our qualitative finding, that job value is less persistent than earnings, is robust to sampling error in job values: split-sample and bootstrap exercises show that the error is small. The finding is

[3]The predicted gaps are similar when we replace the linear fit with local linear regressions.

also insensitive to specification choices, including the sample from which we estimate the model and an alternative method of ranking jobs from worker flows, the PageRank approach of Sorkin (2018).

Second, *a key force behind the gap is that the children of higher-earning parents work in high-paying but demanding jobs.* We reach this conclusion in two steps. We begin by disentangling the economic forces behind our finding with a statistical decomposition of the difference between the rank-rank slopes in job value and in earnings. The decomposition is built on each worker's "rank wedge": the difference between the worker's rank in the job value distribution and the worker's rank in the earnings distribution. Higher-earning parents have children working in careers with lower rank wedges, and this term is the most important part of the gap, accounting for 70% of it. In other words, children from more advantaged families tend to hold jobs that rank higher in earnings than in job value, which suggests that the amenities of these jobs rank lower than their pay. The finding therefore suggests that a wealth channel, in which affluent children trade pay for amenities, is not the dominant force in Denmark.[4] Next, mapping this difference to occupations, we examine how entry into each occupation varies with parental earnings, how occupations rank by job value relative to earnings, and which occupational attributes are related to this difference. We find that the children of higher-earning parents disproportionately become professionals and managers, and most of these occupations rank lower by job value than by earnings. The evidence on job attributes suggests that these occupations rank lower because they tend to be more demanding. They involve longer hours, more competition, and greater time pressure: across all occupations, each of these attributes is associated with a lower rank wedge.

Third, *observed job attributes from linked surveys and registers complement our estimates.* We document the intergenerational transmission of individual job attributes. Some attributes are transmitted strongly, with rank-rank slopes of about 0.24 to 0.26, compared with 0.175 for earnings: workplace injury risk, exposure to minor injuries, and determining one's own tasks and goals. Other attributes are only weakly related across generations, with slopes between 0.04 and 0.09: layoff risk, irregular work schedules, and time pressure. To our knowledge, the persistence of exposure to injury, disease, and layoff risk between parents and children has not been documented in administrative records before. This attribute-by-attribute approach is fruitful, but it tells us little about the entire bundle of attributes that workers value: each job combines many attributes, and how workers value the bundle is not observed. Our estimated amenity addresses both limitations. It summarizes how workers value the non-pay attributes of

[4] A natural hypothesis emerges from models of job search with consumption-saving decisions. In these frameworks, workers with lower assets accept jobs with higher wages and lower amenities. Once this constraint is relaxed through an improvement in their asset position, workers substitute toward jobs with lower wages and higher amenities.

a job. Measured this way, amenities are transmitted from parents to children with a rank-rank slope of 0.109, below the slopes of the most strongly transmitted attributes.

In addition, we compare our estimated amenities with job attributes that workers regard as desirable and undesirable. Sorkin (2018) notes that he has no measures of working conditions with which to compare his estimates. The Danish data allow us to make this comparison. When we hold the job-destruction rate and the other attributes fixed, the estimated amenities are lower in occupations with more irregular schedules and more competition, and higher in occupations whose work involves more caring for others, consistent with evidence on how workers value these attributes (Flory et al., 2015; Mas and Pallais, 2017; Maestas et al., 2023).

We demonstrate the robustness of our main finding along five dimensions. First, we address the concern that job values are estimated with sampling error. We show that this error is quantitatively small. Estimating the model separately on two halves of each estimation sample, we find that the job value ranks from the two halves are highly correlated, at 0.97 for children and 0.94 for parents. A bootstrap procedure that resamples workers and re-estimates the model 100 times barely increases the standard error of the rank-rank slope in job value, from 0.0036 to 0.0038. Second, our finding is robust to alternative measures of family background: ranking families by the sum rather than the average of the parents' outcomes yields qualitatively similar results. Third, re-estimating job values using only workers in their thirties yields similar results. Fourth, we relax the assumption that every job-to-job move is a choice by allowing some moves to be involuntary through "Godfather" shocks (Jolivet et al., 2006). Fifth, we replace our estimates with an off-the-shelf ranking of jobs, the PageRank approach of Sorkin (2018). Our qualitative finding is insensitive to these choices: under each specification, intergenerational persistence in job value is lower than in earnings. Job value is between 16% and 54% less persistent than earnings, compared with 37% in our baseline estimate.

Related Literature. This paper relates to three strands of literature. First, we contribute to the literature on intergenerational mobility and its measurement.[5] The standard approach in economics measures mobility in earnings or income, using either the intergenerational elasticity (IGE), motivated by theoretical work (Becker and Tomes, 1979, 1986; Solon, 2004), or the rank-rank slope (Dahl and DeLeire, 2008; Chetty et al., 2014a; Chetty and Hendren, 2018a,b; Chetty et al., 2026). The limitation of this approach is that it abstracts from compensation in the form of amenities. Our contribution to this literature is twofold. First, we develop a measure of intergenerational mobility in the value of a job. We use a revealed-preference approach to infer how workers value jobs, including both pay and non-pay attributes. Our methodology can be applied in any country or time period for which researchers have access

[5]For reviews, see Black and Devereux (2011) and Deutscher and Mazumder (2023).

to matched employer-employee data and links between parents and children.[6] Second, using Danish administrative data, we document the intergenerational transmission of the value of a job and compare it with the transmission of earnings. We find that earnings-based measures understate intergenerational mobility in the value of a job in Denmark, which suggests that income or earnings alone give an incomplete picture of intergenerational mobility, in line with Davis et al. (2025). We view our approach as complementary to existing approaches: it provides information on a new dimension of intergenerational transmission.

Second, our paper relates to a burgeoning literature that uses frictional models of the labor market to study workers' valuation of the non-pecuniary components of jobs and the joint determination of wages and amenities (Hwang et al., 1998; Bonhomme and Jolivet, 2009; Sullivan and To, 2014; Hall and Mueller, 2018; Sorkin, 2018; Taber and Vejlin, 2020; Lamadon et al., 2024; Arcidiacono et al., 2025; Morchio and Moser, 2026).[7] Our model is largely off the shelf: it adapts the framework of Arcidiacono et al. (2025) and incorporates a feature of Sorkin (2018): workers may choose to quit into nonemployment. As in both papers, idiosyncratic taste shocks tie the probability of each voluntary move to the value of its destination relative to its origin, so that worker flows reveal how workers value jobs.[8] Our contribution to this literature is empirical: we separate voluntary quits into nonemployment from involuntary separations. The distinction allows quits to reveal workers' valuations of jobs, whereas layoffs measure job security, itself a valued attribute of jobs (Jarosch, 2023). Survey reports of why a job ended are a natural source of this information and have been used to discipline structural models of job search (Sullivan and To, 2014; Taber and Vejlin, 2020; Simmons, 2025), but they cover too few separations to measure separation risk for finely defined jobs. Administrative benefit records have been used to identify layoffs through the receipt or timing of unemployment insurance (e.g., Woodcock, 2023; Lehmann, 2023), but none of these papers classify every separation into nonemployment or check their classifications against workers' own reports for the same separations. We classify every separation into nonemployment with weekly benefit records, and we check the classification against the reasons that workers report in the Danish Labour Force Survey, which we link to the same separations. To our knowledge, no structural model of the labor market has separated voluntary quits into nonemployment from layoffs in this way.[9] We

[6]The method also benefits from information that separates quits from layoffs, such as records of unemployment benefits. Both our value-based measure and existing earnings-based measures are subject to the biases discussed in the literature, such as measurement error, transitory fluctuations, and life-cycle bias (see Deutscher and Mazumder, 2023). Mazumder (2016) and Nybom and Stuhler (2017) show that these biases are considerably smaller for rank-rank measures than for the IGE.

[7]See Mas (2025) for a review.

[8]As in the empirical specification of Arcidiacono et al. (2025), we also allow preferences, offer distributions, and job-destruction risk to differ across worker types. Section 2 describes how our model relates to these frameworks.

[9]Survey reports have also been combined with administrative records to measure the share of job-to-job moves that are involuntary (Taber and Vejlin, 2020) and to measure how many mutual-agreement terminations

also make two secondary contributions. First, we extend the firm-level approach of Sorkin (2018) to the job level, defined as three-digit occupations within establishment types. Different occupations within the same establishment can differ substantially in both pay and amenities. Second, because our estimates vary across occupations, we compare our estimated amenities with observed working conditions, a comparison that Sorkin (2018) notes he could not make.

Third, by bridging two strands of literature on intergenerational mobility and on amenities, we contribute to a growing body of work on the intergenerational transmission of features of jobs. Children of higher-earning parents are more likely to work for their parents' employers, at firms that pay higher wage premia, and in occupations with higher pay (e.g., Corak and Piraino, 2011; Dobbin and Zohar, forthcoming; Haeck and Laliberté, 2025). Each of these studies focuses on a single feature of jobs, and evidence on the transmission of job desirability as a whole remains limited. The two papers closest to ours relate broader measures of job quality to parental income: Boar and Lashkari (2025), whom we discuss at the end of this section, and Forsberg et al. (2026), who show that children of higher-earning fathers in Sweden work at firms that are both better paying and more desirable, as measured by worker flows. We extend this work in three directions. Rather than focusing on any single feature, we use worker transitions between jobs to infer the value of the entire bundle of attributes that a job offers, and we relate the value of children's jobs to that of their parents' jobs, not only to parental income. By separating this value into pay and amenities, we measure the transmission of the entire bundle of amenities. Finally, using administrative records of workplace injuries and occupational diseases, together with survey measures of working conditions, we document that a broad set of individual working conditions is transmitted across generations.

Lastly, the paper most closely related to ours is Boar and Lashkari (2025). They incorporate non-pecuniary job attributes into the measurement of intergenerational mobility and examine how parental income shapes children's access to occupations with desirable non-monetary qualities. They construct an index of occupational attributes from the General Social Survey, such as respectful treatment, opportunities to learn, and the absence of heavy lifting, and show that children of higher-income parents in the United States are more likely to work in occupations that score higher on this index. Our contribution is distinct along three dimensions. First, we use a revealed preference approach embedded in a partial-equilibrium job ladder model to infer the value of each job from workers' moves between jobs, rather than valuing a survey-based index of occupational attributes. This allows us to infer how workers value the entire bundle of attributes of each job, including unmeasured attributes, using millions of job-to-job transitions observed in high-quality administrative data. Second, we study the intergenerational transmission of both the value of a job and its amenities from parents to children. We also

in France would otherwise have been dismissals (Carry and Schoefer, 2024). Section 3.1 describes our approach.

relate the value of children's jobs to parental earnings, the comparison closest to theirs. Third, we study Denmark rather than the United States. We find more mobility in the value of a job than in earnings, whereas they find less mobility once earnings are adjusted for the quality of occupations.

Road Map. Section 2 presents our search model, a revealed preference approach to ranking jobs across worker types. Section 3 establishes identification of the model parameters. Section 4 describes our Danish administrative data and sample construction. Section 5 describes the estimation procedure and the parameter estimates. Section 6 presents our main results on intergenerational mobility in job value and earnings. Section 7 decomposes the difference between value transmission and earnings transmission and interprets our estimates in light of observed job attributes. Section 8 reports robustness checks and additional results, and Section 9 concludes.

2 A Search Model of Job Value with Worker Heterogeneity

In this section, we lay out the model that we use to measure the value of a job to workers of different types. We build on a partial-equilibrium job ladder model with random, on-the-job search that goes back to Burdett (1978): workers passively receive offers at random from an offer distribution that we take as given. We add three key features to this model: amenities, idiosyncratic preference shocks, and worker heterogeneity. We discuss each extension in turn below.

First, we allow workers to be compensated for employment in a job through wages and an amenity, which reflects the utility derived by the worker from non-wage features of the job. We assume that workers of the same type employed in the same job receive the same amenity, whereas we allow wages to be dispersed. As in Arcidiacono et al. (2025), this allows amenities to be identified separately from worker preferences for consumption. Second, following Sorkin (2018), we assume that each alternative available to a worker carries an idiosyncratic taste shock. A worker then accepts an offer with a probability that rises with the difference in value between the offered job and her own job. Accordingly, voluntary transitions reveal differences in the value of jobs at different wages. Third, we incorporate worker heterogeneity by assuming that workers belong to a discrete number of observed, permanent types. Each worker type is in its own segmented labor market as in Morchio and Moser (2026). Preferences, offers, and the risk of job destruction may all differ by type, so each type has its own job ladder. We measure the value of a job, for every type, as the gain over that type's own value of nonemployment, in units of the scale of the taste shocks, which we assume to be the same for all types. A higher

value for one type than for another therefore means that the first type gains more relative to its own value of nonemployment.

2.1 Environment

Workers. Workers are infinitely lived, risk-averse, and discount the future by the factor $\beta \in (0, 1)$. Each worker belongs to one of L types, indexed by ℓ. A worker's type is observed and permanent.[10] Every object below that carries the index ℓ may differ across types. The discount factor, the utility function and the distribution of the taste shocks are the same for all types. In each period, workers are either employed or nonemployed.[11] Workers cannot transfer resources across periods: they neither save nor borrow and consume all of their income in each period.

Jobs. There is a finite set of jobs $\mathcal{J}$, indexed by j. For a type-ℓ worker, a job j has two attributes that are fixed over time and do not vary with the wage: an *amenity* $\phi_{\ell j}$ and a *destruction probability* $\delta_{\ell j}$, the probability that the job is destroyed in a given period, in which case the worker becomes nonemployed. A job also pays a wage w, which may differ among the same type-ℓ workers who hold the same job. Conditional on worker type, an employment state is therefore a *job–wage pair* $(j, w) \in \mathcal{J} \times \mathcal{W}$.

Offers. Each worker type searches in its own labor market. Search within that labor market is random. In each period, a nonemployed type-ℓ worker receives an offer with probability λ_ℓ^0, and an employed type-ℓ worker whose job is not destroyed receives an offer with probability λ_ℓ^1, which is constant regardless of the job she holds. A worker receives at most one offer in a period. An offer is a job–wage pair (j, w) drawn from the joint offer distribution G_ℓ, which has probability mass function $g_\ell(j, w)$.[12] The worker either accepts an offer or rejects it: there is no bargaining, and employers do not counter outside offers. The joint offer distribution is the same for employed and nonemployed workers of a type. We take λ_ℓ^0, λ_ℓ^1 and G_ℓ as given.

Taste shocks. In every period, a worker draws a *taste shock* ι for each alternative that is open to her in that period: nonemployment, an offered job, or the job that she already holds, which we call her *incumbent job*. We assume all taste shocks are idiosyncratic and independently and identically distributed (i.i.d.). A taste shock captures idiosyncratic reasons to prefer an

[10] In our application, the types are the eight combinations of gender and four education groups.

[11] Nonemployment in the model covers every worker who holds no job: unemployed workers and workers who are out of the labor force for a time, for example on parental leave or in education.

[12] We can think of $g_\ell(j, w) = f_{\ell j}\, h_{\ell j}(w)$. Here $f_{\ell j}$ is the probability that the offer comes from job j, which measures how intensively job j recruits type-ℓ workers, and $h_{\ell j}(w)$ is the probability that it pays wage w given that it comes from job j; we write F_ℓ and $H_{\ell j}$ for the two distributions.

alternative that are specific to the worker at a point in time. Persistent differences in tastes among workers therefore enter the model only through worker types.[13] The taste shocks are independent across workers, alternatives and periods. They are also independent of the offers that workers receive. They follow a Type-I extreme-value distribution with location zero. Its scale is the same for all worker types and normalized to one, so the difference between two taste shocks is standard logistic. A worker observes her taste shocks for the current period before she chooses among alternatives. She does not know her future taste shocks, so her continuation value is an expectation over them.

2.2 Worker's Problem

Flow payoffs. The flow utility for a type-ℓ worker employed at job j and wage w is

$$v_{\ell j}(w) = \alpha_\ell \, u(w) + \phi_{\ell j} \tag{1}$$

where $w > 0$ is the monetary wage, $\phi_{\ell j}$ is utility from job amenities, and $\alpha_\ell > 0$ is the type-specific weight on wage utility relative to amenities, similar to Taber and Vejlin (2020) and Arcidiacono et al. (2025). The function $u(w)$ is increasing and concave. An equivalent parameterization normalizes the coefficient on wage utility to one and allows the shock scale to vary. Under that parameterization, α_ℓ is the inverse of the scale of the preference shocks.[14] While nonemployed, a worker of type ℓ receives flow utility b_ℓ, which includes unemployment benefits and the value of nonmarket time and household production.

Employed Workers. The Bellman equation for an employed worker of type ℓ in a job j with flow utility $v_{\ell j}(w)$ is:[15]

[13] Persistent differences in preferences among workers of the same type are outside our model. For our results, the main concern is that the children of higher-earning parents value a given job differently from other workers of their type. Evidence on why children work in their parents' occupations suggests that a preference for the parent's occupation plays a small role: preferences for the parent's occupation account for 9 percent of occupational persistence in the United Kingdom (Lo Bello and Morchio, 2022) and 8.5 percent in Finland (Solomon, 2026).

[14] Given that the preference shocks are drawn from a Type-I extreme-value distribution, the flow payoffs and value functions below are both measured in (normalized) units of the preference shocks; α_ℓ is the number that converts consumption utility into those units. An equivalent casting of the model instead fixes the coefficient on consumption utility at one and leaves the shock scale free; α_ℓ is reinterpreted as the inverse of the shock scale—with the caveat that amenity utilities are then measured in these rescaled units as well. See Appendix A.1 for more details.

[15] We follow Arcidiacono et al. (2025), Sorkin (2018), and the wider literature on dynamic discrete choice models by placing the idiosyncratic shock in forward-looking values rather than in the flow payoff.

$$V^e_{\ell j}(w) = \underbrace{\alpha_\ell u(w) + \phi_{\ell j}}_{\text{flow payoff}} + \beta\,\mathbb{E}\Big[\underbrace{\delta_{\ell j}\{V^n_\ell + \iota_1\}}_{\text{exogenous job destruction}} + (1-\delta_{\ell j})\Big[\underbrace{\lambda^1_\ell \sum_{(j',w')} g_\ell(j',w')\,\max\{V^e_{\ell j'}(w') + \iota_2,\; V^e_{\ell j}(w) + \iota_3\}}_{\text{offer arrives: endogenous job-to-job}} + \underbrace{(1-\lambda^1_\ell)\,\max\{V^n_\ell + \iota_4,\; V^e_{\ell j}(w) + \iota_5\}}_{\text{no offer: worker chooses stay vs. quit}}\Big]\Big] \tag{2}$$

The value that an employed worker of type ℓ receives at job j with wage w, $V^e_{\ell j}(w)$, derives from the flow payoff, $v_{\ell j}(w)$, and the expected continuation value of the job, which is discounted by β. The expectation $\mathbb{E}$ is over the next period's taste shocks, $\iota_1, \ldots, \iota_5$. The continuation value is composed of three terms, which correspond to three mutually exclusive events. The first event is the case where the worker exogenously separates into nonemployment, which occurs with probability $\delta_{\ell j}$, in which case she receives V^n_ℓ, the value of nonemployment, together with a taste shock, ι_1.[16] The second event is the case where the job survives and the worker receives an outside offer, which occurs with probability $(1-\delta_{\ell j})\lambda^1_\ell$. The probability that she draws a given (j', w') offer is $g_\ell(j', w')$, so the sum in equation (2) averages over the job–wage pairs that the offer might be. In the case where she draws this offer, the worker selects whichever of the offered job and her incumbent job grants her more utility, which is determined by the taste shock attached to each job together with the underlying value of each job. In the last case, the job survives and no offer arrives, which occurs with probability $(1-\delta_{\ell j})(1-\lambda^1_\ell)$, and the worker chooses between staying in her job and entering nonemployment.

Under the assumption that the taste shocks follow a Type-I extreme-value distribution, a worker does not know, ex ante, whether or not she would accept a (j', w') offer over her incumbent job (j, w). Instead, she expects to accept the offer with probability:

$$\mathbb{P}_{\ell, j'w'|jw} = \frac{\exp V^e_{\ell j'}(w')}{\exp V^e_{\ell j'}(w') + \exp V^e_{\ell j}(w)} \tag{3}$$

[16] Our formulation is closer to Sorkin (2018) than to Arcidiacono et al. (2025). Arcidiacono et al. (2025) attach a single standard logistic shock to accepting a newly offered job. For a binary choice, the difference between two independent Type-I extreme-value draws is standard logistic. Consequently, both formulations generate the same binary logit acceptance probability, after accounting for switching costs. Unlike Sorkin, we do not include a separate exogenous reallocation shock in our baseline specification.

Nonemployed Workers. A nonemployed worker has the Bellman equation:

$$V_\ell^n = \underbrace{b_\ell}_{\text{flow payoff}} + \beta\,\mathbb{E}\Big[\underbrace{\lambda_\ell^0 \sum_{(j',w')} g_\ell(j',w')\,\max\{V_{\ell j'}^e(w') + \iota_6,\; V_\ell^n + \iota_7\}}_{\text{offer arrives: worker chooses job vs. remain nonemployed}} + \underbrace{(1-\lambda_\ell^0)\{V_\ell^n + \iota_8\}}_{\text{no offer}}\Big]. \tag{4}$$

The value that a nonemployed worker receives, V_ℓ^n, derives from two sources: the flow value of nonemployment, b_ℓ, and the expected continuation value of nonemployment. In the next period, she may receive an offer, which occurs with probability λ_ℓ^0, and she decides to accept or reject it based on the realization of the taste shocks together with the underlying values of the offered job and of nonemployment. In this case, the probability that the offer is (j', w') is the same as for the employed worker, $g_\ell(j', w')$, as the offer distribution is assumed to be common to nonemployed and employed workers of the same type. If no offer arrives, which occurs with probability $1 - \lambda_\ell^0$, she remains nonemployed and draws a new taste shock.

Using the same assumption on the taste shocks, we can write down the probability that a worker accepts an offer (j, w) out of nonemployment as:

$$\mathbb{P}_{\ell,jw} = \frac{\exp V_{\ell j}^e(w)}{\exp V_{\ell j}^e(w) + \exp V_\ell^n} \tag{5}$$

2.3 Discussion of Model Assumptions

We discuss some of our more restrictive modeling assumptions and their implications. See Appendix A.2 for details.

2.3.1 Key Assumptions

Assumption 1 (Fixed job-level amenities)**.** *For a given worker type, $\phi_{\ell j}$ is constant across the wage cells of job j.*

This assumption makes within-job wage dispersion informative about α_ℓ, which governs the preference weight type-ℓ workers place on wage utility relative to amenities. Wage utility varies across wage cells within a job, while the amenity component remains fixed. We develop this identification argument in the next section.

Assumption 2 (Common joint offer distribution)**.** *Conditional on worker type, employed and nonemployed workers draw job–wage offers from the same joint offer distribution G_ℓ.*

Conditional on worker type, employed and nonemployed workers draw from the same joint distribution of job and wage offers, although their offer-arrival rates may differ. This restriction allows hires from nonemployment to discipline the distribution of offers faced by employed workers.

Assumption 3 (Common taste-shock scale)**.** *There exists a scalar $\sigma > 0$ such that, for every worker type ℓ, alternative, and choice occasion, the Type-I extreme-value taste shocks have scale σ. Equivalently, $\sigma_\ell = \sigma$ for every worker type ℓ.*

Normalization 1 (Shock scale)**.** *We normalize the common taste-shock scale to one, $\sigma = 1$.*

Normalization 2 (Value location)**.** *For each worker type, we set the value of nonemployment to zero, $V_\ell^n = 0$.*

Worker flows identify differences in choice-specific values within each worker type, but not their scale or location. Assumption 3 imposes a common taste-shock scale across worker types, and Normalization 1 sets this scale to one. Therefore, all type-specific value functions are measured in the same taste-shock units. Normalization 2 sets $V_\ell^n = 0$ for every worker type. Employment values can therefore be compared across types as gains relative to each type's nonemployment value.

2.3.2 Exogenous Job-to-Job Reallocation

The model allows for exogenous job destruction but not exogenous reallocation shocks. Conditional on survival of the incumbent job, a worker moves directly to another job-wage pair only after receiving an outside offer and choosing it over the incumbent job. Unlike a one-dimensional wage ladder, our model can nevertheless accommodate wage-decreasing job-to-job (EE) transitions: a worker may prefer a lower-paying destination because it offers better amenities or because an idiosyncratic taste realization favors it. Separating choice-based from forced EE transitions would require auxiliary restrictions because observed worker flows do not reveal whether the incumbent job remained available.[17] We therefore interpret observed EE transitions as endogenous choices that are informative about the relative values of the origin and destination jobs.

[17] Sorkin (2018) uses employer growth as auxiliary information, assigning exogenous weights to excess separations at contracting employers. We do not adopt this classification in our baseline because employer growth does not directly reveal whether the incumbent job remained available. Section 8.1.4 reports estimates from a version of the model that adopts it.

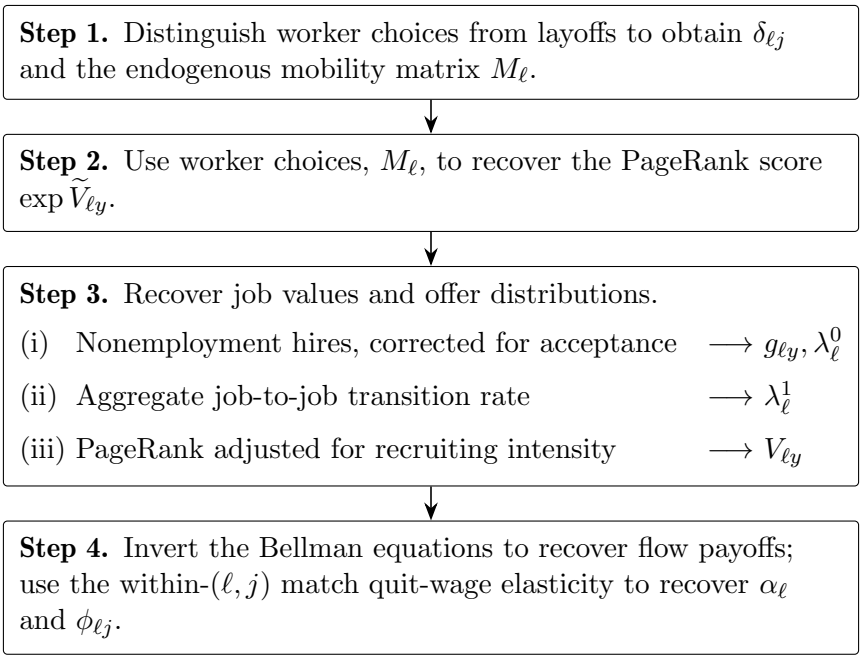
3 Identification

This section shows constructively that matched employer-employee data identify every parameter of the model, given two calibrated parameters and two normalizations.

The argument proceeds in four steps. Step 1 separates exogenous layoffs from endogenous quits, which identifies the destruction probabilities $\delta_{\ell j}$ and the endogenous mobility matrix M_ℓ. Step 2 uses the endogenous mobility matrix to recover the PageRank score of every job–wage pair. Step 3 recovers job values and the offer distribution: for each possible value of λ_ℓ^1, we recover the implied employment values, the joint job–wage offer distribution, and the offer-arrival probability for nonemployed workers; we then use aggregate job-to-job mobility to select λ_ℓ^1. Step 4 inverts the Bellman equations to recover the flow payoff of every job–wage pair and of nonemployment, and then uses the within-job quit-wage elasticity to identify the preference weight on wages and separate wage utility from job amenities. Every step is performed within worker type. Figure 1 summarizes the argument.

Steps 2 and 3 adapt the revealed preference argument of Sorkin (2018) to a setting with worker heterogeneity. Step 4 follows Arcidiacono et al. (2025) in using variation in wages within a job to separate wage utility from amenities. Unlike them, we recover these differences from quits into nonemployment, a margin their model does not have.

Figure 1: Overview of the Identification Argument



Notes: We denote a job–wage pair by $y \equiv (j, w)$.

Calibrated parameters and normalizations. There are two exogenously set parameters in our framework. First, the discount factor is $\beta = 0.95$ at an annual frequency. Second, we parameterize $u(\cdot)$ as CRRA with risk aversion parameter γ,

$$u(w) = \begin{cases} \dfrac{w^{1-\gamma}}{1-\gamma}, & \gamma \neq 1, \\ \log w, & \gamma = 1. \end{cases}$$

We set $\gamma = 1$.

3.1 Step 1: Identifying Exogenous and Endogenous Separations

Step 1 separates observed employment-to-nonemployment (EN) transitions into layoffs, which identify the destruction probabilities $\delta_{\ell j}$, and quits, which reflect the choices of workers. We obtain the worker-type, job-specific destruction probabilities $\delta_{\ell j}$, together with the endogenous mobility matrix M_ℓ. First, we classify employment-to-nonemployment (EN) transitions as involuntary or voluntary separations. We then use the implied involuntary separation rate to set $\delta_{\ell j}$, collecting the remaining voluntary separations, hires from nonemployment, and job-to-job moves in the endogenous mobility matrix M_ℓ.

The distinction between exogenous and endogenous separations is central to our identification. In our model, EN transitions may occur either because the worker is hit by a job destruction shock or because she chooses nonemployment over remaining in the job. We refer to the first event as a layoff and to the second as a quit. A layoff leaves the worker no choice, so only a quit provides information about her preferences. We assume that every job-to-job transition is endogenous.[18] Separating quits from layoffs is therefore sufficient to determine which moves reveal the values of jobs.

To formalize the construction, fix an observed worker type ℓ and treat every object below as type-specific. For ease of notation, we denote a job–wage pair by $y \equiv (j, w)$, $V_{\ell y} \equiv V^e_{\ell j}(w)$, and $g_{\ell y} \equiv g_\ell(j, w)$. The state space $\mathcal{A}$ comprises the nonemployment state n and the job–wage pairs y.[19] The matched employer-employee panel records the employment mass $N_{\ell y}$ at each pair, the nonemployment mass N^n_ℓ, and every dated transition between states. The EN transitions, however, mix exogenous separations which are forced on the worker and voluntary transitions chosen by the worker. Distinguishing them is where we begin.

A novelty of our approach is to combine population-wide weekly benefit records and stated

[18] Section 8.1.4 relaxes this assumption by allowing for involuntary job-to-job moves.

[19] We retain a state if it belongs to the largest set of job–wage pairs that is strongly connected through job-to-job moves and receives at least one hire from nonemployment. Appendix D.3.2 states the support conditions.

separation reasons from the Danish Labour Force Survey (AKU) to distinguish exogenous layoffs from endogenous quits. In the estimation section, we lay out the rules used to classify separations with administrative benefit records and explain the underlying reasons for these rules. Importantly, our identification argument does not require perfect classification accuracy.

Assumption 4 (Offsetting classification errors)**.** *For every worker type ℓ and job–wage pair y, the expected number of EN transitions from y that are generated by exogenous destruction but labeled quits equals the expected number of endogenous EN transitions from y that are labeled layoffs.*

Assumption 4 allows any single EN transition to be misclassified, in either direction. A laid-off worker may enroll in education with a student grant so that her separation is labeled a quit. A worker who resigns without a valid reason may claim unemployment insurance after a waiting period of a few weeks, and her separation is then labeled a layoff. The assumption requires only that the two kinds of error occur equally often, in expectation, at each job–wage pair. In expectation, the number of transitions labeled layoffs then equals the number generated by destruction, and the number labeled quits equals the number of quits. Step 1 uses the labels only through these two counts.[20] Under Assumption 4, transitions labeled layoffs measure job destruction on average, and transitions labeled quits measure quits into nonemployment on average. The endogenous mobility matrix M_ℓ collects all job-to-job transitions, hires from nonemployment, and quits into nonemployment, excluding layoffs.[21]

Proposition 1 (Quit, layoff rates and endogenous flows)**.** *Under Assumption 4, for each worker type ℓ, the job-specific destruction probabilities $\delta_{\ell j}$ and the endogenous mobility matrix M_ℓ are identified from observed transitions.*

Proof. See Appendix B.2.1. □

Proposition 1 completes Step 1. The destruction probabilities $\delta_{\ell j}$ and the endogenous mobility matrix M_ℓ are identified, while the state masses and person-period counts are directly observed. All are treated as known hereafter.

[20] The assumption concerns the labels that we use in estimation: the label based on benefit records, which the stated reason replaces for transitions matched to the AKU. For the destruction probabilities, the errors need to offset only within each job because $\delta_{\ell j}$ does not vary with the wage. Appendix B.2.1 states both conditions formally.

[21] Appendix B.2.1 gives the formal definitions.

3.2 Step 2: Recover the PageRank Score

In Step 2, we use endogenous worker flows M_ℓ from Step 1 to recover the PageRank score of every job–wage pair. The model maps the primitives into the three endogenous flows:

$$\underbrace{M^\ell_{y\to n}}_{\substack{\text{flow from } y\\ \text{to nonemployment}}} = \underbrace{N_{\ell y}}_{\substack{\text{employed workers}\\ \text{at origin}}} \underbrace{(1-\delta_{\ell j})}_{\text{job survives}} \underbrace{(1-\lambda^1_\ell)}_{\text{no offer arrives}} \underbrace{\frac{1}{1+\exp V_{\ell y}}}_{\substack{\text{nonemployment}\\ \text{is chosen}}} \tag{6}$$

$$\underbrace{M^\ell_{n\to y}}_{\substack{\text{flow from nonemployment}\\ \text{to } y}} = \underbrace{N^n_\ell}_{\substack{\text{nonemployed}\\ \text{workers}}} \underbrace{\lambda^0_\ell g_{\ell y}}_{\text{offer of } y} \underbrace{\frac{\exp V_{\ell y}}{1+\exp V_{\ell y}}}_{\text{offer is accepted}} \tag{7}$$

$$\underbrace{M^\ell_{y\to y'}}_{\substack{\text{flow from } y\\ \text{to } y'}} = \underbrace{N_{\ell y}}_{\substack{\text{employed workers}\\ \text{at origin}}} \underbrace{(1-\delta_{\ell j})}_{\text{job survives}} \underbrace{\lambda^1_\ell g_{\ell y'}}_{\text{offer of } y'} \underbrace{\frac{\exp V_{\ell y'}}{\exp V_{\ell y'}+\exp V_{\ell y}}}_{\text{offer is accepted}} \tag{8}$$

for every destination $y' \neq y$. Equations (6) and (7) impose the location normalization from Normalization 2. The three equations represent a quit into nonemployment, a hire from nonemployment, and a job-to-job move, respectively.

To connect worker flows to values, we compare the flow in equation (8) with the flow in the opposite direction. The common job arrival probability and the logit denominators cancel. What remains depends on values, offer shares, and effective sizes, which we summarize with the PageRank score of a job–wage pair:

$$\underbrace{\exp \widetilde{V}_{\ell y}}_{\text{PageRank score}} \equiv \underbrace{\frac{g_{\ell y} \exp V_{\ell y}}{N_{\ell y}(1-\delta_{\ell j})}}_{\text{offer} \times \text{ value } / \text{ effective size}} \tag{9}$$

where $\exp \widetilde{V}_{\ell y}$ is the PageRank score of a job–wage pair. It combines the underlying value of a job at a particular wage with its offer share and effective size.[22] Relative flows then equal relative PageRank scores:[23]

$$\underbrace{\frac{M^\ell_{y\to y'}}{M^\ell_{y'\to y}}}_{\text{relative flows}} = \underbrace{\frac{\exp \widetilde{V}_{\ell y'}}{\exp \widetilde{V}_{\ell y}}}_{\text{relative PageRank scores}} \tag{11}$$

[22] For flows between employment and the nonemployment state, an analogous derivation applies; we can derive

$$\exp \widetilde{V}_\ell{}^n \equiv \frac{1-\lambda^1_\ell}{\lambda^0_\ell N^n_\ell} \tag{10}$$

We provide more details in Appendix B.4.

[23] Appendix B.3 gives the intermediate steps.

Following Sorkin (2018), these pairwise comparisons can be combined into a recursion that recovers PageRank scores jointly across the mobility network. Summing the pairwise flow relations over destinations yields:

$$\underbrace{\exp \widetilde{V}_{\ell y}}_{\text{PageRank score}} = \frac{\overbrace{\sum_{y' \neq y} M^{\ell}_{y' \to y} \exp \widetilde{V}_{\ell y'} + M^{\ell}_{n \to y} \exp \widetilde{V}^{n}_{\ell}}^{\text{score-weighted endogenous inflows}}}{\underbrace{\sum_{y' \neq y} M^{\ell}_{y \to y'} + M^{\ell}_{y \to n}}_{\text{endogenous outflows}}}. \tag{12}$$

The PageRank score of a job–wage pair equals its score-weighted endogenous inflows divided by its total endogenous outflows. Inflows from job–wage pairs with higher PageRank scores receive greater weight. This is the recursive logic behind the PageRank interpretation: each job–wage pair is valued according to the scores of the states from which it attracts workers, relative to its endogenous outflows. An analogous relation determines the PageRank score of nonemployment.

Let $\exp \widetilde{V}_{\ell}$ stack the PageRank scores of all employment states and nonemployment in $\mathcal{A}$. The recursions can be written jointly as

$$S_{\ell}^{-1} M_{\ell} \exp \widetilde{V}_{\ell} = \exp \widetilde{V}_{\ell}, \tag{13}$$

where S_{ℓ} is diagonal, with each diagonal entry equal to the total endogenous outflow from the corresponding state.

Proposition 2 (Identification of PageRank scores)**.** *For each worker type ℓ, suppose the flow equations (6)–(8) hold and the endogenous mobility network is strongly connected. Then M_{ℓ} identifies the vector of PageRank scores $\exp \widetilde{V}_{\ell}$ up to a common positive scale. This vector is the unique positive eigenvector, up to scale, of $S_{\ell}^{-1} M_{\ell}$ associated with eigenvalue one.*

Proof. See Appendix B.3. □

3.3 Step 3: Recover Job Values and Offer Distribution

At this point, the employment and nonemployment masses, the destruction probabilities, the endogenous mobility matrix, and the PageRank scores are known. In Step 3, we jointly identify the remaining unknowns: the employment values $V_{\ell y}$, the offer shares $g_{\ell y}$, and the two arrival probabilities, λ^0_{ℓ} and λ^1_{ℓ}.

We proceed in three parts. First, for any possible value of λ_ℓ^1, we can recover employment values and their implied acceptance probabilities. Second, combining these probabilities with the observed hire flows then recovers the joint offer shares and λ_ℓ^0. Third, the observed aggregate level of job-to-job mobility pins down λ_ℓ^1.

Job values for a given λ_ℓ^1. Fix a candidate value of $\lambda_\ell^1 \in \Lambda_\ell$.[24] The PageRank score and hires from nonemployment recover job values,

$$1 + \exp V_{\ell y}(\lambda_\ell^1) \;=\; (1-\lambda_\ell^1)\,\frac{\exp \widetilde{V}_{\ell y}}{\exp \widetilde{V}_\ell^{\,n}}\,\frac{N_{\ell y}\,(1-\delta_{\ell j})}{M_{n\to y}^{\ell}}. \tag{14}$$

Every remaining object on the right-hand side of equation (14) is known once λ_ℓ^1 is specified. Then, we can recover $V_{\ell y}(\lambda_\ell^1)$ using the above equation.

Offer shares and λ_ℓ^0. Let $\mathbb{P}_{\ell y}(\lambda_\ell^1) = \exp V_{\ell y}(\lambda_\ell^1)/(1+\exp V_{\ell y}(\lambda_\ell^1))$ be the probability of accepting an offer of y from nonemployment. Given that employed and nonemployed workers draw from the same offer distribution, we obtain

$$g_{\ell y}(\lambda_\ell^1) = \frac{M_{n\to y}^{\ell}}{N_\ell^n\,\lambda_\ell^0(\lambda_\ell^1)\,\mathbb{P}_{\ell y}(\lambda_\ell^1)}, \qquad \lambda_\ell^0(\lambda_\ell^1) = \frac{1}{N_\ell^n}\sum_y \frac{M_{n\to y}^{\ell}}{\mathbb{P}_{\ell y}(\lambda_\ell^1)} \tag{15}$$

The relative distribution of hire flows across job-wage pairs identifies the joint offer shares, while its total level identifies the offer-arrival probability from nonemployment.

Selecting λ_ℓ^1. All recovered objects depend on the candidate λ_ℓ^1. We select it by matching the aggregate job-to-job transition rate:

$$\underbrace{\frac{1}{N_\ell}\sum_y \sum_{y'\neq y} M_{y\to y'}^{\ell}}_{\text{observed aggregate job-to-job transition rate}} = \lambda_\ell^1 \sum_y \frac{N_{\ell y}}{N_\ell}\,(1-\delta_{\ell j}) \sum_{y'\neq y} g_{\ell y'}(\lambda_\ell^1)\,\mathbb{P}_{\ell,y'|y}(\lambda_\ell^1). \tag{16}$$

where $\mathbb{P}_{\ell,y'|y}$ denotes the probability that a worker at y accepts an offer of y', evaluated at the candidate value of λ_ℓ^1, and $N_\ell \equiv \sum_y N_{\ell y}$ denotes total beginning-of-period employment. The left-hand side is the observed aggregate job-to-job transition rate for type-ℓ workers. The right-hand side is its model-implied counterpart: the employment-share weighted average of job-to-job transition probabilities. Both the offer shares and acceptance probabilities vary with λ_ℓ^1. Constructively, this is a search over a grid of candidate values of λ_ℓ^1: each candidate implies

[24] The admissible set is defined in Appendix B.4.3.

an aggregate job-to-job transition rate, and we select the candidate that matches the observed one.[25]

Proposition 3 (Joint Identification of Job Values and Offer Distribution)**.** *Fix a worker type ℓ and suppose that Assumptions 2, 3, 4, and A.5, and Normalizations 1 and 2 hold. Suppose $M^{\ell}_{y\to n} > 0$ and $M^{\ell}_{n\to y} > 0$ for every employment node, so the mobility graph is strongly connected through nonemployment. Then the endogenous histories jointly identify $V_{\ell y}$, the joint offer shares $g_{\ell y}$, λ^0_ℓ, and λ^1_ℓ.*

Proposition 3 identifies the value of employment relative to nonemployment, the joint offer shares, and the two arrival probabilities. The search block is now in hand. It is worth noting that we never invoke the specific parametric structure of the flow payoff in recovering any parameters in this block. Next, we turn to the structure of the Bellman equations and within-job variation to separate wage utility from amenities.

3.4 Step 4: Separating Wage Utility and Amenities

In the final step, we separate the flow value of a job into wage utility and flow amenities. We proceed in three parts. First, we invert the Bellman equations to recover the flow payoff of every job–wage pair. Second, we use the within-job quit-wage elasticity to identify the preference weight on wages, α_ℓ. Third, we recover job amenities, $\phi_{\ell j}$, as a residual.

Bellman Inversion. The flow payoff for employed workers is identified by inverting equation (2), since both components on the right-hand side are known:

$$v_{\ell j}(w) = V^e_{\ell j}(w) - \beta\, C_{\ell j}(w) \tag{17}$$

where $C_{\ell j}$ denotes the expected continuation value in equation (2). The same inversion applied to nonemployment, under $V^n_\ell = 0$, gives

$$b_\ell = -\beta\, C^n_\ell \tag{18}$$

where C^n_ℓ is the expected continuation value in equation (4).

The within-job quit-wage elasticity. The identification of the two remaining unknowns, the preference weight on wages α_ℓ and job-level amenities $\phi_{\ell j}$, uses both the parametric structure of

[25] We maintain that equation (16) has a unique admissible root, so that the procedure selects a unique value of λ^1_ℓ, thereby identifying the arrival probabilities. Appendix B.4.3 states the assumption formally and discusses the case of multiple roots.

the flow payoffs and within-job wage variation. We also use the assumption that, conditional on worker type, amenities are constant across wage cells within a job. We leverage the within-job quit-wage elasticity to identify the preference weight, α_ℓ. Holding the job fixed, a higher wage raises the value of remaining employed and therefore lowers the probability that a worker quits into nonemployment. How sharply quit propensities decline with wages reveals the weight the worker attaches to wage utility relative to job amenities.[26]

Let $m_{\ell y} \equiv (1-\delta_{\ell j})(1-\lambda^1_\ell)(1-\mathbb{P}_{\ell y})$ denote the voluntary quit probability: the probability that the match survives exogenous destruction, no outside offer arrives, and the worker chooses nonemployment over remaining on the job. Holding outside opportunities fixed, when $u(w) = \log w$, the wage gradient of quit log odds within a job satisfies

$$\frac{\partial \log[m_{\ell y}/(1-m_{\ell y})]}{\partial \log w} = -\alpha_\ell \underbrace{\mathbb{P}_{\ell y} \frac{A_{\ell y}}{1-m_{\ell y}}}_{\text{known}} \tag{19}$$

where $1-m_{\ell y}$ is the probability of not quitting and $A_{\ell y}$ is the annuity factor that capitalizes a one-period payoff gain over the expected duration of the incumbent employment relationship.[27] Everything in equation (19) is known except α_ℓ: the within-job response of quit log odds to wages identifies α_ℓ.

Amenities as a residual. Once α_ℓ is identified, the amenity of every job with an identified flow payoff follows as a residual:

$$\phi_{\ell j} = v_{\ell j}(w) - \alpha_\ell u(w). \tag{20}$$

A job need not itself contain multiple wage cells for its amenity to be identified: the common type-specific coefficient α_ℓ can be recovered from within-job wage variation elsewhere in that type's labor market. These restrictions provide a constructive identification argument.

Proposition 4 (Constructive identification)**.** *Fix a worker type ℓ and suppose the conditions of Proposition 3 and Assumption 1 hold, and that at least one job has two populated wage cells $w \neq w'$ and $u(w) \neq u(w')$. Then the observed histories identify $\delta_{\ell j}$, $V^e_{\ell j}(w)$, G_ℓ, λ^0_ℓ, λ^1_ℓ, $v_{\ell j}(w)$, α_ℓ, $\phi_{\ell j}$, and b_ℓ.*

Proof. See Appendix B.5.3. □

[26] This is not the only way to identify α_ℓ. Appendix B.5.2 develops an alternative which works directly with the flow payoffs. We emphasize the method of quit–wage elasticity here because it maps directly into the empirical moment used in estimation.

[27] Formally, $A_{\ell y} = \mathbb{E}\Big[\sum_{t=0}^{\infty} \beta^t \, \mathbf{1}\{\text{incumbent relationship survives through period } t\}\Big]$. Appendix B.5.2 derives equation (19), and Section 5.2.3 states the regression that delivers its left-hand side.

Reference point and units. Like job values, amenity levels are identified only relative to a reference point. We take nonemployment as this reference point for each worker type. This means that $\phi_{\ell j}$ captures everything in the flow payoff of job j, relative to nonemployment, that the wage does not account for. The amenity is thus net of the value of nonemployment to a worker of type ℓ, which includes benefits, nonmarket time, household production and the prospect of job offers. As in Lamadon et al. (2024), who also measure jobs relative to unemployment, differences in amenities across worker types also reflect differences in the value of nonemployment. Measuring wages in another unit, or relative to the mean wage of each type, would leave choices and job values unchanged, but it would move part of each type's flow payoff between wage utility and amenities.

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 the value of a job, highlighting institutional features that make non-wage job attributes particularly salient. We then describe our administrative and survey data and outline our sample construction.

4.1 Modern Danish Welfare State

Reducing inequality and promoting social mobility are central objectives of the modern Danish welfare state. After taxes and transfers, income inequality is substantially lower and intergenerational income mobility is higher in Denmark than in the United States. One distinctive feature of Denmark is the high level of social services: universal health care, free college tuition, equal per-pupil expenditures across all neighborhoods, and generous childcare and maternity leave policies. A key implication of this distinction is that, in Denmark, there is limited scope for variation in access to childcare, parental leave, health insurance or tuition subsidies across employers, unlike in the United States: job amenities in Denmark have a different character than in the United States. It is important to note that the equal provision of these social services, together with high rates of redistribution, does not imply that Denmark has high rates of intergenerational mobility in outcomes. In particular, intergenerational persistence in educational attainment and net wealth is substantial (Landersø and Heckman, 2017; Boserup et al., 2014; Karlson and Landersø, 2025).

The Danish labor market further motivates examining the total compensation of a job beyond earnings. Progressive taxation (40–55%) compresses pay differentials across the earnings distribution. Collective bargaining agreements covering 84% of workers also serve to compress

pay differentials, by establishing minimum standards for wages, working hours, and workplace conditions (Dansk Industri, 2024). Yet employers retain significant discretion to offer terms exceeding these minimums, facilitated by both firm-level negotiations with union assistance and individual negotiations, particularly for high-skilled workers (Dahl et al., 2013; Kreiner and Svarer, 2022; Humlum et al., 2025b). Critically, while workers' monetary compensation faces high marginal tax rates, non-wage amenities remain largely untaxed. This may create incentives for both employers and workers to shift compensation toward non-pecuniary job attributes (Bagger et al., 2021). This asymmetry, where monetary compensation is taxed but amenities are largely untaxed, makes Denmark a particularly informative setting for studying the intergenerational transmission of job value.

4.2 Data

We use full-population administrative register data from Denmark from 1985 to 2022. The data contain unique individual identifiers, which enable us to combine information on a wide range of aspects of life over individuals' lifetimes. Unique identifiers of parents and spouses allow us to link families throughout the entire period. In addition to information on income, assets, and liabilities for both parents and children, we add information on completed education, household structure, and demographic characteristics.

Matched Employer–Employee Data. We use two matched employer–employee data sources. From 2008 onwards, we use the *Employment Statistics of Employees* (BFL), which records job spells, occupation codes, and hours worked for all employees in Denmark, linked to their employing establishment and firm. For 1985–2007, we construct spell-level data from employers' mandatory salary reports (*Oplysningssedler*, CON), following the procedure of the Labour Market Dynamics Group at Aarhus University (Hejlesen, 2016), which assigns a firm and establishment identifier, along with a start date and an end date, to each employment spell over 1985–2014.

Work Accidents and Occupational Diseases. Our data on work injuries come from Arbejdsmarkedets Erhvervssikring (AES), the entity responsible for handling injury claims under the Workers' Compensation Act of Denmark. The register distinguishes two types of claims: a work accident (*arbejdsulykke*), defined as a sudden, unexpected event during work that causes injury; and an occupational disease (*erhvervssygdom*), defined as a condition that develops from prolonged exposure to harmful workplace conditions. As an example, a fall from scaffolding is a work accident, whereas hearing loss developed due to years of exposure to factory noise is an occupational disease. For each claim, the register records the nature and timing of the injury,

the assessed loss of earning capacity and the degree of permanent impairment.

Government Transfers. The *Danish Register for Evaluation of Marginalization* (DREAM) records social transfers to individuals at the weekly level, including benefits for disability, rehabilitation, education, unemployment, and public pensions. This register records benefit receipt rather than eligibility itself. DREAM retains only one benefit category per person-week; overlapping benefits are resolved using a predetermined priority ordering.[28]

Danish Labour Force Survey (AKU). The *Danish Labour Force Survey* (AKU) is a quarterly survey conducted by Statistics Denmark as part of the harmonized European Labour Force Survey. The survey covers individuals aged 15–74 in a rotating panel, and we use waves from 2010 to 2019 (Statistics Denmark, 2026c). We use the AKU in two ways. First, it refines and checks our classification of employment-to-nonemployment (EN) transitions as quits or layoffs. In the AKU, survey respondents who are nonemployed report why their last job ended. This enables us to compare stated reasons for separation against our benefit-based classification of EN transitions. For the small subset of EN transitions that we can match to a response, the AKU also enables us to refine our classification directly (Section 5.2.1). Second, we compute occupation-level averages of workers' responses about their work schedules, usual and actual weekly hours, paid and unpaid overtime, and desired hours.[29] We then relate these measures to our model estimates of job amenities.

Work Environment and Health in Denmark (WEHD). The *Work Environment and Health in Denmark* survey (WEHD) was conducted every two years by the National Research Center for the Working Environment from 2012 through 2018. It surveyed workers about their physical and psychosocial working conditions and self-reported health.[30] Similar to the AKU, we use the WEHD to compute occupation-level averages of workers' responses about their working conditions, including work schedules, physical demands, autonomy, job insecurity, and relationships with managers and colleagues (Det Nationale Forskningscenter for Arbejdsmiljø, 2018). We relate these observed job attributes to our model estimates of job amenities.

Occupation-Level Job Attributes. We measure occupation-level work content and work activities using the *Occupational Information Network* (O*NET). We select a set of individually

[28] More details are provided in Section 5.2.1.

[29] These complement administrative paid hours, which may reflect contractual hours rather than actual time worked, particularly for salaried employees working unpaid overtime (Statistics Denmark, 2026d; Lachowska et al., 2022; Humlum et al., 2026).

[30] The published cohort includes 88,076 individuals who responded at least once, with personal identifiers enabling linkage to administrative registers (Sørensen et al., 2025).

interpretable occupation-level characteristics, including physical work conditions, interpersonal interactions, and work content, mapped to Danish occupations.[31] We complement O*NET with the *European Working Conditions Survey* (EWCS, 1991–2024), with average worker-reported conditions by two-digit occupation for the Nordic countries (Denmark, Finland, Norway, and Sweden), whose labor market institutions are similar.

4.3 Main Sample

We study the intergenerational transmission of job value 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; 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.[32]

IGM Sample. Our base dataset includes all native Danes born in 1980–1981 who can be linked to at least one parent in the administrative records. 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. 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 identify voluntary job-to-job transitions from the BFL. For parents, we derive the same transitions from the CON-based employment spells introduced above. We restrict the sample to native Danes and focus on their labor market transitions post-education. For each individual, we follow the primary job and exclude 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 with the intergenerational transmission of earnings.[33]

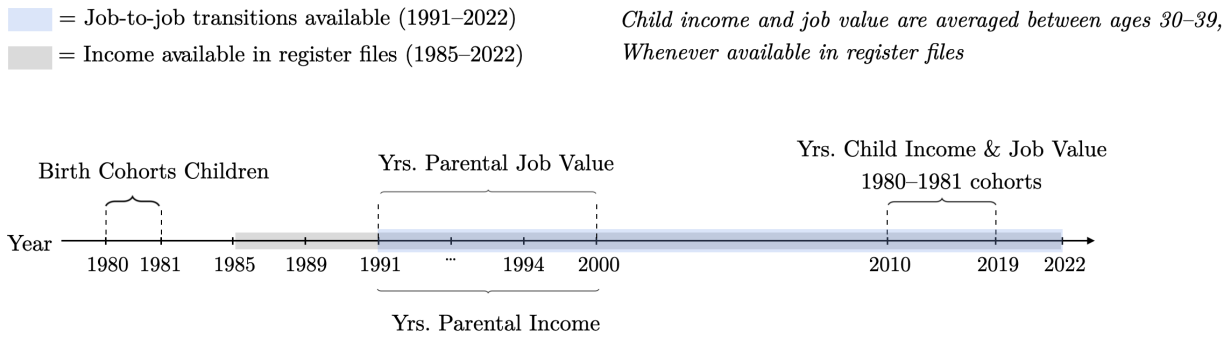
Figure 2 illustrates the data availability and measurement windows for our IGM-Job sample. For each generation, we measure income and job value over the same window. All parental measures, including job value, earnings, pre-tax income, and disposable income, are measured

[31] We link O*NET to Danish ISCO codes using the IBS crosswalk (Institute for Structural Research , IBS) developed by Hardy et al. (2018).

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

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

Figure 2: Data Availability and Our Sample of Parents and Children



Notes: This figure illustrates data availability and measurement windows for our IGM-Job sample. Parental income and job value are both measured over 1991–2000, when parents are in their 30s and 40s. Children's income and job value are both measured at ages 30–39 (2010–2019). All measures are averaged over the available years within their respective windows.

over 1991–2000, when parents are in their 30s and 40s. All child measures are measured when children are aged 30–39, from 2010 to 2019.[34] Throughout the analysis, all monetary variables are converted to 2022 Danish Kroner (DKK).[35]

For parental earnings, we first calculate the mother's and the father's average earnings over the 10-year window (1991–2000). We then define family earnings as the average of the two and rank families by this average. This measure captures the average earnings of a child's parents when the child is aged roughly 10–20. We apply the same procedure to all other parental income measures. For parental job value, we likewise average across both parents over the 10-year window (1991–2000), weighting each job by its spell length, and rank families by this average.[36] Importantly, some children can be linked to only one parent, though the majority are linked to both. For children, we measure earnings and job value at the individual level, rather than constructing a household measure, because household formation is not yet complete for many children (Eshaghnia et al., 2024).

Table 1 presents summary statistics for our sample. The IGM-Job sample contains 76,187 parent-child pairs, approximately 87% of the IGM sample. The reduction arises since some parents or children do not have a well-defined job value from the Job sample.[37] The two

[34]We measure parents and children at different ages because consistent occupation codes are available only from 1991; we therefore use 1991–2000 for parental income as well as parental job value.

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

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

[37]This includes individuals, either parents or children, who are self-employed or work in agriculture, as well as those whose jobs lack sufficient job-to-job transitions for us to estimate a job value during the observation period.

Table 1: Summary Statistics

	IGM Sample	IGM-Job Sample
Panel A: Number of Counts		
Number of Parent-Child Pairs	87,709	76,187
Average Number of Siblings	2.16	2.16
Panel B: Age		
Father Average Age at Birth (years)	28.70	28.67
Mother Average Age at Birth (years)	25.83	25.88
Panel C: Marital Status		
Father: Share Married	0.76	0.77
Mother: Share Married	0.75	0.76
Panel D: Educational Attainment		
Child: High School/Vocational	0.41	0.40
Child: College/Bachelor	0.29	0.31
Child: Postgraduate	0.17	0.19
Father: High School/Vocational	0.49	0.50
Father: College/Bachelor	0.16	0.17
Father: Postgraduate	0.07	0.07
Mother: High School/Vocational	0.39	0.40
Mother: College/Bachelor	0.25	0.27
Mother: Postgraduate	0.03	0.04
Panel E: Earnings		
Child Average Log Earnings	12.50	12.62
Family Average Log Earnings	12.82	12.89
Father Average Log Earnings	12.57	12.62
Mother Average Log Earnings	12.07	12.13

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 36–45 (1991–2000). All earnings are average log earnings over the respective periods, expressed in 2022 Danish Kroner. Compulsory School is the omitted education category.

samples are similar in terms of the number of siblings, parental age at birth, and the share of married parents. Children and parents in the IGM-Job sample are somewhat more educated, and their earnings are 0.05–0.12 log points higher.

5 Estimation

The identification argument is constructive, and our estimator follows it step by step. For each worker type within each generation, we estimate the corresponding parameters using the respective sample: 1991–2000 for parents and 2010–2019 for children. A period is one month, and we set the discount factor to $\beta = 0.95^{1/12}$, the monthly equivalent of the annual discount factor.

In this section, we begin by defining worker types, jobs, wage cells, and transitions used in estimation. Then, we focus on two steps of the estimation procedure. First, we distinguish exogenous layoffs from endogenous quits using weekly benefit records and stated reasons for separation. Second, we estimate within-job quit–wage elasticities, which allow us to separate the preference weight on wages from nonwage amenities. We use these inputs together with observed worker flows to recover the remaining model parameters. Finally, we present the parameter estimates and examine how estimated job values relate to pay.

5.1 Worker Types, Jobs, and Transitions

We first classify workers and jobs into discrete types, and we describe the wage bins and the transitions that we use in estimation.

Worker Types. We define eight worker types by interacting gender with four education groups for each generation: (i) less than high school: workers without a full upper-secondary qualification; (ii) high school or vocational education and training: workers with upper-secondary or post-secondary non-tertiary education; (iii) college: workers with short-cycle or bachelor's-level higher education; and (iv) above college: workers with master's or doctoral education.[38] The second group includes both general upper-secondary education and vocational qualifications at that level. The third combines short-cycle qualifications with university and professional bachelor's-level qualifications, including those in nursing and primary and lower-secondary teaching. We allow preferences over wages and nonwage amenities, as well as job-offer pro-

[38]Educational attainment is measured by the highest observed completed qualification, classified using its associated ISCED code. Appendix D.1 provides the details.

cesses, to differ across these education–gender groups.[39]

Definition of a Job. 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, in the spirit of Bonhomme et al. (2019). 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.[40] Our occupation codes are three-digit DISCO-08 codes for children and three-digit DISCO-88 codes for parents. Both are the official Danish versions of the International Standard Classification of Occupations (ISCO-08 and ISCO-88), developed by the International Labour Organization (ILO).[41]

This definition reflects two choices. The first is to group establishments into types. Defining a job as an occupation within an individual establishment would lead to excessive sparsity: the connected set would be small, and the values of jobs in small establishments would be measured with more error than those of jobs in large establishments. Clustering establishments mitigates this issue while preserving meaningful variation across establishments. The second choice is to keep the occupational dimension fine, for two reasons. We have rich information on non-wage attributes that vary at the level of the occupation, and much less information on attributes that vary at the level of the establishment. Moreover, occupational status is central to the literature on intergenerational mobility.

Wage bins and transitions. For the purpose of estimation, we discretize daily wages into $W = 12$ bins. The bins are common to all jobs and worker types, so that workers of different types in the same job face the same wage grid. We restrict a worker's wage to be constant within each establishment-occupation match. In practice, we set it to the average daily wage over the match. This restriction implies that wage changes within the same job are not a

[39] We use observed worker types instead of unobserved latent types in our baseline analysis for two reasons. First, the observed type approach provides a transparent and comparable benchmark for measuring job values across generations. Grouping workers based on gender and education provides more concrete and tangible content for further discussion. Second, while it is computationally feasible to estimate and recover latent worker types in the first step of estimation, comparing unobserved types for parents and children across generations would require an additional step to align type classifications across periods.

[40] Formally, the algorithm solves $\min_{C_1,\ldots,C_{12}} \sum_{k=1}^{12} \sum_{i \in C_k} \|x_i - \mu_k\|^2$, where x_i represents the wage distribution moments for establishment i, C_k denotes cluster k, and μ_k is the centroid of cluster k. We take the number of establishment types as given.

[41] DISCO-08 is a six-digit, five-level classification for occupations, and DISCO-88 is a four-digit, four-level classification. In both, the first digit identifies major occupational groups (e.g., managers, professionals, and clerical workers), while subsequent digits provide finer distinctions within these categories.

source of information about the value of a job, as such wage changes are not treated in a manner analogous to job-to-job transitions. This restriction still allows for wage changes within the same job to occur through transitions across establishments. We follow three criteria when we count transitions in the labor market. First, a change of occupation within the same establishment is a job-to-job transition, like a move between employers, because it changes the worker's job. Second, we treat every job-to-job transition as a choice made while the incumbent position remains available, so the classification in Step 1 concerns only employment-to-nonemployment (EN) transitions. Third, an EN transition is a separation into nonemployment that is followed by reemployment, which is the hire from nonemployment that enters the mobility matrix; we exclude spells that end in reemployment with the same employer, often referred to as recall.[42]

5.2 Estimation Overview

Estimation has four steps, which carry the numbers of the identification steps. In Step 1, we use administrative benefit records, informed by and compared with survey-reported reasons for leaving employment, to label every transition into nonemployment as a quit or a layoff, and we recover the job-destruction probabilities $\delta_{\ell j}$ and the endogenous mobility matrix. In Step 2, we compute the PageRank scores from this matrix. In Step 3, we recover the job values, the offer shares and the arrival probabilities. In Step 4, we invert the Bellman equations and estimate an auxiliary regression that gives the quit–wage elasticity of each worker type in each generation, the empirical target that separates the preference weight α_ℓ from the amenities $\phi_{\ell j}$.

5.2.1 Step 1: Exogenous and Endogenous Separations

Step 1 delivers the job-destruction probabilities $\delta_{\ell j}$ and the endogenous mobility matrix M_ℓ. It labels every EN transition in the two estimation samples as a quit, a separation that the worker chooses (voluntary, or endogenous), or as a layoff, a separation that job destruction forces on the worker (involuntary, or exogenous). The identification argument takes this as given; here we state how we construct it. Weekly benefit histories from the DREAM register provide the baseline classification for every EN transition of the full population in both generations. We next replace the benefit-based label with the stated separation reason for transitions matched to responses to the Danish Labour Force Survey (AKU).[43] We assess the benefit-based classification by comparing its labels with stated reasons for separation in the estimation sample.[44]

[42] Appendix D.2 gives the reasons for these conventions.

[43] Reliable AKU responses are available only after 2008. The responses that we use cover 2010–2019, so the replacement applies only to the child generation.

[44] See Table A-7.

Why benefit timing and type are informative in Denmark. Two features of the Danish benefit system make the timing and type of the first benefit received after a separation informative about its cause. First, the generosity of the system and its registration rules give insured workers strong incentives to report unemployment at the onset of a separation. Denmark ranks near the top of high-income countries in both the duration and the level of unemployment compensation, with a maximum benefit duration of two years and a net replacement rate of 83 percent after three months of unemployment for workers with low earnings (Kreiner and Svarer, 2022).[45] Official guidance also instructs these workers to register on the first day of unemployment and submit an unemployment declaration. The declaration records the previous employment, notice period, and the reason for leaving.[46]

Second, DREAM contains information beyond unemployment insurance. It covers everyone who has received public transfer income at a weekly frequency, so a week without a benefit record means that the person received no public transfer in that week. When programs overlap, DREAM reports one category according to a fixed priority ordering.[47] Our classification exploits both the priority ordering and the benefit type. For example, parental-leave benefits and sickness benefits both rank above unemployment insurance. If a worker is coded as receiving unemployment insurance in a given week, then she cannot have received either of those higher-priority benefits in that week.

Weekly benefit records: population-wide classification. For every EN transition, we merge the weekly EN panel with the weekly benefit register. We use the first benefit code after the job ends, or a no-benefit label if no benefit category is observed during the first six months after the job ends. The initial classification distinguishes three broad groups:

1. *Exogenous separation.* The first benefit after separation is unemployment insurance, unemployment-related support, or education support without payment.[48] We classify such a separation as a layoff.

2. *Endogenous separation.* The worker moves onto a life-cycle benefit, such as education support with payment, parental-leave benefits or retirement benefits, following separation. We classify such separations as quits.

[45] Even after unemployment insurance is exhausted, means-tested benefits can replace up to 67 percent.

[46] An unemployed member must register as a jobseeker on jobnet.dk or at a job center on the first day of unemployment, and benefits cannot be paid for periods preceding registration (Styrelsen for Arbejdsmarked og Rekruttering, 2026).

[47] See Table A-4 in Appendix D.3.1 for more details.

[48] We include education support that does not involve a direct payment because most workers whose first benefit is education support without payment state that their job ended because of a dismissal, a redundancy, or the end of a fixed-term contract. Appendix Table A-6 reports, for each benefit category, the share of matched transitions with such a reason.

3. *No observed benefit.* No benefit is observed during the follow-up period after the separation.[49] We classify this as an endogenous quit: the worker leaves employment without entering the unemployment-insurance system or another observed benefit program.

To define this rule, we compare benefit receipt with the reasons that workers state in the AKU, in a wider sample of matched separations that also includes workers who are still in school. See Appendix B.2.2 and Table A-6.

Danish Labour Force Survey stated reasons: direct classification of matched transitions. For each response in the AKU in which a worker reports her reason for separation, we match this response to the corresponding EN transition.[50] If a worker reports that her job ended because of a dismissal, redundancy, or the end of a fixed-term contract, we interpret this as the worker stating that her separation was involuntary, and we label it a layoff. If she instead reports family responsibilities, own illness or disability, education or training, retirement, or another reason, we interpret this as the worker stating that her separation was voluntary, and we label it a quit. For these transitions, we replace the benefit-based label with the worker's stated reason for separation. The matched sample also allows us to assess the accuracy of our benefit-based classification. We report the comparison in Appendix B.2.2.

Layoffs, quits, and the endogenous mobility matrix. We estimate the job-destruction rate $\widehat{\delta}_{\ell j}$ as the number of EN transitions of type-ℓ workers from job j that we label layoffs, per person-month at risk. Transitions labeled quits, job-to-job transitions, and hires from nonemployment form the endogenous mobility matrix. For each worker type, we retain job–wage pairs that belong to the strongly connected set defined by job-to-job transitions and receive at least one hire from nonemployment.

5.2.2 Steps 2 and 3: PageRank Scores, Job Values, and Offer Distribution

We apply the identification procedure to the sample, computing PageRank scores from $\widehat{M}_\ell$ and measuring employment mass by the number of person-period observations, $G_{\ell y}$. For each candidate λ_ℓ^1 on a grid, we recover the implied job values, offer shares, and offer-arrival probability in nonemployment, λ_ℓ^0. We select the candidate whose implied aggregate job-to-job transition rate most closely matches its empirical counterpart.[51]

[49] We follow each EN separation for 26 weeks to identify benefit receipt.
[50] We match based on personal identifiers, exact end dates of job spells, and establishment identifiers.
[51] More details are provided in Appendix D.3.2.

5.2.3 Step 4: Separating Wage Utility and Amenities

Step 4 delivers the quit–wage elasticity of each worker type in each generation: the slope of the log odds of quitting on the log wage across the wage bins of the same job.

The within-job quit–wage elasticity. We first calculate how likely a worker is to leave employment through a quit at each job–wage pair. With $EN_{\ell y}$ the EN transitions of type-ℓ workers from the pair y and $G_{\ell y}$ the number of person-period observations at it, the empirical counterpart of the quit probability $m_{\ell y}$ is

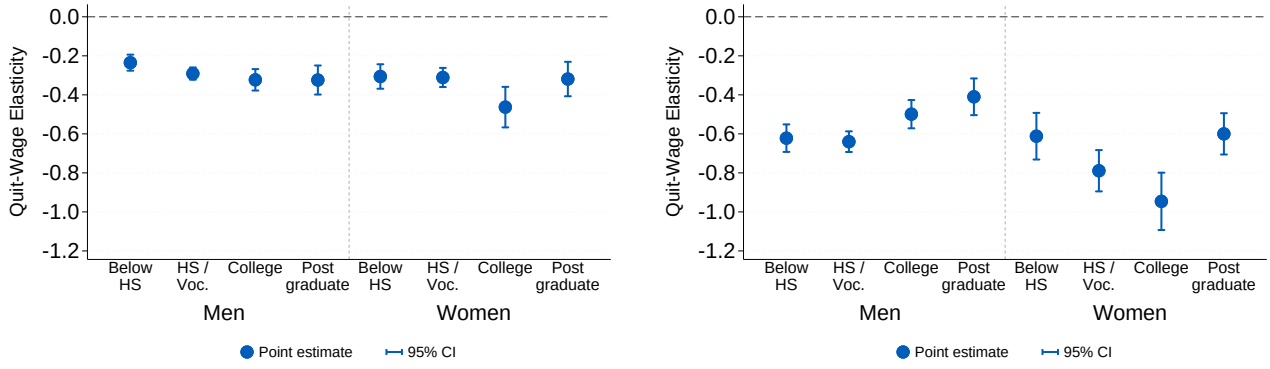
$$\widehat{m}_{\ell y} = \frac{\sum_{r \in EN_{\ell y}} \theta_r}{G_{\ell y}}. \tag{21}$$

We then estimate, for each worker type separately, the specification

$$\log\left[\frac{\widehat{m}_{\ell y}}{1-\widehat{m}_{\ell y}}\right] = \kappa_{\ell j} + \widehat{\varepsilon}_{\ell} \log w + r_{\ell y}, \tag{22}$$

where $\kappa_{\ell j}$ is a job fixed effect, $r_{\ell y}$ is a residual, and the slope $\widehat{\varepsilon}_{\ell}$ is the quit–wage elasticity of type ℓ. We control for job fixed effects because the destruction probability and the amenity vary across jobs and worker types, but not across the wage bins of a job. The regression therefore relates the wage to the likelihood of a quit using only wage variation within jobs, and $\widehat{\varepsilon}_{\ell}$ summarizes this relationship. The slope is not itself an estimate of $-\alpha_{\ell}$, because the gradient varies across job–wage pairs.

Figure 3: Quit–Wage Elasticity by Worker Type (Daily Wage)



(a) Parent generation, 1991–2000

(b) Child generation, 2010–2019

Notes: This figure plots the point estimate of the quit–wage elasticity and its 95 percent confidence interval for each of the eight worker types, for the parent generation in panel (a) and the child generation in panel (b). Worker types are defined by gender and by the four education groups.

Figure 3 reports the quit–wage elasticity $\widehat{\varepsilon}_\ell$ of Step 4 for each worker type, for the parent generation in panel (a) and for the child generation in panel (b). All sixteen estimates are negative and their confidence intervals exclude zero: within a job, a higher wage lowers the odds that a worker quits. The estimates are roughly twice as large in absolute value for children (about -0.4 to -0.95) as for parents (about -0.25 to -0.45).

Amenities as a residual. In the population, the residual $v_{\ell j}(w) - \alpha_\ell u(w)$ is the same in every wage bin of a job. In a sample it is not, because each value is estimated with error, so we impose Assumption 1 in estimation as a regularization, under the functional form $u(w) = \log w$.

For each candidate α_ℓ, we choose each job's amenity so that model-implied and recovered job values agree on average across wage bins, weighted by person-months. We then compute the implied quit probabilities and estimate the same within-job quit–wage regression. We select $\widehat{\alpha}_\ell$ so that the model-implied slope, $\varepsilon_\ell(\alpha_\ell)$, matches the empirical slope:

$$\varepsilon_\ell(\widehat{\alpha}_\ell) = \widehat{\varepsilon}_\ell. \tag{23}$$

The corresponding amenities are our estimates $\widehat{\phi}_{\ell j}$. We solve this single moment condition for each worker type and generation using grid search followed by root-finding. Quit probabilities are available in closed form, so no simulation is required.

5.3 Parameter Estimates and Descriptive Patterns

Parameter Estimates. Table 2 reports selected model parameters for the 1990s (parents, Panel A) and the 2010s (children, Panel B), separately for the eight worker types defined by gender and educational attainment. Three patterns stand out.

First, the education gradient in the estimated weight on wage utility, α_ℓ, differs across generations and between men and women. In the child generation, this weight declines across the four education groups for men, from 0.018 to 0.011. For women, it is highest in the two middle groups and lower in the bottom and top groups. In the parent generation, it varies little with education: it lies between 0.005 and 0.006 in every group except college-educated women. Under the model's common preference-shock normalization, a higher α_ℓ implies a larger change in flow utility for a given change in wage utility, $u(w)$.

Second, the monthly offer-arrival probability for employed workers, λ_ℓ^1, is generally higher among more educated workers in both generations. For men, the estimates increase across education groups in the child generation, from 0.030 to 0.036; in the parent generation, they are lowest below high school and lie between 0.026 and 0.029 in the other three groups. For

women, the relationship is not monotonic, although the offer-arrival probability is highest among workers with postgraduate qualifications in both generations.

Third, we document that there is substantial heterogeneity in job-destruction probabilities, $\delta_{\ell j}$, across both jobs and worker types. For each type, the interquartile range captures dispersion in exposure to layoff risk across jobs. Among men below high school in the child generation, for example, the 25th and 75th percentiles are 0.003 and 0.009 per month. Across types, mean job-destruction probabilities are declining in education in both generations. In the child generation, the mean falls from 0.006 to 0.003 for men. The education gradient is less pronounced among women in the child generation, whose mean falls from 0.006 below high school to 0.004 in the college group and is 0.005 in the postgraduate group.

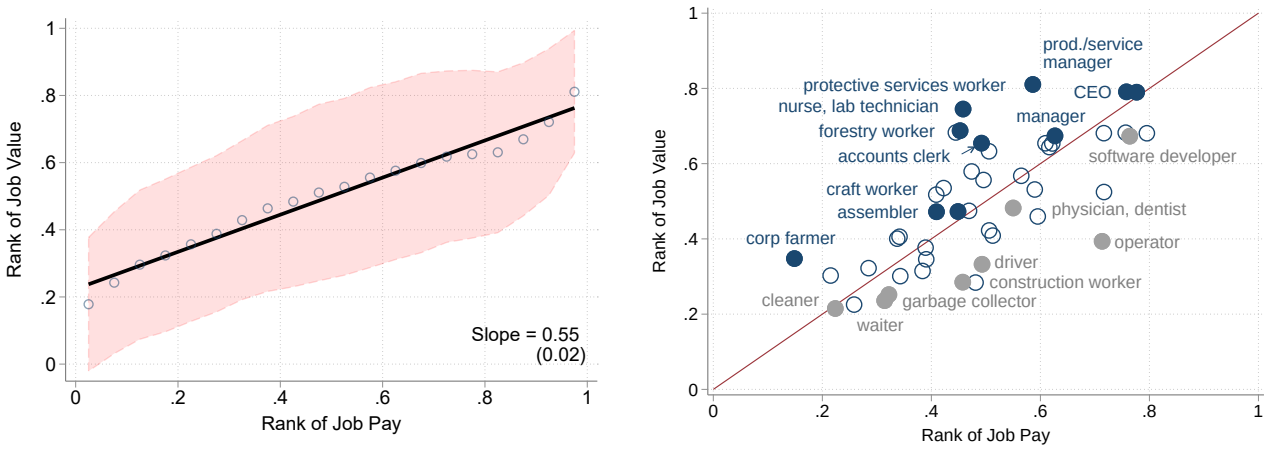
Table 2: Estimated Search-Model Parameters by Demographic Group

	Men				Women			
	Below HS	HS/Voc	College	Above College	Below HS	HS/Voc	College	Above College
Panel A: Parents								
α_ℓ	0.005	0.006	0.006	0.006	0.006	0.006	0.009	0.006
λ_1	0.022	0.029	0.026	0.027	0.019	0.026	0.022	0.027
δ_j: mean	0.003	0.003	0.001	0.001	0.004	0.003	0.002	0.002
δ_j: p25	0.002	0.001	0.001	0.000	0.002	0.002	0.001	0.001
δ_j: p75	0.004	0.004	0.002	0.001	0.005	0.004	0.003	0.002
Panel B: Children								
α_ℓ	0.018	0.016	0.013	0.011	0.020	0.024	0.024	0.019
λ_1	0.030	0.032	0.035	0.036	0.034	0.036	0.030	0.040
δ_j: mean	0.006	0.005	0.003	0.003	0.006	0.005	0.004	0.005
δ_j: p25	0.003	0.002	0.002	0.001	0.004	0.003	0.002	0.002
δ_j: p75	0.009	0.007	0.004	0.004	0.007	0.007	0.004	0.006

Notes: Panel A reports the estimates for 1991–2000, which we use to value the jobs of parents, and Panel B those for 2010–2019, which we use to value the jobs of children. Parameters are estimated separately for eight worker types: men and women, each split by highest completed education into below high school, high school/vocational, college/bachelor, and postgraduate. α_ℓ is the preference weight on wage utility, estimated within each type so that the model reproduces the type's within-job quit–wage elasticity. λ_ℓ^1 is the monthly offer-arrival probability for employed workers, chosen so that the model reproduces the type's aggregate job-to-job transition rate (Section 3.3). The $\delta_{\ell j}$ rows summarize the distribution across jobs of the monthly job-destruction probability, estimated as the number of layoffs per person-month at risk (Section 5.2.1): mean, 25th, and 75th percentiles. Reported to three decimal places.

Job Pay and Job Value. Table 3 presents the pairwise correlations between our job value and flow wage, flow amenities, and exogenous separation risk for the children's sample and the parents' sample. Three key patterns emerge. First, in both generations, jobs with higher flow wages and lower job insecurity have higher values; job insecurity is the strongest correlate of job value (-0.76 for parents and -0.79 for children). Second, flow amenities are negatively related to flow wages (-0.24 for parents and -0.25 for children), consistent with compensating

Figure 4: Relationship between Job Pay and Job Value



(a) Overall (b) Occupation

Notes: This figure plots the relationship between job pay (earnings) and 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 value rank within each pay bin. Panel (b) plots occupation-level means. The solid line shows the 45-degree line for reference.

Table 3: Correlation Matrix of Job Values and Their Components

Variables	(1) Job Value	(2) Flow Wage	(3) Flow Amenity	(4) Insecurity
Panel A. Parents' sample (1991–2000)				
(1) Job Value $V^e_{\ell j}(w)$	1.00			
(2) Flow Wage $\alpha_\ell u(w)$	0.52	1.00		
(3) Flow Amenity $\phi_{\ell j}$	0.28	−0.24	1.00	
(4) Job Insecurity $\delta_{\ell j}$	−0.76	−0.51	0.27	1.00
Panel B. Children's sample (2010–2019)				
(1) Job Value $V^e_{\ell j}(w)$	1.00			
(2) Flow Wage $\alpha_\ell u(w)$	0.62	1.00		
(3) Flow Amenity $\phi_{\ell j}$	−0.13	−0.25	1.00	
(4) Job Insecurity $\delta_{\ell j}$	−0.79	−0.39	0.51	1.00

Notes: This table reports unconditional pairwise correlations between job value and its components. Panel A uses the parents' sample (1991-2000 matched employer-employee data, $N = 15{,}788{,}132$ observations); Panel B uses the children's sample (2010-2019 matched employer-employee data, $N = 135{,}175{,}819$ observations). Job Value $V^e_{\ell j}(w)$ is the present discounted value of employment at job j at wage w for a type-ℓ worker, recovered from revealed preference in job-to-job transitions. Flow Wage $\alpha_\ell u(w)$ and Flow Amenity $\phi_{\ell j}$ are the pecuniary and non-pecuniary components of the per-period flow payoff, $v_{\ell j}(w) = \alpha_\ell u(w) + \phi_{\ell j}$. Job Insecurity $\delta_{\ell j}$ is the per-period probability that the employment relationship is exogenously terminated.

differentials. Third, the two generations differ in how flow amenities relate to job value. For parents, jobs with higher flow amenities also have higher values (0.28). For children, this correlation is negative (-0.13), and job value is more closely tied to flow wages (0.62, compared with 0.52 for parents). To understand this difference, recall that we recover amenities as a residual. For a given wage and a given value, a higher risk of destruction lowers the continuation value and hence raises the estimated amenity. Amenities are positively correlated with job insecurity in both generations, and more strongly among children (0.51, compared with 0.27 for parents). Because less secure jobs have lower values, these patterns suggest that the negative correlation between amenities and job value among children reflects the stronger link between job amenities and job insecurity.

Pay and estimated job value are positively related, but imply different rankings of jobs. Figure 4 compares these rankings for the child sample in 2010–2019, aggregating type-specific valuations using person-year weights. Panel (a) plots mean job-value ranks within 20 pay-rank bins. The regression of job-value rank on pay rank has a slope of 0.55. Substantial dispersion in value ranks remains among jobs with similar pay ranks, as illustrated by the shaded band showing one standard deviation on either side of each bin's mean value rank.

Panel (b) illustrates these differences across occupational groups, weighted by the number of person-years represented by each occupation. The solid line shows the 45-degree line for reference. Notably, construction workers, drivers, and garbage collectors have lower mean ranks in job value than in pay, while nursing and protective-service occupations exhibit the opposite pattern. These comparisons describe differences in occupational rankings. Their interpretation encompasses flow amenities, exogenous separation risk, and continuation opportunities, together with differences in worker composition across occupations.

We present additional model estimates and descriptives in Appendix D.4, including decompositions of flow-payoff variation across worker types and within and between jobs; occupational and industry comparisons; and split-sample assessments of the reliability of estimated job values.

6 Mobility in Job Value vs. Mobility in Earnings

This section presents our main empirical findings on intergenerational mobility in the value of a job in Denmark. We begin by reviewing the canonical earnings-based mobility measure and introducing our rank-rank measure of job value. We then estimate earnings mobility in Denmark for four income measures, before turning to our primary contribution: estimating the intergenerational transmission of job value. We close by examining how each component of job value is transmitted across generations and summarizing our additional results and robustness

exercises.

6.1 From Mobility in Earnings to Mobility in Job Value

A conventional approach to measuring intergenerational mobility in earnings is to summarize the joint distribution of parent and child earnings with a summary statistic. Two such statistics are standard: the intergenerational elasticity (IGE) (Becker and Tomes, 1979) and the rank-rank slope (Dahl and DeLeire, 2008; Chetty et al., 2014a; Chetty and Hendren, 2018a,b).[52] Our focus in this paper is the rank-rank specification. We rank children by their earnings relative to the other children of the same birth cohort, in our sample, and we rank parents by their average earnings relative to other parents in our sample. For parents, the average is the mean of the mother's and the father's earnings when both can be linked, and the earnings of the single linked parent otherwise.[53] We characterize mobility by regressing the child's rank in the pre-tax earnings distribution, R_i^c, on the parents' rank in the pre-tax earnings distribution, R_i^p:

$$\underbrace{R_i^c}_{\text{Child's Earnings Rank}} = a_E + \beta^{\text{Earnings}} \underbrace{R_i^p}_{\text{Parents' Earnings Rank}} + \epsilon_i \tag{24}$$

The slope β^{Earnings} is the canonical measure of relative earnings mobility. It measures how much the expected earnings rank of a child changes when the earnings rank of the parents increases by one percentile.

We construct job value ranks as follows. For each person, we average the value of the jobs held during a ten-year window, weighting each job by its spell length. For parents, we then average the mother's and the father's job values when both can be linked, as we do for earnings, and use the single linked parent's job value otherwise. We rank the resulting values within each generation. Our primary specification regresses the child's job value rank on the parents' job value rank:

[52] The IGE characterizes the joint distribution by regressing the log of child earnings on the log of parent earnings, excluding children with zero earnings. However, this canonical log-log specification can yield unstable estimates of mobility given the nonlinearity of the joint distribution and sensitivity to the treatment of zero earnings. Chetty et al. (2014a) 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 children with zero income a value of \$1 yields an IGE of 0.618, while assigning them \$1,000 yields an IGE of 0.413.

[53] A more typical approach is to sum the earnings of the father and the mother when both can be linked, and to use the earnings of the single linked parent otherwise (Chetty et al., 2014b; Landersø and Heckman, 2017). Because we study the transmission of relative position in the labor market, the sum is less appropriate: it ranks a family with one linked parent below a family with two linked parents, even when every parent earns the same amount. The average ranks the two families equally.

$$\underbrace{\widetilde{V}_i^c}_{\text{Child's Job Value Rank}} = a_V + \beta^{\text{Job Value}} \underbrace{\widetilde{V}_i^p}_{\text{Parents' Job Value Rank}} + \epsilon_i \tag{25}$$

where $\widetilde{V}_i^c$ denotes the rank of the child's average job value over 2010–2019 and $\widetilde{V}_i^p$ denotes the rank of the parents' average job value over 1991–2000.[54] This specification is the value analog of the canonical earnings rank-rank regression. The slope $\beta^{\text{Job Value}}$, the *rank-rank slope in job value*, is our primary measure of intergenerational mobility in the value of a job. We report both relative mobility ($\beta^{\text{Job Value}}$) and absolute upward mobility ($a_V + 0.25\beta^{\text{Job Value}}$). The rank-rank slope in job value measures relative mobility, i.e., how much the expected job-value rank of a child changes when the parents' 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 and the absolute job prospects for children of lower-ranked parents.[55]

We focus on rank-based measures for two key reasons. First, job values are measured in taste-shock units, not in monetary units. The scale parameter of the taste shocks is not identified from worker flows, so we assume that it is common across worker types and normalize it to one. We impose this normalization separately for parents and for children, because we estimate the model separately for 1991–2000 and for 2010–2019. The level of job value can therefore be compared across generations only if the scale parameter is the same in the two periods. Rank-based measures do not require this assumption. Ranks are computed within a generation and are unaffected by its scale parameter: the rank-rank slope depends only on the joint distribution of parent and child ranks (Chetty et al., 2014a). Second, ranking earnings in the same way expresses both outcomes in percentile ranks, so the rank-rank slope in job value is directly comparable to the rank-rank slope in earnings.[56]

[54] We describe the construction of parental measures in Section 4. Appendix Table A-17 reports the slopes for the sum and the maximum of parental job values.

[55] As a supplementary measure, we also examine how parents' *earnings* relate to children's job value:

$$\underbrace{\widetilde{V}_i^c}_{\text{Child's Job Value Rank}} = a_{VE} + \beta^{\text{Value-Earnings}} \underbrace{R_i^p}_{\text{Parents' Earnings Rank}} + \epsilon_i \tag{26}$$

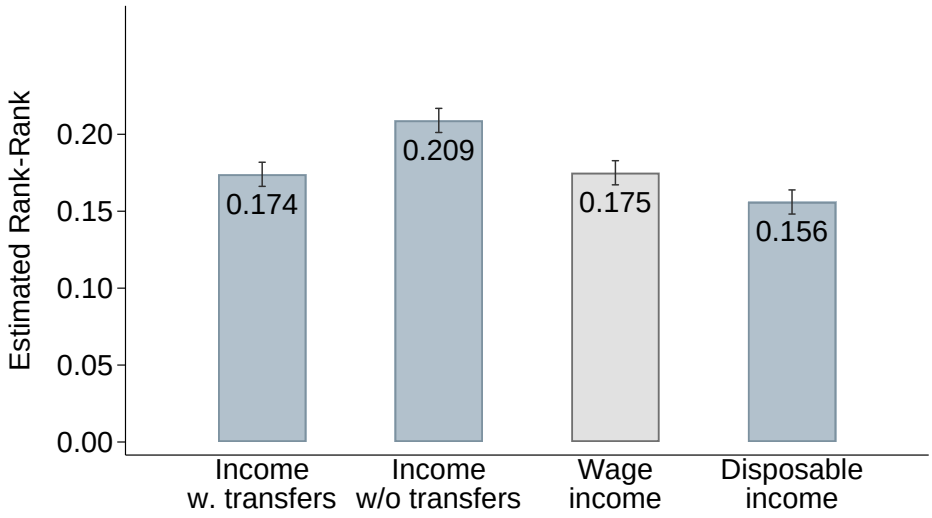
This value-earnings slope allows us to connect our value-based approach to canonical mobility studies and assess whether high-earning parents transmit advantages in overall job quality beyond just earnings. Our main focus, however, remains the rank-rank specification in job value of equation (25), which provides a more holistic measure of mobility in the full bundle of job attributes. The value-earnings specification also highlights a key difference between our framework and that of 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 preference, capturing pecuniary and non-pecuniary components simultaneously, and we examine how this job value is transmitted across generations.

[56] However, an important limitation of the rank-rank slope is that it is a purely ordinal measure. As such, it does not capture changes in the level of inequality across generations. To the extent that inequality has

6.2 Earnings Mobility in Denmark

Figure 5 presents rank-rank slope estimates for four income measures: wage income (pre-tax earnings), income with transfers, income without transfers, and disposable income.[57] Children are ranked by their own income, averaged over 2010–2019, and parents by the mean of the mother's and father's income, averaged over 1991–2000.

Figure 5: Rank-Rank Slope Estimates by Income Measures



Notes: This figure presents rank-rank slope estimates for four income measures. Each bar shows the coefficient β from the regression $R_i^c = a_E + \beta R_i^p + \epsilon_i$, where R_i^c denotes the percentile rank of the child's own income, averaged over 2010–2019 (ages 30–39), and R_i^p denotes the percentile rank of the parents' income, the mean of the mother's and the father's income, averaged over 1991–2000. Error bars represent 95% confidence intervals. Appendix Table A-16 presents the full regression results.

The slope is 0.175 for wage income, our baseline, and 0.174 for income with transfers. It is highest for income without transfers (0.209) and lowest for disposable income (0.156). The rank-rank slope in earnings of 0.175 means that a 10-percentile increase in parents' earnings rank is associated with a 1.75-percentile increase in the child's earnings rank. These estimates are in line with Denmark's position as a high-mobility society: intergenerational persistence in income with transfers is substantially lower than the 0.34 estimate for the United States reported by Chetty et al. (2014a).[58]

increased, the gap between workers at two given percentiles has widened.

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

[58] Their income measure includes labor earnings, capital income, unemployment insurance, Social Security, and disability benefits.

6.3 Intergenerational Transmission in Job Value

We now turn to our primary question: how does intergenerational mobility change when we measure the value of a job rather than earnings alone?

Figure 6 presents the estimate from regressing the child's job value rank on the parents' job value rank, alongside the earnings benchmark. By capturing the full bundle of job attributes, both pecuniary and non-pecuniary, on both sides of the equation, this slope measures intergenerational transmission in the value that workers receive from employment relationships.

Figure 6: Intergenerational Mobility in Job Value ($\beta^{\text{Job Value}}$) Estimates



Notes: This figure presents the estimated rank-rank slopes in job value and in earnings. The job value slope is the coefficient $\beta^{\text{Job Value}}$ from the regression $\widetilde{V}_i^c = a_V + \beta^{\text{Job Value}}\widetilde{V}_i^p + \epsilon_i$, where $\widetilde{V}_i^c$ denotes the percentile rank of the child's average job value over 2010–2019 and $\widetilde{V}_i^p$ denotes the percentile rank of the parents' average job value over 1991–2000, the mean of the mother's and the father's job values. Brackets report percentage differences and p-values between the job-value slope and each comparison slope. Error bars represent 95% confidence intervals. Appendix Table A-17 presents the full regression results.

This result establishes the first key finding of the paper: there is more intergenerational mobility in the value of a job (0.111) than there is in earnings (0.175)—a 37% difference that is both statistically significant and economically meaningful. The estimated rank-rank slope in earnings captures intergenerational transmission through the pecuniary dimension of jobs, while the job value slope captures transmission in both pecuniary and non-pecuniary components.

Four additional points are worth noting. First, job values are estimated from a structural model. Readers may wonder whether noise in the estimated job values of parents and children mechanically generates more mobility in job value than in earnings. Two exercises show that this noise is small (Section 8.1.1). A bootstrap procedure with 100 replications shows that the

error in the estimated job values raises the standard error of the rank-rank slope in job value only from 0.0036 to 0.0038. Moreover, a split-sample approach, which estimates job values separately on two halves of the estimation sample, ranks children and parents very similarly in the two halves, with correlations of 0.97 for children and 0.94 for parents.

Second, our finding does not depend on how we combine the two parents into a family measure. Ranking families by the sum of the parents' outcomes rather than by the average yields qualitatively similar results in Section 8.1.2: there is more mobility in job value than in earnings under either definition.

Third, if the conditional mean function relating child outcomes to parental outcomes is linear, this gap has a clear interpretation: the difference in expected job value rank between children of parents at the top and children of parents at the bottom of the job value distribution is 37% smaller than the corresponding difference in earnings rank. In our setting, however, the relationship between parents' earnings rank and child's earnings rank is nonlinear, as shown in Section 8.2.1: it is much steeper at the top of the parental earnings distribution. In contrast, the relationship between parental value rank and child's value rank is approximately linear.

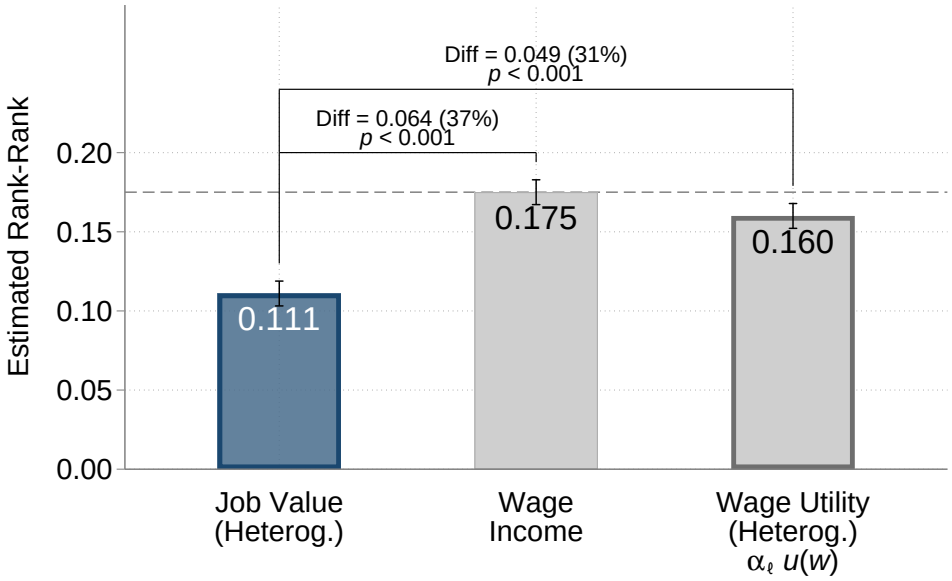
Fourth, one may wonder why we compare heterogeneous job values with a homogeneous earnings benchmark. Earnings are the canonical measure in the intergenerational mobility literature, but this comparison is asymmetric: we allow workers of different types to value the same job differently, whereas a common earnings ladder assumes that every worker values a krone equally. Therefore, part of the gap could reflect different valuations of earnings rather than amenities and job prospects.

To address this concern, Figure 7 adds the rank-rank slope in heterogeneous wage utility, $\alpha_\ell u(w)$. This slope is 0.160, close to the earnings slope, and the job value slope (0.111) remains 31% lower. Even after accounting for heterogeneous preferences over earnings, there is substantially more mobility in job value than in wage utility.

6.4 Job Value Transmission by Component

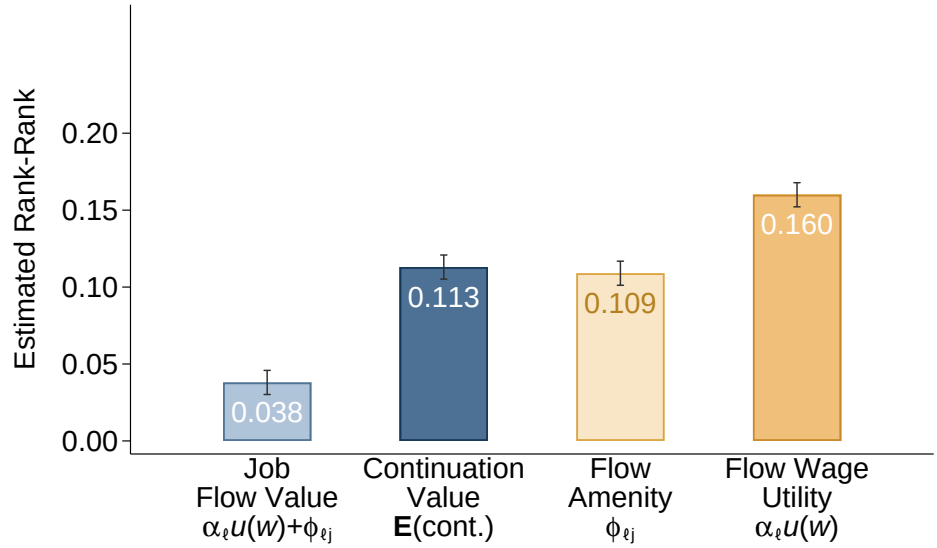
A key advantage of estimating the dynamic search model is that it allows us to examine how each component of parental job value transmits to each component of children's job value. By estimating each component of the value function, we gain additional insight into the specific channels through which parental earnings transmit to children's job quality. We highlight four components: the job flow value, job continuation value, flow amenity, and flow wage utility. For every individual in the parent and child generations, we compute the average of each component over the jobs held during the measurement window. We then rank individuals by each component within their generation and estimate a rank-rank regression for each component.

Figure 7: Intergenerational Mobility in Job Value and Heterogeneous Preferences over Wage



Notes: This figure presents the estimated rank-rank slopes in job value, wage income, and flow wage utility, $\alpha_\ell u(w)$. Brackets report the percentage differences and p-values between the job value slope and each comparison slope. Error bars represent 95% confidence intervals. Appendix Table A-18 presents the full regression results.

Figure 8: Intergenerational Job Value Transmission by Component



Notes: This figure reports estimated intergenerational rank-rank slopes for four components of job value: job flow value, continuation value, flow amenity, and flow wage utility. Error bars represent 95% confidence intervals. Appendix Table A-18 presents the full regression results.

Figure 8 displays the coefficient from each regression. Two patterns emerge. First, intergenerational transmission is substantial not only in the utility that workers receive from wages but also in amenities: just as the parents' position in the earnings distribution persists in the next generation, so does their position in the amenity distribution. Second, consistent with the cross-sectional relationships documented in Table 3, intergenerational persistence in the flow value rank is attenuated, because the wage rank and the amenity rank are negatively related in both the child and the parent generations.

6.5 Robustness and Additional Results

Here, we briefly summarize the additional results and the robustness exercises that we perform.

Robustness. Section 8.1 examines the sensitivity of our main finding that there is more mobility in job value than in earnings. The finding holds in every exercise.

Measurement Error. We discuss how estimation error in job values affects the rank-rank slope, and we report the bootstrap and split-sample exercises.

Alternative Family Measures. We rank families by the sum of the parents' outcomes instead of the average.

Sample Restrictions. We estimate job values using only workers in their thirties.

Involuntary Job-to-Job Moves. We allow some job-to-job moves to be forced on workers through "Godfather" shocks.

PageRank. We rank jobs with an off-the-shelf method, the PageRank approach of Sorkin (2018).

Additional Results. We provide four sets of additional results. Details can be found in Section 8.2 and Appendix H.2.

Absolute Mobility. We compare the expected ranks of children in job value and in earnings at each point of the parental distribution, using linear and local linear fits.

Other Intergenerational Transmission. We estimate intergenerational transmission across other pairs of outcomes, where the first outcome is the child's and the second is the parents': value-earnings and amenity-earnings.

Gender Differences. We estimate the intergenerational transmission of job value and of its components separately for sons and daughters.

Alternative Decompositions. We decompose the transmission of job value into wages and

amenities, and into transmission within and across worker types.

7 Understanding Differences in Value and Earnings Transmission

Thus far, we have documented that there is substantially more intergenerational mobility in job value than in earnings: the rank-rank slope is 0.111 in job value and 0.175 in earnings. The flatter slope reflects that both ends of the distribution are pulled toward the middle: children born to families at the bottom reach a higher position in the job value distribution than in the earnings distribution, while children born to families at the top reach a lower position in job value than in earnings.

An important question remains: *what* explains this gap? We address it in three steps. First, to disentangle the economic forces behind our finding, we provide a statistical decomposition of the difference between the rank-rank slopes in job value and in earnings. Second, mapping this difference to occupations, we examine how entry into each occupation varies with parental earnings, how occupations rank by job value relative to earnings, and which occupational attributes are related to this difference. Third, we complement our revealed-preference approach with observed job attributes: we document the intergenerational transmission of individual job attributes and relate our estimated amenities to these attributes.

7.1 Decomposing the Difference in Value and Earnings Transmission

To investigate the source of the gap between value and earnings transmission, we provide a simple statistical decomposition. We define the "rank wedge" as the difference between a worker's rank in the job value distribution and the worker's rank in the earnings distribution. The definition applies to parents and to children:

$$D_i^p = \widetilde{V}_i^p - R_i^p, \qquad D_i^c = \widetilde{V}_i^c - R_i^c, \tag{27}$$

where $\widetilde{V}_i$ and R_i denote the job value ranks and earnings ranks defined in the previous section, and the superscripts p and c refer to the parents and the child of family i. Workers with a positive rank wedge rank higher in job value than in earnings. In other words, their earnings understate how attractive their jobs are once amenities and job security are taken into account. By contrast, workers with a negative rank wedge rank higher in earnings than in job value. For instance, a worker at the 80th percentile of earnings and the 70th percentile of job value has a

rank wedge of -0.10.[59]

Since a worker's value rank is the sum of the earnings rank and the rank wedge, the gap between the two slopes is the sum of three terms:

$$\beta^{\text{Job Value}} - \beta^{\text{Earnings}} = \underbrace{\frac{\text{Cov}(R_i^p,\, D_i^c)}{\sigma_p^2}}_{(1)} + \underbrace{\frac{\text{Cov}(D_i^p,\, R_i^c)}{\sigma_p^2}}_{(2)} + \underbrace{\frac{\text{Cov}(D_i^p,\, D_i^c)}{\sigma_p^2}}_{(3)}, \tag{28}$$

where $\sigma_p^2 = \text{Var}(R_i^p) = \text{Var}(\widetilde{V}_i^p)$ is the variance of parental ranks.[60]

Each term answers a distinct question about how family background shapes the jobs of children. The first term asks: do higher-earning parents have children in careers with positive wedges? A positive sign would arise if children from affluent families took pleasant jobs with lower pay. Two possible reasons are that these children are less financially constrained and/or that they place more weight on amenities. The term would be negative if the children of higher-earning parents selected into well-paid but demanding careers, such as certain managerial positions, law, and investment banking. The second term asks: do parents with positive wedges have children in higher-paying careers? The third term sheds light on the intergenerational transmission of such wedges: do positive wedges pass from parents to children? A positive sign would arise if children inherited their parents' tastes over jobs or followed them into the same occupation or sector.

Figure 9 displays the decomposition results. Three findings emerge. First, higher-earning parents have children in careers with lower wedges. The first term is -0.045, which amounts to 70% of the total gap. Put differently, parental earnings rank predicts the child's value rank (0.131) less strongly than the child's earnings rank (0.175).[61] To give a sense of magnitude, the fitted line puts the children of the highest-earning parents about 2 percentile points lower by job value than by earnings, and the children of the lowest-earning parents about 2 points higher. This sign is more consistent with the children of higher-earning parents selecting into well-paid but demanding careers.

The first finding warrants a careful interpretation. It does not imply that children from higher-earning families never take jobs with low pay and attractive amenities. It says that, on average, children from more advantaged families tend to hold jobs that rank higher in earnings

[59] The rank wedge compares two rankings of the same worker. It does not compare the worker with other workers who have the same earnings, and it is distinct from the estimated flow amenity $\phi_{\ell j}$. Because the two ranks are imperfectly correlated, workers with higher earnings tend to have a lower rank wedge.

[60] The decomposition follows from substituting $\widetilde{V}_i^p = R_i^p + D_i^p$ and $\widetilde{V}_i^c = R_i^c + D_i^c$ into $\beta^{\text{Job Value}} = \text{Cov}(\widetilde{V}_i^p, \widetilde{V}_i^c)/\sigma_p^2$ and subtracting $\beta^{\text{Earnings}} = \text{Cov}(R_i^p, R_i^c)/\sigma_p^2$. The two variances are equal since both are percentile ranks.

[61] The first term equals the difference between these two slopes, up to rounding.

than in job value, which suggests that the amenities of these jobs rank lower than their pay. A wealth channel, in which affluent children trade pay for amenities, would work against this pattern. A natural hypothesis emerges from models of job search with consumption-saving decisions.[62] In these frameworks, workers with lower assets accept jobs with higher wages and lower amenities. Once this constraint is relaxed through a change in their asset position, workers substitute toward jobs with lower wages and higher amenities. We examine this channel further in Appendix G in two ways. First, we ask whether the same pattern holds when parents are ranked by their wealth instead of their earnings. Second, we test for a direct effect of wealth on job choices by exploiting quasi-experimental variation from unexpected inheritances induced by the sudden death of the last surviving, unmarried parent, following Druedahl and Martinello (2022).[63] We find that parental wealth is negatively related to children's rank wedges, about as strongly as parental earnings are, and, surprisingly, that large wealth shocks do not induce workers to shift toward jobs with higher amenities. The absence of an effect of large inheritances on the amenities of their jobs suggests that a direct wealth effect plays a limited role in Denmark.

Second, parents with lower wedges have children who rank higher in earnings: the second term is -0.039. Third, the rank wedges of parents and children are positively related: the third term is 0.021. The second and third terms partly offset each other, and together they account for the remaining 30% of the gap. The first term accounts for most of the gap; in the next subsection, we examine it in more detail.

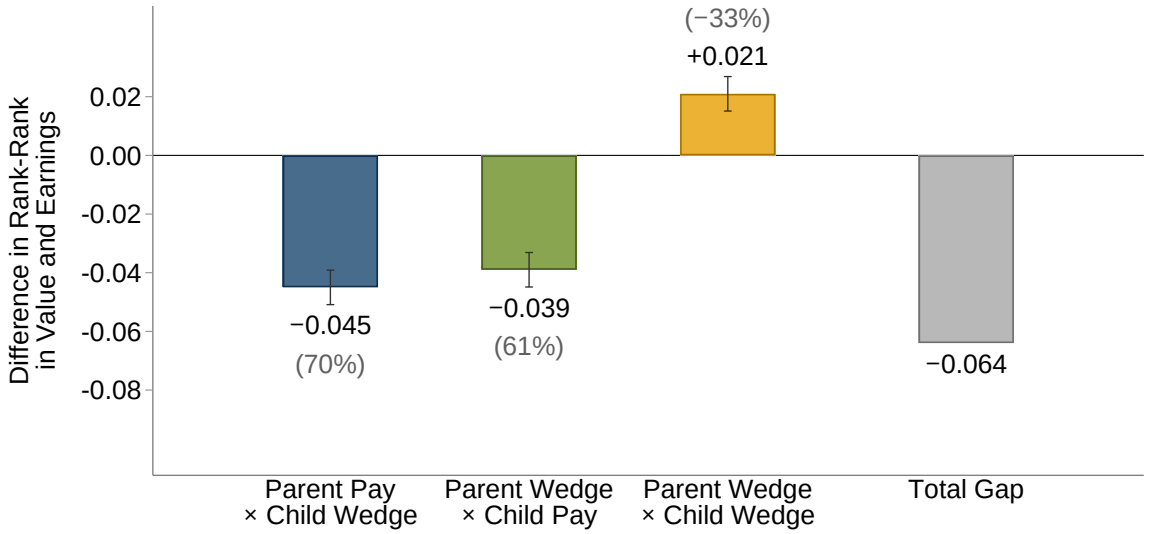
Our findings complement existing evidence on how non-wage job attributes vary with family background. Boar and Lashkari (2025) show that, in the United States, the children of higher-income parents choose occupations of higher "intrinsic quality," a survey-based index of attributes such as respectful treatment and opportunities to learn. We find the same pattern for observed attributes of this kind in Denmark. Importantly, our measure of job value captures a broader object in two respects. First, because it is inferred from the voluntary moves of workers across jobs, it reflects the entire bundle of measured and unmeasured job attributes. Second, it is a dynamic notion of value: beyond the flow amenities and flow wage that a worker enjoys today, it also includes the continuation value of the job, which reflects its security and the prospects for climbing up the job ladder. Our findings are also consistent with recent evidence from Sweden (Forsberg et al., 2026): the value of the child's firm is less strongly correlated with fathers' income than the firm's pay premium is.[64]

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

[63] Large, unexpected inheritances provide a clean test: if the trade-off between wages and amenities is governed by asset positions, substantial wealth shocks should induce workers to re-optimize their job choices and accept positions with higher amenities at the cost of lower wages.

[64] Appendix F.1 discusses both comparisons in detail.

Figure 9: Decomposition of the Difference between Value and Earnings Transmission



Notes: This figure shows the total gap, $\beta^{\text{Job Value}} - \beta^{\text{Earnings}} = 0.111 - 0.175$, and three slopes that correspond to the terms of equation (28). The first bar is the slope from a regression of the child's rank wedge on the rank of average parental earnings; it equals the first term. The second and third bars are the slopes from regressions of the child's earnings rank and of the child's rank wedge on the rank wedge of the parents. Percentages in parentheses are shares of the total gap. Error bars represent 95% confidence intervals.

7.2 More Demanding Jobs Tend to Rank Lower in Value than in Earnings

Why do children of higher-earning parents tend to rank lower by job value than by earnings? To answer this question, we examine the occupations that they enter.

We first document how occupational entry varies with parental earnings. Figure 10(a) displays, for each occupation, the elasticity of occupational choice with respect to parental earnings: the percentage change in the likelihood that a child works in the occupation that is associated with a one percent increase in parental earnings.[65] The likelihood of working in a professional or managerial occupation generally rises with parental earnings, while the likelihood of working in a manual occupation generally falls. This pattern is in line with evidence of occupational sorting by parental income in Canada and by parental class in Britain.[66] The elasticities are largest for business and administration professionals, administrative and commercial managers, and information technology professionals. They are most negative for skilled agricultural workers and for agricultural and industrial laborers.

We then ask how these occupations rank by job value relative to earnings. Figure 10(b)

[65]For each occupation o, we estimate a Poisson regression of an indicator for working in that occupation, $y_{io} = \mathbf{1}\{o(i) = o\}$, on log parental earnings: $\mathbb{E}[y_{io} \mid \text{parental earnings}_i] = \exp\big(a_o + \beta_o \log(\text{parental earnings}_i)\big)$. Because the conditional mean is exponential, the coefficient β_o is itself the elasticity of the probability of working in occupation o with respect to parental earnings.

[66]See Haeck and Laliberté (2025) and Laurison and Friedman (2016), respectively.

displays the average rank wedge of the children in each occupation. In five of the six professional groups, the average is negative, by 3.5 to 9.0 percentile points. Teaching is the exception: the average rank wedge of teachers is positive, at 10.6 percentile points, and teaching is also the profession whose entry is least related to parental earnings. Outside the professions, there is no uniform pattern. The average rank wedge is positive for most clerical occupations, health associate professionals, and protective services workers, and it is negative in the building and electrical trades and for drivers.[67] The main takeaway is that the careers that the children of higher-earning parents disproportionately enter tend to rank lower by job value than by earnings.

What distinguishes occupations that rank lower by job value than by earnings? Several measures of how demanding an occupation is are negatively related to the rank wedge: hours, paid overtime, irregular schedules, competition, and time pressure. To document this, we relate each child's rank wedge to the attributes of the child's occupation, one attribute at a time:

$$D_i^c = \mu_k + \theta_k X_{o(i),k} + \epsilon_{ik}, \tag{29}$$

where $o(i)$ is the occupation of child i and $X_{o(i),k}$ is attribute k of that occupation, standardized to have unit standard deviation. A negative θ_k means that the rank wedge is lower in occupations with more of attribute k.

Figure 11 displays the estimates. We consider three sets of attributes. First, we consider working hours as reported in the AKU. The rank wedge is lower in occupations with longer hours. A difference of one standard deviation in usual weekly hours is associated with a rank wedge that is 2.3 percentile points lower, and the corresponding numbers are 3.7 points for actual hours and 6.4 points for paid overtime hours. Unpaid overtime is an exception. Second, we consider how work is organized, as measured in O*NET. The rank wedge is lower in occupations with less regular work schedules, with a higher level of competition, and with greater time pressure.[68] Third, we use the WEHD to learn how workers experience these occupations. The rank wedge is lower in occupations whose survey respondents more often report that their work ability is below its best and that they are not given the information they need to do their work. Conversely, it is higher in occupations whose respondents say that their work is important to them beyond the income it provides.[69]

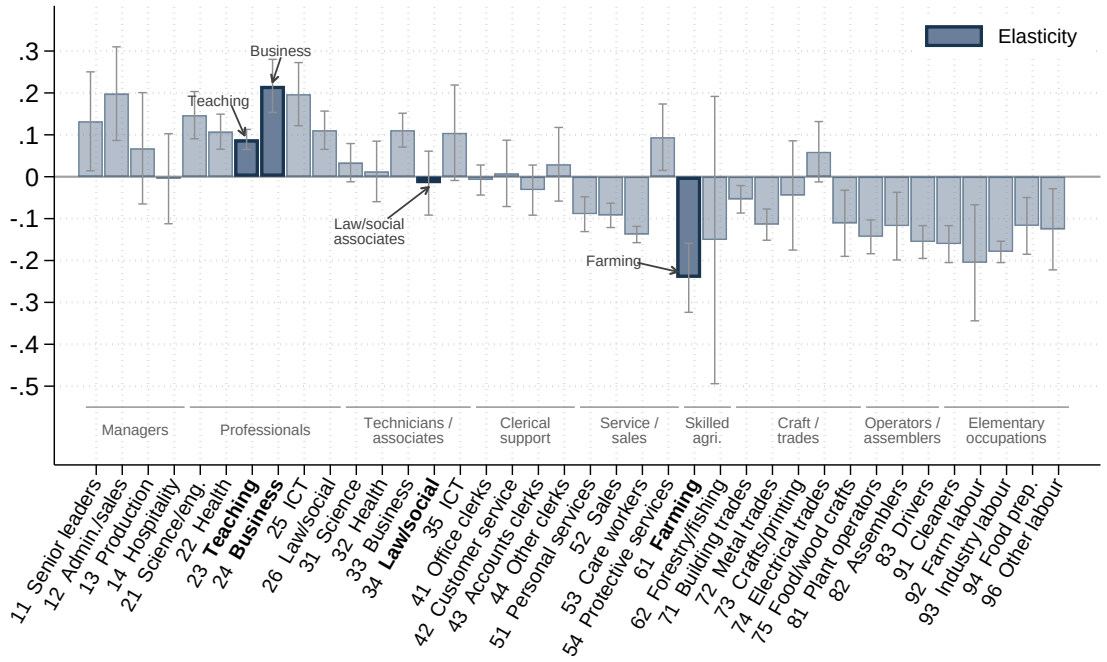
These associations describe occupations with a low rank wedge in general. They do not yet

[67] This pattern resembles what Sorkin (2018) finds across sectors in the United States: employers in construction and transportation pay well relative to the value that workers attach to them, and employers in education and public administration pay little relative to it. For Denmark, Humlum et al. (2025b) find that education is the industry with the highest estimated amenity value.

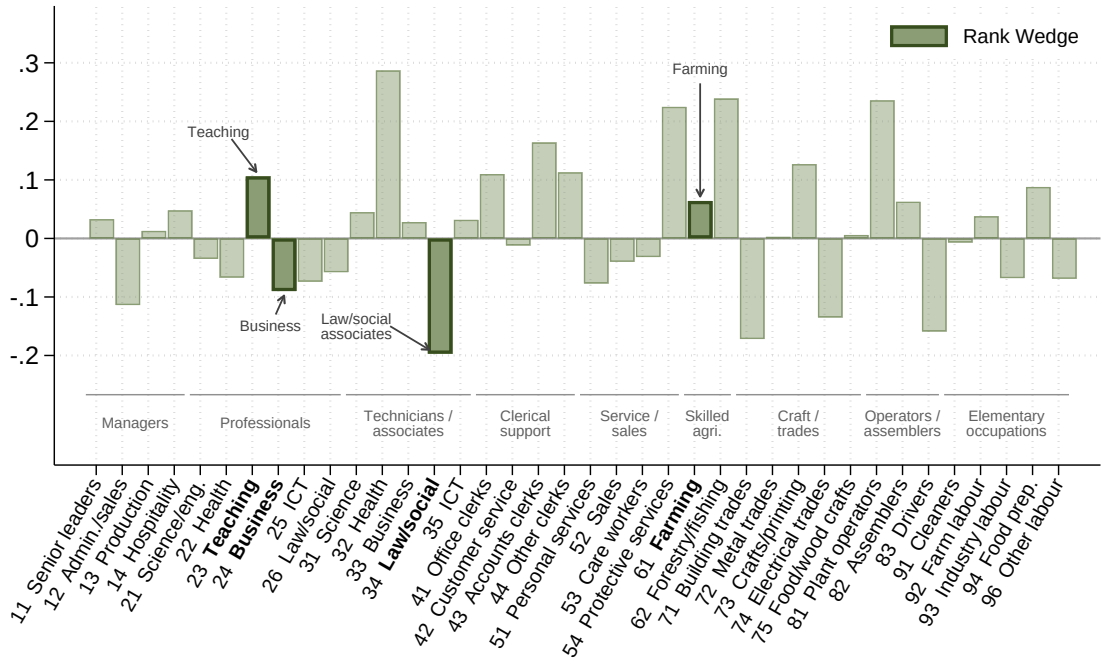
[68] Not every O*NET measure of job demands follows this pattern: the item for the length of the typical work week is only weakly related to the rank wedge.

[69] See Appendix Figure A-3.

Figure 10: Parental Earnings, Occupations, and the Value–Earnings Rank Difference



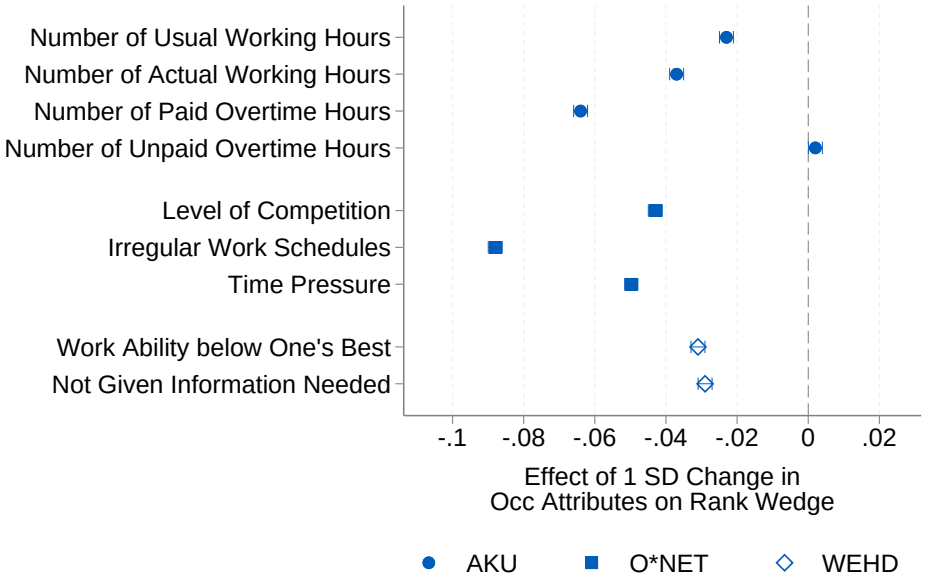
(a) Occupational entry and parental earnings



(b) Average rank wedge by occupation

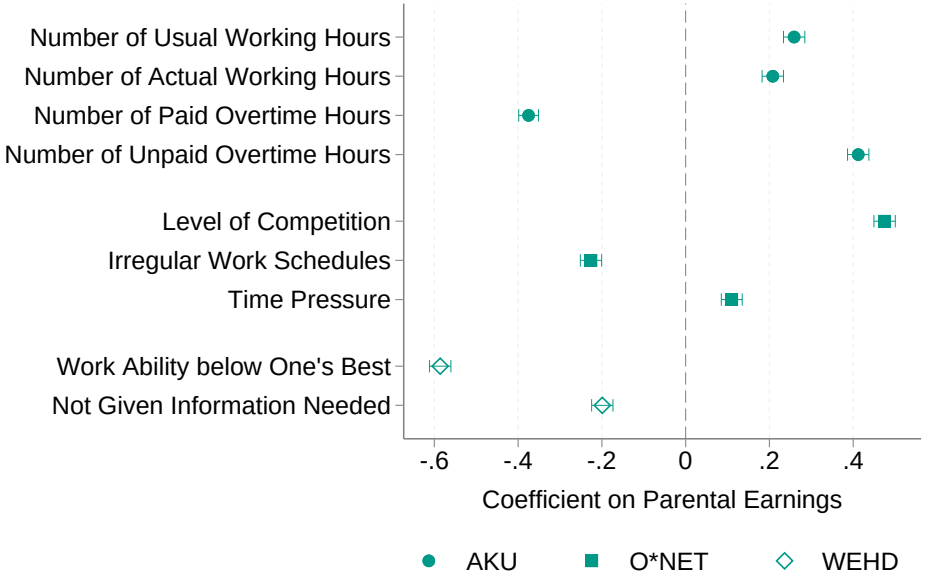
Notes: Panel (a) shows, for each two-digit occupation, the elasticity of the probability that a child works in the occupation with respect to log parental earnings. Panel (b) shows the average rank difference, the child's value rank minus the child's earnings rank, among children in each occupation. Error bars in panel (a) represent 95% confidence intervals.

Figure 11: Job Attributes and the Value–Earnings Rank Wedge



Notes: Each marker shows the coefficient θ_k from a separate regression of the child's rank wedge on one occupation-level attribute. Attributes are measured at the two-digit occupation level and standardized. Horizontal bars represent 95% confidence intervals.

Figure 12: Job Attributes and Parental Earnings



Notes: Each marker shows the estimated coefficient from a separate regression of one attribute of the child's occupation on the parents' earnings rank. Attributes are measured at the two-digit occupation level and standardized. Horizontal bars represent 95% confidence intervals.

show that the occupations entered by the children of higher-earning parents are the demanding ones. In Figure 12, we show that the children of higher-earning parents work in occupations with longer hours, more unpaid overtime, more competition, and greater time pressure.

Our findings are consistent with recent evidence that higher-paying jobs are more demanding. In Denmark, workers who move to higher-paying jobs obtain more flexibility and better benefits, but they also work longer hours and report more stress (Humlum et al., 2026). In Germany, jobs with more work pressure tend to pay more, and workers would give up almost a tenth of their wage to face tight deadlines only occasionally instead of frequently (Nagler et al., 2025). In France, workers in the highest-paying jobs report less exposure to workplace hazards than those in the lowest-paying jobs, but more stress and overwork (Scott, 2026). Higher-paying jobs are therefore not worse in every respect, and in the United States most measured working conditions are better in higher-paying jobs and at higher-paying firms (Maestas et al., 2023; Sockin, 2022). The same holds for the jobs of the children of higher-earning parents, which carry a lower risk of injury and offer more freedom to make decisions. Our estimates of job value add an overall valuation of this bundle of attributes, inferred from the choices of workers. They do not identify the value of each attribute separately.

7.3 Intergenerational Transmission of Job Attributes and Amenities

Section 6 showed that the estimated flow amenity is transmitted from parents to children, with a rank-rank slope of 0.109. We infer the flow amenity of a job from the choices of workers, and we do not observe it directly. In this subsection, we complement our revealed-preference approach with observed job attributes from linked surveys. We do so in two steps. First, we document the intergenerational transmission of individual job attributes. Second, we relate the estimated amenities to these attributes.

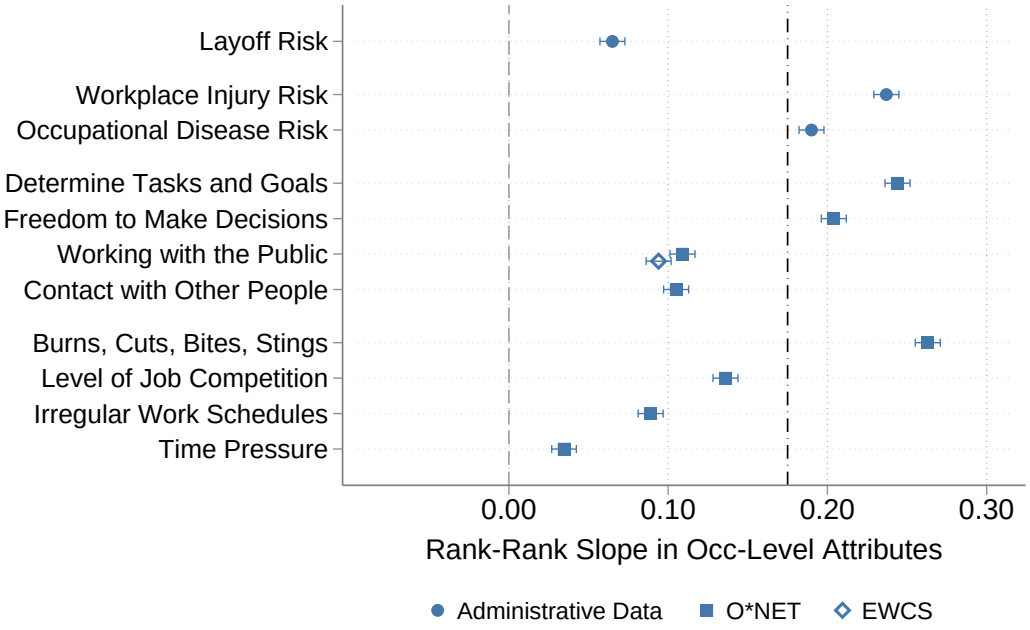
7.3.1 Intergenerational Transmission of Individual Job Attributes

We begin with the intergenerational transmission of *exposure* to job attributes. Our approach is to merge occupation-level measures of working conditions and tasks, drawn from several data sources, with the employment histories of parents and children. For each worker and each attribute, we average the measure over the jobs held during the measurement window. We then rank parents and children by this average and estimate a rank-rank slope for each attribute. The slope measures how much the expected rank of a child in exposure to an attribute changes when the parents' rank in exposure to that attribute increases by one percentile.

Figure 13 displays the estimates. The rank-rank slopes in the figure range from 0.04 to 0.26, compared with 0.175 for earnings. Some attributes are transmitted strongly, more so than

earnings. For example, the slope is 0.237 for workplace injury risk, 0.263 for exposure to minor injuries such as burns, cuts, bites, and stings, and 0.244 for determining one's own tasks and goals. Other attributes are only weakly related across generations: the slope is 0.065 for layoff risk, 0.089 for irregular work schedules, and 0.035 for time pressure.[70]

Figure 13: Intergenerational Transmission of Job Attributes



Notes: This figure shows the rank-rank slope from regressing child's rank in an occupation-level attribute on the parents' rank in the same attribute. Marker shapes indicate the data source. Horizontal bars represent 95% confidence intervals, and the dashed line marks the rank-rank slope in earnings. Appendix Figure A-4 shows additional attributes.

Related evidence comes from York et al. (2025), who document intergenerational persistence along several dimensions of occupational characteristics.[71] To the best of our knowledge, the persistence of exposure to injury, disease and layoff risk, measured in administrative registers, has not been documented before.

These slopes show substantial intergenerational persistence from the working conditions of parents to those of their children for several attributes. The main limitation is that these

[70]Layoff risk is the risk of an employment-to-nonemployment transition in the occupation, computed from matched employer-employee data. Workplace injury risk and occupational disease risk are the incidence of workplace accidents and of occupational diseases in the occupation, measured from social insurance claims. Claims are assessed by Labour Market Insurance (Arbejdsmarkedets Erhvervssikring; until July 2016, the National Board of Industrial Injuries, Arbejdsskadestyrelsen), which decides whether an injury is recognized and assesses permanent injury and the loss of earning capacity. See Humlum et al. (2025a) for a description of the register, and Appendix F.2 for the construction of the injury measures.

[71]Burger et al. (2025) estimate a standardized association of 0.14 between the self-direction at work of parents and of their adult children in a cohort from the United States.

measures are silent about the intergenerational transmission of the value of these attributes. Our estimates of amenities address this limitation, as they summarize the value that workers place on the bundle of non-pay attributes of a job, other than its security. Intergenerational persistence in the amenity rank (0.109) is below that of the most strongly transmitted attributes, such as workplace injury risk (0.237). One reason is that jobs pair attributes that workers dislike with attributes that they value, such as greater exposure to hazards with less stress in manual occupations, and this pairing can dampen the transmission of valuations.[72] We next examine how the amenity estimates relate to observed attributes.

7.3.2 Interpreting Estimated Amenities Through Observed Job Attributes

We relate the flow amenity estimates for the child generation to occupation-level measures of job attributes, for two reasons. The first is to compare our amenity estimates with existing evidence on how workers value these attributes. The second is to identify the attributes that underlie the transmission of amenities across generations. We draw on three sources: hours worked from the AKU, workers' assessments of their work from the WEHD, and work activities and work context from O*NET.

We first regress the amenity rank of a job on one measure at a time:

$$\widetilde{\phi}_{i\ell j} = \gamma_{0k} + \gamma_k X_{o(i,j),k} + \epsilon_{i\ell jk}, \tag{30}$$

where $\widetilde{\phi}_{i\ell j}$ is the rank of the flow amenity of job j, held by worker i of type ℓ, in the distribution of estimated flow amenities, and $X_{o(i,j),k}$ is measure k for the occupation $o(i,j)$ of that job, standardized to have unit standard deviation. The slope γ_k is the difference in the amenity rank that is associated with a difference of one standard deviation in the measure: a slope of -0.050 means that the amenity rank is 5 percentile points lower.

We use eight O*NET measures to capture eight job attributes of interest. Existing studies find that workers dislike six of these attributes, or closely related ones: time pressure, competition, irregular or seasonal schedules, exposure to hazardous conditions, repeating the same tasks, and dealing with unpleasant or angry people. They find that workers value the other two: assisting and caring for others, and freedom to determine one's own tasks, priorities and goals.[73]

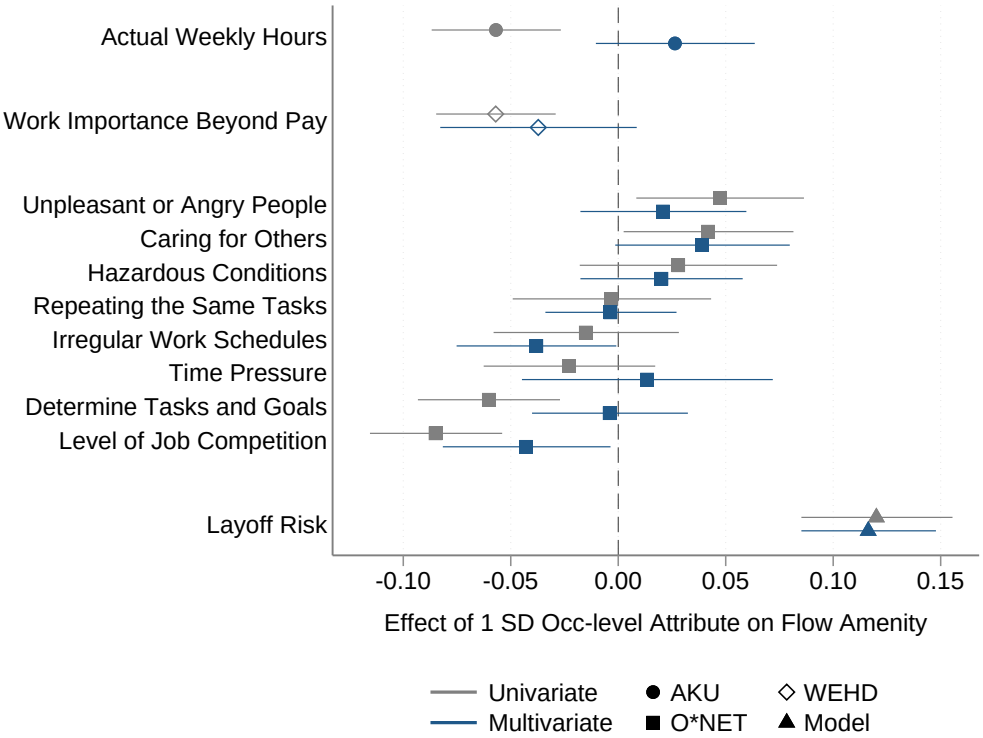
Figure 14 shows these slopes in gray. The figure also reports the job-destruction rate and two

[72] In addition, the amenity estimates reflect unmeasured attributes, and they vary across establishment types within the same occupation, whereas the measured attributes vary only across occupations.

[73] The studies measure tight deadlines (Nagler et al., 2025), pay that depends on outperforming a coworker (Flory et al., 2015), schedules set by the employer (Mas and Pallais, 2017), the risk of fatal injury (Lavetti and Schmutte, 2016; Morchio and Moser, 2026), variety in tasks (Boar and Lashkari, 2025), stress (Humlum et al., 2026), and having a positive impact on others and choosing how to do one's work (Maestas et al., 2023; Humlum et al., 2025b).

survey measures: actual weekly hours, from the AKU, and how important workers say their work is to them beyond the income it provides, from the WEHD. As expected, the amenity rank is lower in occupations with more competition and higher in occupations whose work involves more assisting and caring for others. In contrast, it is lower in occupations that give workers more freedom to determine their own tasks, and higher in occupations whose workers deal more often with unpleasant or angry people. These slopes reflect two features of our amenity estimates: the amenity rank falls with the pay rank of the job, and it rises with the job-destruction rate. Attributes that are concentrated in well-paid occupations therefore tend to have negative slopes, and attributes of manual occupations that pay less tend to have positive slopes.

Figure 14: Estimated Flow Amenities and Observed Job Attributes



Notes: Each row shows two estimates for one measure. Gray markers show the slope from a separate regression of the amenity rank on the measure alone, equation (30). Navy markers show the coefficient from the joint regression on all eleven measures, equation (31). Marker shapes indicate the source of the measure: the AKU (circle), the WEHD (diamond), O*NET (square), and the model (triangle). Layoff Risk is the job-destruction rate estimated in the model. Horizontal bars represent 95% confidence intervals, with standard errors clustered by three-digit occupation.

To separate these attributes from one another and from job-destruction risk, we then estimate

a multivariate regression of the amenity rank on all ten measures and the job-destruction rate:

$$\widetilde{\phi}_{i\ell j} = \gamma_0 + \sum_{k=1}^{10} \gamma_k \, X_{o(i,j),k} + \beta \, \delta_{\ell j} + \epsilon_{i\ell j}, \tag{31}$$

where $\delta_{\ell j}$ is the job-destruction rate of job j for workers of type ℓ. We include the job-destruction rate since jobs with higher destruction rates have lower continuation values, all else equal, and therefore need higher flow amenities to rationalize their values.

Holding the other measures and the job-destruction rate fixed, the coefficients on freedom to determine one's own tasks and on dealing with unpleasant or angry people become small and are not statistically significant. The amenity rank is lower in occupations with more competition and more irregular or seasonal schedules. It is also higher, though less precisely estimated, in occupations whose work involves more caring for others. These findings are consistent with the evidence on how workers value these attributes.

Taken together, these comparisons reassure us that our amenity estimates reflect attributes of jobs that workers value. They also give content to the transmission of amenities documented above. A job with high estimated amenity tends to involve more caring for others. A job with a low estimated amenity tends to involve more competition and more irregular or seasonal schedules.

8 Robustness and Additional Results

This section provides additional evidence on intergenerational mobility in job value and assesses robustness to alternative specifications and heterogeneous job rankings.

8.1 Robustness

Our main finding is that there is more mobility in job value than in earnings: the rank-rank slope is 0.111 for job value and 0.175 for earnings. This section examines the sensitivity of this finding. First, we discuss how estimation error in job values affects the rank-rank slope, and we report the bootstrap and split-sample exercises. Second, we rank families by the sum of the parents' outcomes instead of the average. Third, we estimate job values using only workers in their thirties. Fourth, we allow for involuntary job-to-job moves through "Godfather" shocks. Fifth, we rank jobs with an off-the-shelf method, the PageRank approach of Sorkin (2018). Table 4 collects the results. We find that there is less persistence in job value than in earnings in every exercise.

Table 4: Rank-Rank Slopes in Job Value and in Earnings under Alternative Specifications

	Job value	Earnings	Difference		Pairs
			Level	Percent	
	(1)	(2)	(3)	(4)	(5)
Panel A: Bootstrap standard errors from 100 re-estimates					
Baseline	0.111	0.175	-0.064^{***}	-37	76,187
	(0.0038)	(0.0036)			
Panel B: Alternative family measures					
Sum of mother and father	0.122	0.146	-0.024^{***}	-16	76,187
	(0.004)	(0.004)			
Panel C: Sample restrictions					
Job values from workers aged 30–39	0.114	0.177	-0.063^{***}	-36	76,187
	(0.004)	(0.004)			
Panel D: Alternative model					
Model with Godfather shocks	0.092	0.176	-0.084^{***}	-48	76,187
	(0.004)	(0.004)			
Panel E: One ranking of jobs for all workers					
PageRank	0.080	0.175	-0.095^{***}	-54	76,187
	(0.004)	(0.004)			

Notes: This table reports rank-rank slopes from regressions of the child's rank on the parents' rank, for job value in column (1), as in equation (25), and for earnings in column (2), as in equation (24). Parents are ranked by the average of the mother's and the father's outcome, except in Panel B. In each row, the two slopes are estimated on the same parent-child pairs, whose number is in column (5). Column (3) reports the difference between columns (1) and (2), and column (4) expresses it as a percentage of column (2). Standard errors are in parentheses. Stars in column (3) mark a difference that is significantly different from zero: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Panel A reports the baseline, with a standard error in column (1) that includes the estimation error in job values, measured across 100 re-estimates of the model on bootstrap samples of workers; without it, the standard error is 0.0036. Panel B ranks parents by the sum of the mother's and the father's outcome. Panel C re-estimates the model for 2010–2019 on workers aged 30 to 39. Panel D re-estimates the model with a Godfather shock, an outside offer that the worker cannot refuse. Panel E ranks jobs with the PageRank approach of Sorkin (2018), which yields one ranking of jobs for all workers.

8.1.1 Sampling Error in Job Values

A key concern is that job values are estimated, so the job-value ranks of both parents and children contain sampling error. One might wonder whether this error, rather than the transmission of job value across generations, explains why job value is less persistent than earnings. Error in the job-value rank of a person can arise for two reasons. First, job-to-job moves are, in principle, rare events, so the value of a job with few workers may be estimated from few moves, even though we use all voluntary moves of prime-age workers over a ten-year window. Second, the job values themselves are estimated from a dynamic search model, and they inherit the sampling error of its parameters.

As Nybom and Stuhler (2017) show for the rank-rank slope in earnings, such error similarly attenuates estimated slopes toward zero. In our case, error attenuates both the rank-rank slope of job value on parental earnings and the rank-rank slope of job value on parental job value toward zero, provided that the error in each generation's rank is unrelated to the other generation's true rank and to the other generation's error.[74] Our estimates are then a lower bound on the true intergenerational persistence of job value, and what matters for our finding is the size of the error. To assess it, we take two approaches. First, we estimate the model separately on two disjoint halves of the estimation sample and correlate the job-value ranks that the two halves give each child and each family. Second, we account for the error in our standard errors. The conventional standard error of the rank-rank slope treats the estimated job values as data. To capture the error in the job values themselves, we draw 100 bootstrap samples of workers, keeping each worker's entire history, re-estimate the model on each sample, and recompute the rank-rank slope for the same parent-child pairs. We then add the variance of the slope across the 100 draws to the conventional variance.[75]

Panel A of Table 4 reports the results. The standard deviation of the slope in job value across the 100 draws is 0.0011, so the standard error rises only from 0.0036 to 0.0038. Even if we treat the two slopes as independent, which likely overstates the standard error of their difference because both are estimated on the same parent-child pairs, the standard error of the difference is 0.005, an order of magnitude below the difference of 0.064. The split-sample exercise points in the same direction: the correlation between the job value ranks from the two halves is 0.971

[74] We estimate the model separately for 1991–2000 and 2010–2019, on different samples, so the sampling errors in the job values of parents and of children are unrelated.

[75] The overall standard error is the square root of the sum of the two squared standard errors, which assumes that the two sources of error are uncorrelated. They could be correlated, because the linked parents and children are also part of the estimation samples. This correlation is likely small. The estimation samples cover the prime-age working population in each window, so the job values are estimated mostly from the moves of workers who are neither linked parents nor linked children: the linked children, for example, are two of the 34 birth cohorts in the 2010–2019 sample. In the worst case, the standard error is the sum of the two standard errors, $0.0036 + 0.0011 = 0.0047$ (Cocci and Plagborg-Møller, 2025), and the standard error of the difference between the two slopes is at most $0.0047 + 0.0036 = 0.0083$, about an eighth of the difference of 0.064.

for children and 0.944 for parents, which suggests that the attenuation of the rank-rank slope is modest.[76] Our finding thus does not hinge on sampling error in the estimated job values.

8.1.2 Measures of Family Job Values

A potential concern is that our comparison depends on how we combine the outcomes of the two parents. In the baseline, the outcome of a family is the average of the mother's and the father's outcomes when both parents are linked to the child, and the outcome of the single linked parent otherwise. An alternative is the sum of the two parents' outcomes, in the spirit of studies that rank parents by family income (Chetty et al., 2014a). The two measures rank families with two linked parents in the same order. They differ in how these families compare with families in which a single parent is linked.

Panel B of Table 4 reports the results with the sum. The rank-rank slope in job value rises from 0.111 to 0.122, and the slope in earnings falls from 0.175 to 0.146. The difference between the two slopes therefore narrows, from 37 percent to 16 percent. Our qualitative finding remains: job value is less persistent than earnings under either measure of family background.

8.1.3 Sample Restrictions

Another potential concern is that the sample from which we estimate job values is too broad. We observe the children in the IGM-Job sample in their thirties, so our goal is to estimate the value of a job to workers of that age. The Job sample for 2010–2019, however, also includes workers in their twenties, in their forties and in their early fifties. The moves of younger and older workers could bias our estimates if workers value jobs differently at different points of the life cycle. For instance, in a choice experiment with workers in the United States, Maestas et al. (2023) find that workers aged 25 to 34 are willing to give up 9 percent of their wage for a job with moderate instead of heavy physical activity, while workers aged 50 to 61 are willing to give up 18 percent. We use the broad sample in our baseline for two reasons. In our model, workers of a given type value jobs in the same way at every age, and a larger sample contains more job moves, which makes our estimates of job value more precise. To address this concern, we estimate the model for 2010–2019 on a more restrictive sample that includes only workers in their thirties.[77]

Panel C of Table 4 reports the results. Our estimates of intergenerational persistence in job value using only transitions of workers in their thirties are similar to our baseline: the rank-rank

[76] See Appendix Table A-14.

[77] Sorkin (2018) reports a related exercise: the values of firms that he estimates from two disjoint groups of workers, those aged 18 to 34 and those aged 35 to 61, have a correlation of 0.83.

slope is 0.114, compared with 0.111. The slope in earnings for the same pairs is 0.177, so the difference between the two slopes is 36 percent, compared with 37 percent in the baseline.

8.1.4 Involuntary Job-to-Job Moves

Our baseline assumes that every job-to-job move is a choice: the worker could have stayed in her job and preferred the outside offer. One might wonder whether our finding depends on this assumption. Some moves may instead be forced on workers, for example when an establishment closes or contracts and a worker moves directly to another employer. If we treat such moves as choices, we wrongly infer that these workers prefer the jobs that they move to, which contaminates our estimates of job value. To assess this possibility, we estimate a version of the model with Godfather shocks (Jolivet et al., 2006): with some probability, an employed worker receives an offer that she cannot refuse and moves to another job regardless of its value.[78] We estimate the probability of the shock from establishments that contract, following Sorkin (2018): job-to-job moves out of these establishments in excess of the rate that the model predicts count as forced, as described in Appendix H.1.2.

Panel D of Table 4 reports the results. With Godfather shocks, the rank-rank slope in job value is 0.092, compared with 0.111 in the baseline, and the slope in earnings for the same pairs is 0.176. The difference between the two slopes widens from 37 percent to 48 percent. Our finding thus does not hinge on treating every job-to-job move as a choice. If anything, job value is less persistent once we allow for involuntary moves.

8.1.5 PageRank

As a related benchmark, we consider the ranking of jobs implied by the PageRank approach of Sorkin (2018). This approach ranks jobs from the moves of workers between them.[79] We apply it to the moves of all workers together, so that it yields one ranking of jobs. It offers a transparent benchmark, without the worker types and the wage dispersion within jobs that our model adds.

Panel E of Table 4 reports the results. When we rank the jobs of children and of parents with this approach, the rank-rank slope in job value is 0.080, compared with 0.175 for earnings, a difference of 54 percent. We thus also find less persistence in job value than in earnings, and the gap is larger than in the baseline.

[78] Formally, a worker of type ℓ whose job j is not destroyed is reallocated with probability $\rho_{\ell j}$ to a job–wage pair drawn from a distribution $\tilde{g}_\ell$, without the option to stay in job j. The probability of the shock is thus specific to both the worker type and the job. When $\rho_{\ell j} = 0$ for all types and jobs, the model reduces to our baseline. See Appendix H.1.2 for the value function.

[79] See Appendix H.1.3.

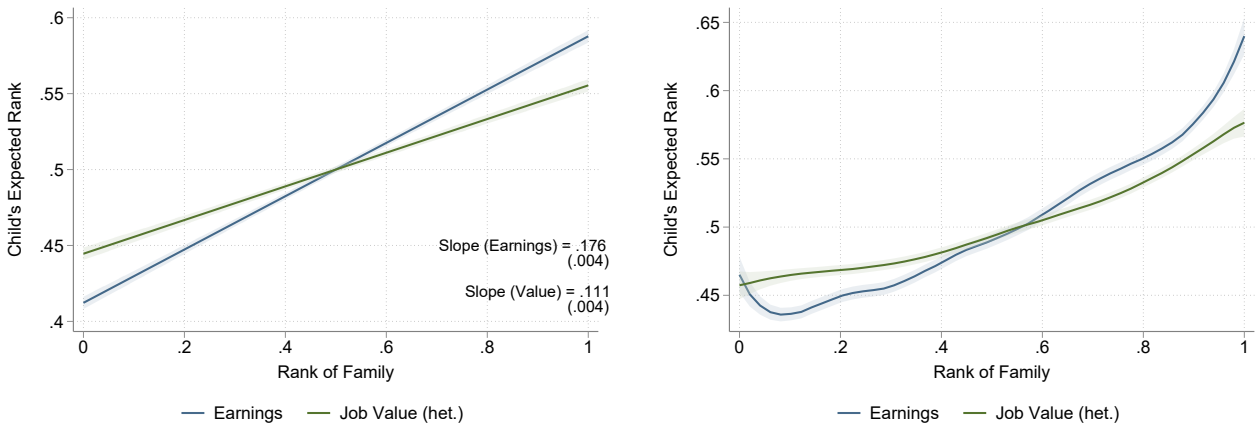
8.2 Additional Results

8.2.1 Absolute Mobility

A single linear rank–rank slope can mask important nonlinearities in the parent–child relationship. To address this possibility, we consider a flexible specification that imposes no linear restriction on how the expected rank of children varies with the rank of their parents, for both job value and earnings.

Figure 15 plots children's expected rank as a function of parental rank, comparing outcomes when both generations are measured by job value versus when both are measured by earnings. Panel (a) presents the linear comparison. Below the median of the parental distribution, children's expected rank is higher in job value than in earnings. Above the median, the opposite holds. Panel (b) shows the non-linear comparison using local linear regression. The gap between the two curves becomes more pronounced at the top of the parental distribution: above the 90th percentile, the expected earnings rank of children rises from 0.58 to 0.64, whereas their expected job value rank rises from 0.55 to 0.58. Children from families above the 56th percentile of the parental distribution achieve higher expected ranks when outcomes are measured by earnings than by job value.

Figure 15: Absolute Mobility in Value-Value Specification



(a) Linear Comparison

(b) Non-linear Comparison

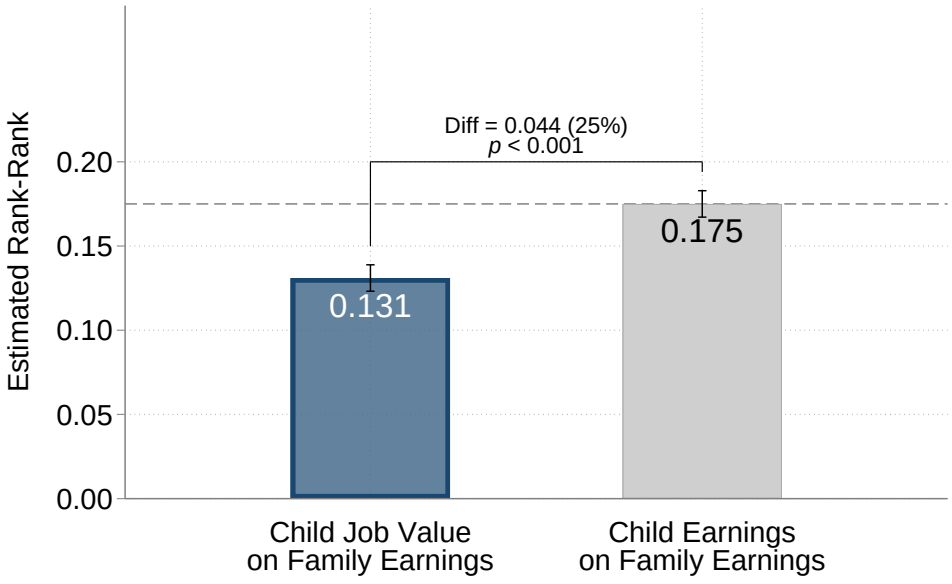
Notes: This figure plots children's expected rank (vertical axis) against the rank of their families (horizontal axis), when both generations are ranked by earnings (blue line) or by job value (green line). Families are ranked by the average of their parents' earnings or job values. Job value allows preferences to differ across worker types. Panel (a) shows linear fits and panel (b) shows local linear regression fits. Shaded areas represent 95 percent confidence intervals. Appendix Figure A-12 adds binned means.

8.2.2 Other Intergenerational Transmission

Our baseline estimates rank children and parents by the same outcome. We also estimate rank–rank slopes in which the child's outcome differs from the parents' outcome, ranking families by their earnings in both cases. We consider two pairs, listing the child's outcome first and the parents' outcome second: value–earnings and amenity–earnings. The value–earnings slope measures how strongly the job value of children depends on the earnings of their parents, the measure of family background used in most of the literature. The amenity–earnings slope measures how parental earnings relate to the amenities of children's jobs.

Figure 16 compares the value–earnings slope with the earnings–earnings slope. A one-percentile increase in family earnings rank is associated with a 0.131 percentile increase in the child's job-value rank, compared with a 0.175 percentile increase in the child's earnings rank. The difference is 0.044, or 25 percent of the earnings–earnings slope. Family earnings therefore predict children's job value less strongly than their earnings. The value–earnings slope is still higher than the value–value slope (0.111; Figure 6). Appendix H.2.2 reports the amenity–earnings slopes.

Figure 16: Value–Earnings and Earnings–Earnings Transmission



Notes: The figure reports rank–rank slopes of the child's job value (left) and the child's earnings (right) on the family's earnings rank. Families are ranked by the average of their parents' earnings. Job value allows preferences to differ across worker types. Whiskers show 95 percent confidence intervals. The p-value is from a two-sample z-test that treats the two estimates as independent.

8.2.3 Further Results

Appendix H.2 collects further results. We estimate the intergenerational transmission of job value and of its components separately for sons and daughters in Appendix H.2.4, and we decompose the transmission of job value into transmission within and across worker types in Appendix H.2.5. Appendix H.2.6 also shows how job value, pay, and job security vary with age.

9 Conclusion

This paper develops a novel measure of intergenerational mobility in job value, which reflects both pay and amenities. Using a revealed preference approach, we infer the value of each job from voluntary moves in the labor market, and we allow workers of different types to value the same job differently. In doing so, we bridge the mobility and amenity literatures.

In Denmark, there is 37% less persistence in job value than in earnings alone. This difference is statistically significant and economically meaningful, highlighting that earnings-based measures understate the degree of mobility in the total value of a job across generations in Denmark. Decomposing the difference between value and earnings transmission, we find that the children of higher-earning parents sort into high-wage, more demanding jobs, which involve greater competition, longer hours, and greater time pressure. This sorting is the most important factor behind the difference and suggests that a wealth channel, in which children from affluent families trade pay for better amenities, plays a limited role in Denmark.

Whether Denmark's patterns hold elsewhere remains an open empirical question. We view our method as a template that researchers can apply globally. The approach requires parent-child linkages, longitudinal employer-employee data, and information that distinguishes quits from layoffs, such as administrative benefit records. These data are increasingly available across developed and developing countries. Applying our approach in other countries could help establish new facts about intergenerational mobility and provide new insights into how labor market institutions, social insurance systems, and education policies jointly shape the relationship between wages and amenities across generations.

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

First, our model abstracts from the mechanisms behind the intergenerational transmission of job value to focus on its measurement. In particular, it takes the education of parents and children as given, even though education is associated with a substantial share of the persistence in job value. A natural extension would model how the amenities of parents' jobs shape their children's skill formation, and how this channel interacts with parents' career choices. For example, high-paying jobs with long hours may give parents more money to invest in their

children but less time to spend with them (Del Boca et al., 2014). This channel matters for policies such as parental leave and limits on working hours: if search frictions keep parents from switching to jobs that leave more time for their children, they may impede skill formation in the next generation and widen inequality.

Second, the value of a job represents only one dimension of welfare. Well-being also depends on consumption possibilities beyond one's own pay, family relationships, rich social networks, varied urban amenities, and numerous other factors that extend beyond the labor market. A truly comprehensive measure of intergenerational mobility in welfare would be multidimensional. A systematic, comprehensive approach for measuring the value that individuals receive from non-pecuniary sources of utility outside of the labor market is a fruitful avenue for future research.

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APPENDICES FOR ONLINE PUBLICATION

Intergenerational Mobility in the Value of a Job

by Natalia Khorunzhina, Jesse Wedewer, and Runling Wu

November 2, 2026

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A Model

A.1 Equivalence of Preference Weight and Shock Scale

In this appendix, we show an alternative casting of the model in the main body, where we normalize the preference weight on consumption utility to one and leave the scale of preference shocks free. We allow a type-specific scale of the preference shocks, $\sigma_\ell = 1/\alpha_\ell$.

We mark objects in this alternative casting with a check accent, $\check{V}$, $\check{\phi}_{\ell j}$, $\check{b}_\ell$, to distinguish them from their main-text counterparts V, $\phi_{\ell j}$, b_ℓ. Here, the value functions are measured in consumption-utility units. Written out in full, the value of employment for a type-ℓ worker at (j, w) becomes:

$$\begin{aligned}\check{V}^e_{\ell j}(w) = \underbrace{u(w) + \check{\phi}_{\ell j}}_{\text{flow payoff}} + \beta\,\mathbb{E}\Big[\quad & \underbrace{\delta_{\ell j}\{\check{V}^n_\ell + \sigma_\ell\,\iota_1\}}_{\text{exogenous job destruction}} \\ & + (1-\delta_{\ell j})\Big[\quad \lambda^1_\ell \sum_{(j',w')} g_\ell(j',w') \\ & \qquad \underbrace{\times \max\{\check{V}^e_{\ell j'}(w') + \sigma_\ell\,\iota_2,\ \check{V}^e_{\ell j}(w) + \sigma_\ell\,\iota_3\}}_{\text{offer arrives: endogenous job-to-job}} \\ & \quad + \underbrace{(1-\lambda^1_\ell)\max\{\check{V}^n_\ell + \sigma_\ell\,\iota_4,\ \check{V}^e_{\ell j}(w) + \sigma_\ell\,\iota_5\}}_{\text{no offer: worker chooses stay vs. quit}}\Big]\Big]\end{aligned} \tag{A1}$$

The value of nonemployment becomes:

$$\begin{aligned}\check{V}^n_\ell = \underbrace{\check{b}_\ell}_{\text{flow payoff}} + \beta\,\mathbb{E}\Big[\quad & \lambda^0_\ell \sum_{(j',w')} g_\ell(j',w') \\ & \underbrace{\times \max\{\check{V}^e_{\ell j'}(w') + \sigma_\ell\,\iota_6,\ \check{V}^n_\ell + \sigma_\ell\,\iota_7\}}_{\text{offer arrives: worker chooses job versus remaining nonemployed}} \\ & + \underbrace{(1-\lambda^0_\ell)\{\check{V}^n_\ell + \sigma_\ell\,\iota_8\}}_{\text{no offer}}\Big]\end{aligned} \tag{A2}$$

Conditional on incumbent-job survival, an employed worker of type ℓ at (j, w) holding an offer (j', w') accepts it with probability:

$$\mathbb{P}_{\ell,j'w'|jw} = \frac{\exp\big(\check{V}^e_{\ell j'}(w')/\sigma_\ell\big)}{\exp\big(\check{V}^e_{\ell j'}(w')/\sigma_\ell\big) + \exp\big(\check{V}^e_{\ell j}(w)/\sigma_\ell\big)}. \tag{A3}$$

Dividing equation (A1) by σ_ℓ turns each draw $\sigma_\ell\iota$ back into a standard draw as in the main

body and the flow payoff into $1/\sigma_\ell[u(w) + \check{\phi}_{\ell j}]$, where we can see the equivalence $\alpha_\ell = 1/\sigma_\ell$.

A.2 Further Discussion of Model Assumptions

Assumption A.1 (Permanent observable types and segmented search)**.** *A worker's type ℓ is permanent and observed. Conditional on type, workers search only within the type-specific labor market.*

Assumption A.2 (Posted bundles and job-level amenities)**.** *Each offer is a take-it-or-leave-it job-wage bundle. For a given worker type, $\phi_{\ell j}$ is constant across the wage cells of job j.*

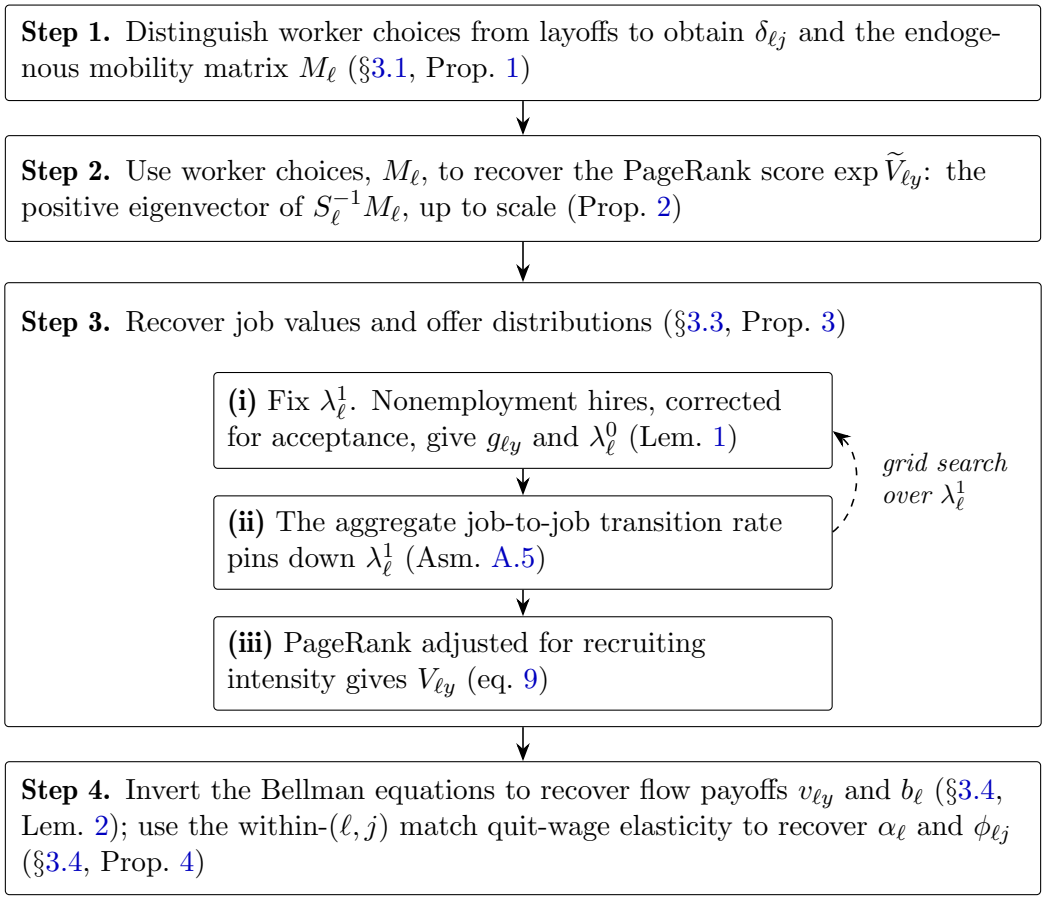
Assumption A.3 (Common joint offer distribution)**.** *Conditional on worker type, employed and nonemployed workers draw job–wage pairs from the same joint offer distribution G_ℓ, with probability mass function $g_\ell(j, w)$. Their meeting probabilities λ_ℓ^1 and λ_ℓ^0 may differ.*

Assumption A.4 (Independent extreme-value taste shocks)**.** *Conditional on the observed state and choice set, taste shocks are independent across alternatives, workers, and choice occasions and follow a Type-I extreme-value family. They are independent of job and wage offers.*

B Identification

B.1 Overview of Identification Procedure

Figure A-1: Overview of the Identification Argument



Notes: We denote a job–wage pair by $y \equiv (j, w)$.

B.2 Details of Step 1: Identifying Exogenous and Endogenous Separations

B.2.1 Destruction Probabilities and the Endogenous Mobility Matrix

Let each EN transition r carry the label θ_r, equal to one for a quit and zero for a layoff. Let $\mathcal{EN}_{\ell j}$ collect the type-ℓ EN transitions from job j, and let $\mathcal{EN}_{\ell y}$ collect those from the job–wage pair y. Let $G_{\ell y}$ denote the number of type-ℓ person-period observations at y, and let $G_{\ell j} \equiv \sum_w G_{\ell,(j,w)}$ denote the number at the job.

Definition 1 (Endogenous Mobility Matrix)**.** For each worker type ℓ, recall $\mathcal{A} = \{n\} \cup \mathcal{Y}$ is the set containing nonemployment and every job–wage pair. We define M_ℓ as a matrix whose

rows index destinations and whose columns index origins. For $a, a' \in \mathcal{A}$, the entry $[M_\ell]_{a',a}$ is the mass of type-ℓ workers who move from origin state a to destination state a' by choice. In particular,

$$M^\ell_{y \to y'} \equiv [M_\ell]_{y',y} \tag{A4}$$

and $M^\ell_{y \to n}$ and $M^\ell_{n \to y}$ denote the quits into nonemployment and the hires from nonemployment.

Offsetting classification errors. Let $\eta^{\text{lay}}_{\ell y}$ denote the probability that an EN transition from y generated by job destruction is labeled a quit, and let $\eta^{\text{quit}}_{\ell y}$ denote the probability that an EN transition from y generated by a quit is labeled a layoff. In each person-period at $y = (j, w)$, a type-ℓ worker loses her job to destruction with probability $\delta_{\ell j}$ and quits into nonemployment with probability $m_{\ell y}$, the voluntary quit probability of Section 3.4. Assumption 4 states that

$$\eta^{\text{lay}}_{\ell y}\, \delta_{\ell j} = \eta^{\text{quit}}_{\ell y}\, m_{\ell y} \qquad \text{for every job–wage pair } y = (j, w). \tag{A5}$$

The left-hand side is the probability that a person-period at y ends in a layoff labeled a quit, and the right-hand side is the probability that it ends in a quit labeled a layoff. Correct classification, $\eta^{\text{lay}}_{\ell y} = \eta^{\text{quit}}_{\ell y} = 0$, satisfies equation (A5). So does any pair of error probabilities whose ratio equals the ratio of quits to layoffs at y, $\eta^{\text{lay}}_{\ell y} / \eta^{\text{quit}}_{\ell y} = m_{\ell y} / \delta_{\ell j}$.

Under Assumption 4, the destruction probability equals the expected number of transitions labeled layoffs per person-period observation at the job, and the quit flow from y equals the expected number of transitions from y labeled quits:

$$\delta_{\ell j} = \frac{\mathbb{E}\Big[\sum_{r \in \mathcal{EN}_{\ell j}} (1 - \theta_r)\Big]}{G_{\ell j}}, \tag{A6}$$

$$M^\ell_{y \to n} = \mathbb{E}\Big[\sum_{r \in \mathcal{EN}_{\ell y}} \theta_r\Big]. \tag{A7}$$

Every job-to-job transition, every hire from nonemployment, and every EN transition labeled a quit enters the matrix. Transitions labeled layoffs are excluded and instead enter the destruction probability. Under Assumption 4, the matrix therefore measures the endogenous transitions in expectation.

Proof of Proposition 1. Fix a worker type ℓ and a job–wage pair $y = (j, w)$. The expected number of transitions from y that are labeled layoffs is

$$G_{\ell y}\big[(1 - \eta^{\text{lay}}_{\ell y})\, \delta_{\ell j} + \eta^{\text{quit}}_{\ell y}\, m_{\ell y}\big] = G_{\ell y}\, \delta_{\ell j},$$

where the equality follows from equation (A5). Because $\delta_{\ell j}$ does not vary across the wage cells of a job, summing over the wage cells of job j gives $G_{\ell j}\,\delta_{\ell j}$ expected transitions labeled layoffs at the job, which is equation (A6). In the same way, the expected number of transitions from y that are labeled quits is $G_{\ell y}\big[(1-\eta^{\text{quit}}_{\ell y})\,m_{\ell y}+\eta^{\text{lay}}_{\ell y}\,\delta_{\ell j}\big] = G_{\ell y}\,m_{\ell y}$. This is the quit flow of equation (6), with the employment mass measured by person-period observations as in Section 5, and it gives equation (A7). Job-to-job transitions and hires from nonemployment need no classification. Hence $\delta_{\ell j}$ and M_ℓ are identified. □

The destruction probabilities use Assumption 4 only after summing over the wage cells of each job. Equation (A6) holds if and only if

$$\sum_w G_{\ell,(j,w)}\,\eta^{\text{lay}}_{\ell,(j,w)}\,\delta_{\ell j} = \sum_w G_{\ell,(j,w)}\,\eta^{\text{quit}}_{\ell,(j,w)}\,m_{\ell,(j,w)}. \tag{A8}$$

When this condition fails, the expected number of transitions labeled layoffs per person-period at the job equals $\delta_{\ell j}$ plus the expected number of quits labeled layoffs, minus the expected number of layoffs labeled quits, per person-period. The condition at each job–wage pair is needed for the quit flows in equation (A7), and therefore for M_ℓ and for the quit probabilities of Step 4, which we compute from the labels at each pair.

B.2.2 Classification Errors and Stated Reasons

Both kinds of error arise under our classification rule. The AKU lets us compare, for separations in the child generation, the benefit-based label with the reason that the worker states. To define our classification rule, we consider a wider sample than the estimation sample: all EN separations of prime-age workers in 2010–2019 that we can match to an AKU response, including those of workers who are still in school. Table A-6 shows how the stated reasons for separation align with benefit receipt in this sample: for each benefit category, it reports the share of matched transitions whose stated reason is a layoff. Of the 3,434 matched transitions that the benefit records label layoffs, 1,082 report a quit reason, and of the 5,360 that they label quits, 1,648 report a layoff reason. Table A-7 restricts the sample to post-education transitions, as in our estimation sample, and reports the same shares by label, together with the overall agreement rate. Of the 2,080 post-education transitions that the benefit records label layoffs, 546 report a quit reason, and of the 858 that they label quits, 349 report a layoff reason. The benefit-based label matches the stated reason for 69.5 percent of post-education transitions, compared with 69.0 percent in the full matched sample.

The comparison is too small to test Assumption 4 pair by pair. It shows that both kinds of error occur, which correct classification of every transition would rule out and Assumption 4

allows. Summed over all job–wage pairs, Assumption 4 implies that the two kinds of error are equally frequent. In the full matched sample, layoffs labeled quits outnumber quits labeled layoffs, 1,648 to 1,082. Transitions whose first benefit is a student grant account for 810 of the 1,648. These transitions are over-represented in the full matched sample, where they make up a third, because the AKU asks for the reason only while a respondent is nonemployed, so that long spells, such as those spent in education, are more likely to be matched. Excluding them, the benefit records label 3,434 matched transitions as layoffs, and 3,190 report a layoff reason, so that the two counts differ by less than 8 percent. In the post-education sample, quits labeled layoffs outnumber layoffs labeled quits. The benefit records label 2,080 of these transitions as layoffs, and 1,883 report a layoff reason, so that the two counts differ by about 10 percent.

B.3 Details of Step 2: Recover the PageRank Score

Dividing the job-to-job flow in equation (8) by the flow in the opposite direction gives

$$\underbrace{\frac{M^{\ell}_{y\to y'}}{M^{\ell}_{y'\to y}}}_{\text{relative flows}} = \underbrace{\frac{g_{\ell y'}}{g_{\ell y}}}_{\text{relative offers}} \cdot \underbrace{\frac{N_{\ell y}\left(1-\delta_{\ell j}\right)}{N_{\ell y'}\left(1-\delta_{\ell j'}\right)}}_{\text{effective relative size}} \cdot \underbrace{\frac{\exp V_{\ell y'}}{\exp V_{\ell y}}}_{\text{relative values}} \tag{A9}$$

Relative flows (accepted offers) are directly related to relative values, but multiplied by relative offers and effective size. Offer frequencies matter because workers tend to flow toward a position that they encounter often. In our model, a job-wage pair may be encountered frequently when the job is sampled more often, when its wage is commonly offered conditional on that job, or both. Accordingly, high inflows may not necessarily reveal that the job–wage pair is more desirable. They may simply reflect more opportunities for favorable idiosyncratic draws. Similarly, a high level of outflows may be a function of the size of the origin pair, or lower job-destruction rates, which have a mechanical effect on outflows, irrespective of job value. Collecting the terms that belong to each job–wage pair gives the PageRank score in equation (9) and the relation in equation (11).

B.4 Details of Step 3: Joint Identification of the Search Block

B.4.1 Job Values for a Given λ^1_ℓ

Fix a candidate value of $\lambda^1_\ell \in \Lambda_\ell$. Taking ratios of equations (9) and (10) and dividing by (7), we have

$$\frac{\exp \widetilde{V}_{\ell y}}{\exp \widetilde{V}_{\ell}^{\,n}} = \frac{\underbrace{N_{\ell}^{n} \lambda_{\ell}^{0} g_{\ell y} \exp V_{\ell y}}_{\text{common product}}}{N_{\ell y}(1-\delta_{\ell j})(1-\lambda_{\ell}^{1})}, \tag{A10}$$

$$M_{n \to y}^{\ell} = \frac{\underbrace{N_{\ell}^{n} \lambda_{\ell}^{0} g_{\ell y} \exp V_{\ell y}}_{\text{same product}}}{1 + \exp V_{\ell y}}. \tag{A11}$$

The unknown offer share and λ_{ℓ}^{0} enter both equations through the same product. Eliminating that product leaves

$$1 + \exp V_{\ell y}(\lambda_{\ell}^{1}) \;=\; \frac{(1-\lambda_{\ell}^{1}) \, \exp \widetilde{V}_{\ell y} \, N_{\ell y} \, (1-\delta_{\ell j})}{\exp \widetilde{V}_{\ell}^{\,n} \; M_{n \to y}^{\ell}} \tag{A12}$$

Every remaining object on the right-hand side of equation (A12) is known once λ_{ℓ}^{1} is specified. Then, we can recover $V_{\ell y}(\lambda_{\ell}^{1})$ using the above equation.

Equivalence to direct quit flows. The direct comparison with nonemployment satisfies

$$\frac{M_{n \to y}^{\ell}}{M_{y \to n}^{\ell}} = \frac{\exp \tilde{V}_{\ell y}}{\exp \tilde{V}_{\ell}^{\,n}}.$$

Substituting this equality into equation (A12) yields the equivalent conditional recovery equation

$$\exp V_{\ell y}(\lambda_{\ell}^{1}) = \frac{N_{\ell y} \, (1-\delta_{\ell j}) \, (1-\lambda_{\ell}^{1})}{M_{y \to n}^{\ell}} - 1 \tag{A13}$$

The network and quit-flow routes therefore impose the same population restriction. Positivity of (A13) requires

$$\lambda_{\ell}^{1} < 1 - \frac{M_{y \to n}^{\ell}}{N_{\ell y} \, (1-\delta_{\ell j})}$$

at every retained node.

B.4.2 Offer Shares and λ_{ℓ}^{0}

Once the value of employment is known, it first pins down $\mathbb{P}_{\ell y}(\lambda_{\ell}^{1})$, the probability of accepting an offer from nonemployment defined in equation (5) for a given λ_{ℓ}^{1}:

$$\mathbb{P}_{\ell y}(\lambda_{\ell}^{1}) = \frac{\exp V_{\ell y}(\lambda_{\ell}^{1})}{1 + \exp V_{\ell y}(\lambda_{\ell}^{1})}$$

Dividing each hire flow by its corresponding acceptance probability, we have

$$\frac{M^{\ell}_{n\to y}}{\mathbb{P}_{\ell y}(\lambda^1_\ell)} = N^n_\ell \lambda^0_\ell(\lambda^1_\ell) g_{\ell y}(\lambda^1_\ell) \tag{A14}$$

The left-hand side, i.e., the acceptance-corrected hire flow, is known for every possible value of λ^1_ℓ. Given that the joint offer shares sum to one, we show

$$g_{\ell y}(\lambda^1_\ell) = \frac{M^{\ell}_{n\to y}/\mathbb{P}_{\ell y}(\lambda^1_\ell)}{\sum_{y'} M^{\ell}_{n\to y'}/\mathbb{P}_{\ell y'}(\lambda^1_\ell)}, \qquad \lambda^0_\ell(\lambda^1_\ell) = \frac{1}{N^n_\ell}\sum_{y'} \frac{M^{\ell}_{n\to y'}}{\mathbb{P}_{\ell y'}(\lambda^1_\ell)} \tag{A15}$$

The relative distribution of such hire flows across job-wage pairs identifies the joint offer shares, while its total level identifies the offer-arrival probability from nonemployment. Replacing the sum in the denominator with $N^n_\ell \lambda^0_\ell(\lambda^1_\ell)$ gives the first expression in equation (15) in the main text.

Lemma 1 (Conditional Identification of the Offer Process)**.** *Fix a worker type ℓ and a given $\lambda^1_\ell \in \Lambda_\ell$, the admissible set defined in equation (A19), and suppose $M^{\ell}_{n\to y} > 0$ for every y. Given the candidate-implied values, equation (A15) determines the joint offer shares $g_{\ell y}$ and λ^0_ℓ uniquely.*

B.4.3 Selecting λ^1_ℓ

For a given $\lambda^1_\ell \in \Lambda_\ell$, the previous section recovers the employment values, joint offer shares, and acceptance probabilities entering the job-to-job flow equation for each pair. What remains unused is the aggregate level of job-to-job mobility, and it pins down λ^1_ℓ as we show below. Define the probability that an offer received at y generates a move,

$$\Gamma_{\ell y}(\lambda^1_\ell) \equiv \sum_{y'\neq y} g_{\ell y'}(\lambda^1_\ell)\, \mathbb{P}_{\ell, y'|y}(\lambda^1_\ell), \tag{A16}$$

where $\mathbb{P}_{\ell,y'|y}(\lambda^1_\ell)$ is the acceptance probability evaluated at the candidate value of λ^1_ℓ. Both the offer shares and acceptance probabilities vary with λ^1_ℓ. Define total beginning-of-period employment as $N_\ell \equiv \sum_y N_{\ell y}$. Summing over all pairs of distinct job-wage pairs and dividing by N_ℓ gives

$$\underbrace{\frac{1}{N_\ell}\sum_{y}\sum_{y'\neq y} M^{\ell}_{y\to y'}}_{\text{observed aggregate job-to-job transition rate}} = \lambda^1_\ell \sum_y \frac{N_{\ell y}}{N_\ell}\,(1-\delta_{\ell j})\,\Gamma_{\ell y}(\lambda^1_\ell) \tag{A17}$$

The left-hand side is the observed aggregate job-to-job transition rate for type-ℓ workers, obtained by summing job-to-job transitions and dividing by total beginning-of-period employment. The right-hand side is its model-implied counterpart: the beginning-of-period employment-share weighted average of job-to-job transition probabilities.[80] Equation (A17) therefore selects the specific λ_ℓ^1 that is consistent with the observed aggregate job-to-job transition rate. Equation (16) in the main text is the same condition with $\Gamma_{\ell y}(\lambda_\ell^1)$ written out.

Derivation of the job-to-job condition. Fix $\lambda_\ell^1 \in \Lambda_\ell$. Summing equation (8) over destinations gives

$$\begin{aligned}\sum_{y' \neq y} M^{\ell}_{y \to y'} &= N_{\ell y}(1-\delta_{\ell j})\lambda_\ell^1 \sum_{y' \neq y} g_{\ell y'}(\lambda_\ell^1)\mathbb{P}_{\ell,y'|y}(\lambda_\ell^1) \\ &= N_{\ell y}(1-\delta_{\ell j})\lambda_\ell^1 \Gamma_{\ell y}(\lambda_\ell^1),\end{aligned} \tag{A18}$$

where the second equality uses the definition in equation (A16). Summing over origins and dividing by $N_\ell = \sum_y N_{\ell y}$ yields

$$\frac{1}{N_\ell}\sum_y \sum_{y' \neq y} M^{\ell}_{y \to y'} = \lambda_\ell^1 \sum_y \frac{N_{\ell y}}{N_\ell}(1-\delta_{\ell j})\Gamma_{\ell y}(\lambda_\ell^1),$$

which is equation (A17).

The admissible set. The conditional formulas determine which candidate values are admissible:

$$\Lambda_\ell = \left\{\lambda_\ell^1 \in [0,1) : \ \exp V_{\ell y}(\lambda_\ell^1) > 0 \text{ at every retained node, } \ \lambda_\ell^0(\lambda_\ell^1) \leq 1\right\}, \tag{A19}$$

an interval $[0, \cdot)$, because each implied value decreases and $\lambda_\ell^0(\lambda_\ell^1)$ increases in the candidate λ_ℓ^1. The true parameter point lies in Λ_ℓ, since the population configuration satisfies every constraint.

Existence, admissibility, and uniqueness of the root.

Assumption A.5 (Unique root on Λ_ℓ)**.** *Equation* (16) *has a unique root in* Λ_ℓ.

Assumption A.5 ensures that the search over candidate values selects a unique value of λ_ℓ^1, thereby identifying the arrival probabilities.

The admissible set Λ_ℓ of (A19) is an interval, and on it every candidate-implied object—values, acceptance probabilities, offer shares, λ_ℓ^0, and the acceptance-and-move probabilities $\Gamma_{\ell y}$ of (A16)—is a continuous function of λ_ℓ^1; hence the model's job-to-job transition rate, the

[80] At origin y, $(1-\delta_{\ell j})\lambda_\ell^1 \Gamma_{\ell y}(\lambda_\ell^1)$ is the probability that the incumbent job survives, an outside offer then arrives, and the offer induces a move, while $N_{\ell y}/N_\ell$ is the corresponding employment-share weight.

right-hand side of (16), is continuous on Λ_ℓ. In the population, a root exists: the true λ_ℓ^1 lies in Λ_ℓ and solves equation (16). We can check existence and uniqueness in the data, because Λ_ℓ and the two sides of equation (16) can be computed at every candidate.

If there are several admissible roots, the individual job-to-job flows can distinguish between them. At the true parameters, equation (8) holds for every flow $M^\ell_{y\to y'}$, whereas equation (16) uses only their sum, so we can rule out a root at which the flows implied by equation (8) differ from the observed ones. At the selected root, comparing the implied and observed flows is an overidentifying check on the model.

B.5 Details of Step 4: Separating Wage Utility and Amenities

B.5.1 Bellman Inversion

Lemma 2 (Recovery of flow payoffs)**.** *Under the conditions of Proposition 3, equations* (17) *and* (18) *identify the flow payoff $v_{\ell y}$ of employment at a job-wage pair and the flow payoff of nonemployment b_ℓ.*

Proof. For independent standard Type-I extreme-value draws, let $\gamma_{\mathrm{E}} = \mathbb{E}[\iota] \approx 0.577\ldots$ denote Euler's constant. Then

$$\mathbb{E}\max\{x+\iota,\, x'+\iota'\} = \gamma_{\mathrm{E}} + \log(e^x + e^{x'}), \qquad \mathbb{E}[x+\iota] = x + \gamma_{\mathrm{E}}.$$

Using these identities, the bracketed expectation in equation (2) can be rewritten as:

$$\begin{aligned} C_{\ell y} = \gamma_{\mathrm{E}} + (1-\delta_{\ell j})\Big[\lambda_\ell^1 \sum_{y'} g_{\ell y'} \,\log\left(\exp V_{\ell y} + \exp V_{\ell y'}\right) \\ + (1-\lambda_\ell^1)\log\left(1+\exp V_{\ell y}\right)\Big] \end{aligned} \tag{A20}$$

Similarly, the bracketed expectation for the nonemployed in equation (4) is

$$C_\ell^n = \gamma_{\mathrm{E}} + \lambda_\ell^0 \sum_{y'} g_{\ell y'} \,\log\left(1+\exp V_{\ell y'}\right) \tag{A21}$$

Under the conditions of Proposition 3, we recover (A20) and (A21). Therefore, $v_{\ell y}$ and b_ℓ are identified from equations (17) and (18). □

B.5.2 The Within-Job Quit-Wage Elasticity

Start with the quit-wage elasticity:[81]

$$\varepsilon(w) \equiv \frac{\partial \log m(w)}{\partial \log w} = \frac{w}{m(w)} \frac{\partial m(w)}{\partial w} \tag{A22}$$

$$\frac{\partial m(w)}{\partial w} \;=\; \Pi \;\cdot\; \underbrace{\frac{dq}{dV}}_{=-q(1-q)} \;\cdot\; \underbrace{\frac{\partial V}{\partial v}}_{=A(w)} \;\cdot\; \underbrace{\frac{dv}{dw}}_{=\alpha\, u'(w)}, \tag{A23}$$

where $q(w) \equiv [1 + e^{V(w)}]^{-1}$, $\Pi \equiv (1-\delta)(1-\lambda^1)$, and $m(w) = \Pi q(w)$.

$$\varepsilon(w) \equiv \frac{\partial \log m(w)}{\partial \log w} = \frac{w}{m(w)} \frac{\partial m(w)}{\partial w} = -\,\alpha \left(1 - q(w)\right) A(w) \cdot w\, u'(w). \tag{A24}$$

The estimator uses the log odds of the hazard. Given $\dfrac{d}{dm} \log \dfrac{m}{1-m} = \dfrac{1}{m(1-m)}$,

$$\frac{\partial \log\big[m(w)/(1-m(w))\big]}{\partial \log w} = \frac{1}{m(1-m)} \cdot \frac{\partial m}{\partial \log w} = \frac{1}{1-m(w)}\, \varepsilon(w) = -\,\alpha\, \frac{\big(1-q(w)\big)A(w)}{1-m(w)}\, w u'(w). \tag{A25}$$

For $u(w) = \log w$, the factor $wu'(w)$ equals one.

Derivation of $\frac{\partial V}{\partial v}$.

$$V(w) = v(w) + \beta\Big\{\gamma_{\mathrm{E}} + (1-\delta)\Big[\lambda^1 \sum_{y'} g_{y'} \log\big(e^{V_{y'}} + e^{V(w)}\big) + (1-\lambda^1)\log\big(1 + e^{V(w)}\big)\Big]\Big\} \tag{A26}$$

Differentiate with respect to the incumbent relationship's flow payoff v, holding the offer distribution, all offered-job values $V_{y'}$, and $V^n = 0$ fixed. Define the probability of accepting any offer, conditional on receiving one, as

$$\widehat{\Gamma}(w) \equiv \sum_{y'} g_{y'} \frac{e^{V_{y'}}}{e^{V_{y'}} + e^{V(w)}}.$$

At a retained wage cell, $\widehat{\Gamma}(w) = \Gamma_{\ell y} + g_{\ell y}/2$: accepting an outside offer in the same cell also

[81] We suppress subscripts wherever possible. Write

$$V(w) \equiv V_{\ell y}, \qquad v(w) \equiv \alpha\, u(w) + \phi, \qquad \delta \equiv \delta_{\ell j}, \qquad \lambda^1 \equiv \lambda^1_{\ell}.$$

ends the incumbent relationship.

$$\frac{\partial V}{\partial v} = 1 + \beta(1-\delta) \underbrace{\left[\lambda^1\big(1-\widehat{\Gamma}(w)\big) + (1-\lambda^1)\big(1-q(w)\big)\right]}_{P^{\text{stay}}(w)} \frac{\partial V}{\partial v}. \tag{A27}$$

$P^{\text{stay}}(w)$ is the probability of retaining the incumbent relationship next period conditional on surviving destruction: with probability λ^1 an offer arrives and the worker stays if and only if she rejects it (probability $1-\widehat{\Gamma}(w)$); with probability $1-\lambda^1$ no offer arrives and she stays if and only if she does not quit (probability $1-q(w)$). Solving the linear equation (A27),

$$\frac{\partial V}{\partial v} = \Big[1 - \beta(1-\delta)\, P^{\text{stay}}(w)\Big]^{-1} \;\equiv\; A(w). \tag{A28}$$

Derivation of $\frac{dq}{dV}$.

$$\frac{dq}{dV} = -\frac{e^V}{\big(1+e^V\big)^2} = -\,q\,(1-q)$$

Derivation of $\frac{dv}{dw}$. Since w enters (A26) only through $v(w) = \alpha u(w) + \phi$,

$$\frac{\partial V}{\partial w} = \frac{\partial V}{\partial v}\, v'(w) = A(w)\,\alpha\, u'(w). \tag{A29}$$

When $u(w) = \log w$, since $1 - q(w) = \mathbb{P}_{\ell y}$, equation (A25) is equation (19) in the main text.

The identifying regression. Section 5.2.3 states the regression of quit log odds on log wages within a type–job cell that delivers the left-hand side of equation (19); it is equation (22). The estimated slope is not $-\alpha_\ell$: it also reflects the choice probability and the expected duration of the wage, both of which are known from the preceding steps.

Alternative identification from recovered flow payoffs. Under Assumption 1, the flow-payoff specification implies that, for any two populated wage cells w and w' at the same job j, that is, for $y = (j, w)$ and $y' = (j, w')$,

$$v_{\ell y} - v_{\ell y'} = \alpha_\ell\big[u(w) - u(w')\big]. \tag{A30}$$

Thus, for each worker type, it is sufficient that at least one job contains two populated wage cells with different wage utilities and identified flow payoffs.

B.5.3 Proof of Proposition 4

Step 1 delivers $\delta_{\ell j}$ through equation (A6), and the endogenous mobility matrix M_ℓ through equation (A7) together with job-to-job transitions and hires from nonemployment, which need no classification (Proposition 1). Proposition 3 point identifies $g_{\ell y}$, λ_ℓ^0, λ_ℓ^1, and $V_{\ell y}$. Lemma 2 then recovers normalized representatives of $v_{\ell y}$ and b_ℓ. Under Assumption 1, within-job differences in the recovered flow payoffs identify α_ℓ through (A30). Given this coefficient, normalized amenities follow from (20).

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). We exclude individuals of immigrant origin from our analysis because our population of interest consists of those who were born and grew up in Denmark, for both parents and children. As Denmark had few individuals of immigrant origin in the early 1980s, for the sake of simplicity we restrict the sample to native Danes (as in Landersø and Heckman, 2017; Eshaghnia et al., 2024). 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 measures of parental economic status during the children's formative years. Our primary analysis sample imposes two additional restrictions:

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 1991 and 2000, when parents are ages 36–45). 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 worker flows, especially voluntary transitions. We construct separate job samples for the parental window (1991–2000) and the child window (2010–2019). Both samples include the broader working population, not only the parents and children in the IGM sample. We estimate job values in these samples and then assign them to the jobs held by parents and children.

For children (2010–2019), we use the BFL, which contains high-quality, comprehensive monthly information on earnings, paid hours, and occupation codes for all employees in Denmark, linked to employers and establishments (Statistics Denmark, 2026a). We compute the daily wage as the earnings in each monthly record divided by the number of days that the record covers. For parents (1991–2000), we use the CON-based employment spells constructed following the Labour Market Dynamics Group at Aarhus University (Hejlesen, 2016), which specify the starting and ending dates of each employment spell. For parents, the daily wage is the earnings from a job spell divided by the duration of the spell in days. Both data sources allow us to distinguish job-to-job (EE) transitions from transitions with intervening nonemployment spells (ENE transitions). In both generations, we classify a change of job as a job-to-job transition if there are at most 30 days of nonemployment between the two consecutive employment spells, and we treat a longer gap as a spell of nonemployment. When a worker holds several jobs at the same time, we keep the primary job.

We impose the same sample restrictions in both periods to ensure that job values are evaluated by a comparable prime-age working population. First, we restrict the sample to native Danes. Second, we exclude self-employment, as these jobs are difficult to compare with standard employment relationships. Third, we focus on labor market histories after education. Using the education registers, we drop observations before a worker completes their highest observed qualification, so that the worker's education type stays fixed throughout the sample. Fourth, we keep cohorts that reach age 30 by the end of each window (born in 1970 or earlier for 1991–2000, and in 1989 or earlier for 2010–2019), and we drop observations above age 54, as jobs should be ranked based on the revealed preferences of workers in their prime working years.

The BFL provides more comprehensive detail on occupation than is available for the parental generation. In the BFL, occupation codes are available for each match, allowing for occupations to be assigned to each job. This detail is not available for the parental generation in CON. Instead, occupation codes in the AKM register are assigned to the match where the worker had the highest earnings in a given year. As a result, for the parental sample, we only use spells and transitions for primary jobs.

Finally, for each worker type ℓ, we restrict estimation to the largest set of job-wage pairs strongly connected by job-to-job transitions. We also keep only job–wage cells with observed hires from nonemployment. Together with the requirement that the occupation is observed for a given match, these restrictions determine the jobs for which we are able to measure value. Given that few workers tend to be employed in jobs excluded from the connected set, the connected-set restriction has a limited effect on the representativeness of our estimates.

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 Estimation Strategy and Results

D.1 Educational Classification and Worker Types

We classify workers by their highest observed completed qualification, using the three-digit ISCED programme code that Statistics Denmark attaches to each qualification (Statistics Denmark, 2026b). Table A-3 aggregates these codes into four education groups, which we interact with gender to obtain eight worker types.

Table A-3: Education groups and associated ISCED codes

Group	Educational attainment	Codes
1	Without a full upper-secondary qualification	100, 241, 244, 341, 342, 351
2	Upper-secondary or post-secondary non-tertiary education	344, 353, 354, 551, 454, 444
3	Short-cycle or bachelor's-level higher education	544, 554, 645, 651, 655, 665, 741
4	Master's or doctoral education	746, 747, 767, 844, 864, 757

Danish education pathways. General upper-secondary qualifications, including STX, HHX, HTX, and HF, and completed vocational qualifications at the upper-secondary level belong to the second group (Danish Agency for Higher Education and Science, 2026c). The third group combines short-cycle higher education, including Academy Profession qualifications, with university and professional bachelor's-level qualifications. The latter include qualifications in nursing and primary and lower-secondary teaching. The fourth group includes master's-level qualifications, including the Danish *kandidat*, and doctorates (Danish Agency for Higher Education and Science, 2026a). Short-cycle and bachelor's-level qualifications occupy distinct formal levels; pooling them is our choice of aggregation.

Historical qualifications. Degree titles changed across the cohorts in our sample. Before reforms in the late 1980s, Danish university education generally followed a single-cycle structure leading to a *kandidat* degree. A general bachelor's/master's structure was introduced in 1993, while the professional bachelor's title was introduced through legislation in 2000 (Danish Agency for Higher Education and Science, 2026b). We therefore use the qualification classification to group older and newer awards, without requiring identical degree titles across cohorts. In particular, bachelor's-level professional qualifications need not have carried the bachelor's title when they were awarded.

D.2 Flows in the Labor Market

Our estimation (Section 5.1) rests on three conventions about flows in the labor market. This appendix gives the reason for each of them.

Occupation changes within an establishment. First, we do not distinguish changes in occupation codes that occur within the same establishment from changes in jobs that occur through mobility across employers: we treat both as job-to-job transitions that reveal a worker's preference for working in a particular job. This treatment is motivated by personnel evidence that employees actively apply for internal vacancies, including promotions and lateral positions (Hospido et al., 2022; Haegele, 2026). A change of occupation within an establishment is in this sense a choice between the position that the worker holds and another position that is open to her. Yet we acknowledge that our model may be less well suited to job moves that occur within employers than to moves across employers. In the model, a worker draws offers at random from a distribution that is the same for all workers of her type, whatever her current employer. A worker's own establishment is, by contrast, likely to account for more of the vacancies that she learns about than random search implies, and some changes of occupation within an establishment may be assignments by the employer and not choices by the worker.

Job-to-job transitions as choices. Our baseline treats job-to-job transitions as choices made while the incumbent position remains available, as discussed in Section 2. Under this restriction, observed transitions are informative about the relative values of origin and destination jobs. This restriction may fail when a position is eliminated and, instead of entering nonemployment, the worker moves directly to another job-wage pair or accepts an internal reassignment. Our administrative data do not directly reveal such transitions. Unlike in canonical job ladder models, in which voluntary moves always raise wages, wage cuts cannot identify involuntary job-to-job transitions because, in our setting, workers may accept lower wages in exchange for better nonwage attributes or because of taste shocks. We therefore retain job-to-job transitions with wage cuts in our baseline specification.

We assess whether our estimates of intergenerational persistence in job value are sensitive to involuntary job-to-job transitions, which may be more common in some jobs than others. To do this, for transitions across establishments, we examine departures from establishments whose headcount falls. We construct an adjustment based on excess departures from contracting establishments, following Sorkin (2018).[82] Section 8.1.4 reports the results.

[82] We do not adopt this adjustment in the baseline because employer growth does not directly reveal whether the incumbent position remained available (Section 2). Appendix H.1.2 describes the adjustment.

Recall nonemployment. We exclude nonemployment spells that end in reemployment with the same employer, often referred to as "recall" nonemployment in the literature. Recall nonemployment spells may represent temporary interruptions of an ongoing employment relationship. Workers temporarily separated from their employer may expect to be recalled. Workers taking temporary leave may retain a position to which they expect to return. These arrangements are difficult to capture in our model: conditional on worker type, neither the value of nonemployment nor the distribution of job offers depends on the worker's previous employer. We therefore exclude these spells, to avoid interpreting the resumption of an existing employment relationship as the formation of a new match through the process described by our model, in the spirit of key papers in the search literature.[83]

[83]See Lentz et al. (2023), Bagger and Lentz (2019), Carrillo-Tudela et al. (2022), and Sorkin (2018). Our treatment of recall nonemployment is consistent with Sorkin (2018) but distinct from that of Lentz et al. (2023), who fuse disjoint employment spells in which the worker was employed at the same establishment if the intervening period of nonemployment is short enough.

D.3 Estimation Overview

D.3.1 Details of Step 1

Table A-4: Priority ordering of weekly records in DREAM

Priority	Recorded category	Danish designation
1	Death	Død
2	Old-age pension, etc.	Folkepension m.v.
3	Early pension	Tidlig pension
4	Transitional benefit	Overgangsydelse
5	Voluntary early retirement pay	Efterløn
6	Flex benefit	Fleksydelse
7	Flex job	Fleksjob
8	Senior pension	Seniorpension
9	Sheltered job	Skånejob
10	Disability pension	Førtidspension
11	Job clarification	Jobafklaring
12	Maternity/parental benefit	Barselsdagpenge
13	Resource program	Ressourceforløb
14	Sickness benefit	Sygedagpenge
15	Service job	Servicejob
16	Adult apprentice	Voksenlærling
17	Job-rotation substitute	Rotationsvikar
18	Leave	Orlov
19	Six weeks of self-chosen education	6-ugers selvvalgt uddannelse
20	Unemployment benefit, activation	Dagpenge, aktivering
21	Temporary benefits (e.g., AMY)	Midlertidige ydelser
22	Unemployment benefit	Dagpenge
23	Holiday unemployment benefit	Feriedagpenge
24	Cash assistance, higher rate, job-ready	Kontanthjælp, forhøjet sats, jobparat
25	Cash assistance, base rate, manifestly education-ready	Kontanthjælp, grundsats, åbenlyst uddannelsesparat
26	Cash assistance, minimum rate, job-ready	Kontanthjælp, mindstesats, jobparat
27	Cash assistance, minimum rate	Kontanthjælp, mindstesats
28	Cash assistance, base rate	Kontanthjælp, grundsats
29	Cash assistance, higher rate	Kontanthjælp, forhøjet sats
30	Unemployment allowance for flex-job applicants	Ledighedsydelse
31	Pre-rehabilitation	For revalidering
32	Rehabilitation	Revalidering
33	Not resident in Denmark	Ikke bosiddende i DK
34	State adult-education support	SVU
35	State education grant	SU

Notes: Rank 1 has the highest priority. When multiple benefits overlap within a person-week, DREAM retains the category with the highest priority. Source: DREAM Database Guide, version 51 (STAR, September 4, 2025), Section 2.

Table A-5: Fixed DREAM-code classification

Benefit group	DREAM codes	Label
Unemployment insurance	111, 115, 121	Layoff
Job-ready cash assistance	130–139, 160–169	Layoff
Special benefits	151, 152, 153	Layoff
UI activation	213–219, 231, 299	Layoff
Education support without payment / related support	652, 661	Layoff
Unemployment allowance	740–748	Layoff
Rehabilitation	760–768	Layoff
Education-ready cash assistance	140–149	Quit
Leave	412, 413	Quit
Job schemes	511, 521, 522	Quit
Retirement	611, 621, 622, 771, 774, 781, 783–786, 996, 998	Quit
Education support with payment	651	Quit
General cash assistance	710–739	Quit
Pre-rehabilitation	750–758	Quit
Other benefits	870–878	Quit
Parental and sickness benefits	881–899	Quit
No benefit during follow-up	No observed code, with adequate coverage	Quit

Notes: The table reports the initial benefit-based classification of employment-to-nonemployment (EN) transitions. We use the first recorded benefit code within 26 weeks after separation. No observed code is classified as no benefit. When benefits overlap within a week, DREAM's priority ordering determines the recorded code (Table A-4). UI denotes unemployment insurance. For transitions matched to AKU, the stated reasons for separation replace the initial label.

Table A-6: AKU-reported separation shares by benefit-based label ($N > 100$)

DREAM code	Benefit category	N	Layoff (%)	Quit (%)
Layoff label				
111	Unemployment insurance	2,227	72.38	27.62
130–139	Job-ready cash assistance	186	66.67	33.33
213–299	UI activation	107	66.36	33.64
652, 661	Education support without payment / related support	914	59.63	40.37
Quit label				
651	Education support with payment	2,965	27.32	72.68
881 and above	Parental, sickness, and other benefits	1,564	36.00	64.00
Missing	Missing benefit code	831	33.09	66.91

Notes: The sample consists of all EN transitions of prime-age workers in 2010–2019 that we match to an AKU response, including those of workers who are still in school; we use it to refine the classification rule (Appendix B.2.2). The estimation sample and Table A-7 exclude transitions before the worker completes her education. Only benefit categories with more than 100 matched transitions are shown, so the rows do not add up to the total.

Table A-7: AKU-Reported Separation Reasons by Inferred Label

		Stated reason in AKU (%)	
Inferred label	N	Layoff	Quit
Layoff	2,080	**73.75**	26.25
Quit	858	40.68	**59.32**
All	2,938	64.09	35.91
Overall agreement rate (%)		**69.54**	

Notes: The sample consists of EN transitions matched to the Danish Labour Force Survey (AKU), restricted to post-education transitions as in the estimation sample. The inferred label is based on weekly benefit records. Each row reports the distribution of stated reasons among transitions with the given inferred label. Bold cells are those where the two labels agree. The overall agreement rate is the share of all transitions whose inferred label matches the stated reason.

Measuring Mass Layoffs To measure mass layoffs in the micro-data, we follow Davis and von Wachter (2011) and say that a worker is displaced in a mass layoff event if the worker separates from establishment j in year t, and the following conditions are met:

1. Establishment j had more than 50 employees in year $t-2$.

2. Employment at establishment j contracts by 30–99 percent from $t-2$ to t.

3. Employment at establishment j in $t-2$ is no more than 130 percent of employment in $t-3$.

4. Employment at establishment j in $t+1$ is less than 90 percent of employment in $t-2$.

D.3.2 Details of Steps 2–4

This subsection describes the sample conventions and restrictions used to implement the estimator. All calculations are performed separately for each worker type.

Sample and weights. Let $\mathcal{Y}_\ell$ denote the retained job–wage pairs and $\mathcal{Y}_{\ell j}$ the retained pairs within job j. Each pair belongs to the largest set of pairs that is strongly connected through job-to-job transitions and receives at least one hire from nonemployment. The weight $G_{\ell y}$ counts person-months at risk, excluding the final sample month, for which no subsequent state is observed. We write x_y for the mean log wage in bin y.

PageRank scores and the offer process. We compute PageRank scores from the endogenous mobility matrix and normalize them relative to the nonemployment score. For each candidate employed offer-arrival probability, we recover the implied job values and offer shares. We select the candidate whose aggregate job-to-job transition rate is closest to the observed rate. The search grid runs from 0.0005 to approximately 0.06 in increments of 0.001. Denote the resulting estimates by $\widehat{V}_{\ell y}$, $\widehat{g}_{\ell y}$, and $\widehat{\lambda}^1_\ell$.

Imposing a common amenity within jobs. Sampling error means that the values recovered from worker flows need not imply the same amenity across wage bins within a job. For each candidate preference weight α, we therefore jointly determine model-implied values $V^*_{\ell y}(\alpha)$ and one amenity $\phi^*_{\ell j}(\alpha)$ per job.

Holding the estimated offer process and destruction probabilities fixed, let $C_{\ell y}(V)$ denote the model's expected continuation value evaluated at the value vector V. The values and amenities satisfy

$$V^*_{\ell y}(\alpha) = \alpha x_y + \phi^*_{\ell j}(\alpha) + \beta C_{\ell y}(V^*_\ell(\alpha))\,, \tag{A31}$$

$$\sum_{y \in \mathcal{Y}_{\ell j}} G_{\ell y}\left[\widehat{V}_{\ell y} - V^*_{\ell y}(\alpha)\right] = 0. \tag{A32}$$

The first condition imposes the Bellman equation with a common amenity within each job. The second keeps each job's mean value, weighted by person-months, equal to the value recovered from worker flows.

Matching the quit–wage elasticity. For each candidate α, the model-implied quit probability is

$$m^*_{\ell y}(\alpha) = \frac{(1-\widehat{\delta}_{\ell j})(1-\widehat{\lambda}^1_\ell)}{1+\exp V^*_{\ell y}(\alpha)}. \tag{A33}$$

We obtain $\varepsilon_\ell(\alpha)$ by regressing the implied quit log odds on x_y, with job fixed effects and person-month weights. Jobs with a single retained wage bin provide no within-job variation.

We choose $\widehat{\alpha}_\ell$ to match $\varepsilon_\ell(\alpha)$ to the empirical slope $\widehat{\varepsilon}_\ell$. We first evaluate 13 candidates equally spaced in logs between 10^{-3} and 1, then use Brent's method within a bracket containing the target. The estimated amenities are $\widehat{\phi}_{\ell j} = \phi^*_{\ell j}(\widehat{\alpha}_\ell)$.

Amenity units. The implementation centers log wages, expresses amenities in wage-utility units, and omits the Euler constant γ_{E} from the continuation value. Let $\phi^c_{\ell j}$ denote the computed amenity and $\bar{x}_\ell = |\mathcal{Y}_\ell|^{-1}\sum_{y\in\mathcal{Y}_\ell} x_y$. The corresponding amenity in the paper's utility units is

$$\widehat{\phi}_{\ell j} = \widehat{\alpha}_\ell\left(\phi^c_{\ell j} - \bar{x}_\ell\right) - \beta\gamma_{\mathrm{E}}. \tag{A34}$$

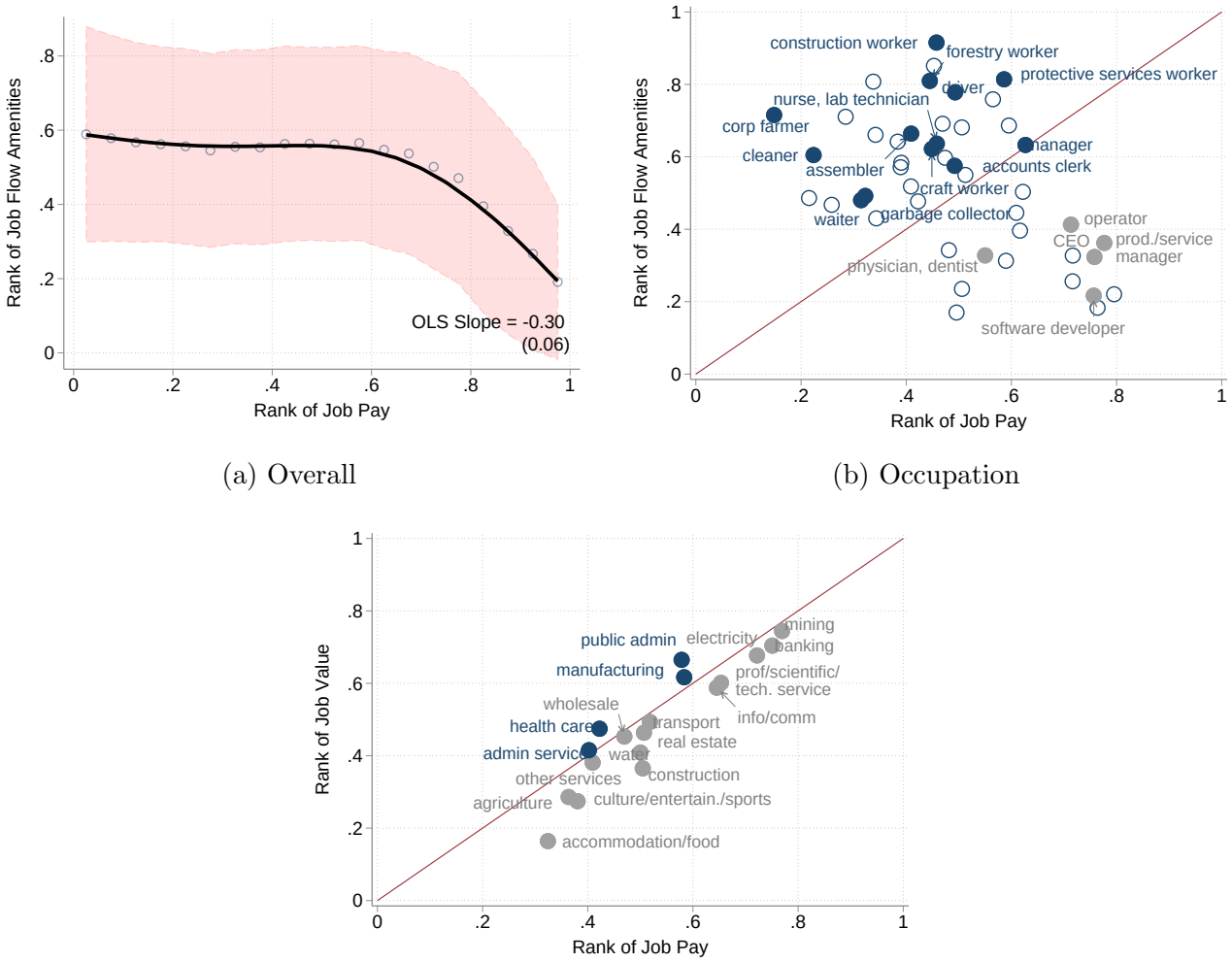
The centering and Euler-constant adjustments are common across jobs within a worker type and therefore do not affect their amenity ranking.

D.4 Parameter Estimates and Descriptive Patterns

D.4.1 Cross-Sectional Relationship

Occupational and industry patterns. Figure A-2 provides complementary descriptions of job rankings.

Figure A-2: Relationships between Job Amenities, Job Pay, and Job Value (Child Sample)



(a) Overall

(b) Occupation

(c) Industry

D.4.2 Sources of Flow-Payoff Dispersion

To complement the correlations in Table 3, we examine dispersion in the model's flow payoff, $v_{\ell j}(w) = \alpha_\ell u(w) + \phi_{\ell j}$. We first decompose its variance into the variance of wage utility, the variance of flow amenities, and twice their covariance. We then separate variation between jobs from variation within jobs.

Wage utility and amenities. Table A-10 reports the wage–amenity decomposition for both generations.

Between-job and within-job variation. Table A-11 reports the decomposition of flow-utility variance into differences between jobs and within jobs.

Table A-8: Education Transition Matrix: Parent-Child

	Child's education			
Parent's education	Below HS	HS/Voc	College	College+
Panel A. Father–child				
Below HS	14.8	49.4	26.4	9.4
HS/Voc	8.9	44.3	32.5	14.2
College	4.2	25.0	38.6	32.2
College+	2.3	12.9	26.1	58.7
Panel B. Mother–child				
Below HS	14.1	50.1	26.7	9.2
HS/Voc	9.0	44.2	32.5	14.3
College	4.8	26.1	37.2	31.9
College+	2.0	11.8	25.2	61.0

Notes: Each row is the parent's highest completed education and reports the percentage distribution of the child's highest completed education, pooling sons and daughters; rows sum to 100 up to rounding. Panel A conditions on the father's education and Panel B on the mother's, so each row averages over the other parent's education. Shaded cells mark the most common destination among the children in each row.

Table A-9: Type Transition Matrix: Parent-Child

	Sons				Daughters			
Parent's education	Below HS	HS/Voc	College	College+	Below HS	HS/Voc	College	College+
Panel A. Father's education								
Below HS	9.9	27.0	9.0	4.1	4.9	22.4	17.3	5.3
HS/Voc	5.9	25.7	12.3	6.4	3.0	18.6	20.3	7.9
College	3.0	15.8	16.4	15.4	1.2	9.2	22.2	16.8
College+	1.6	8.3	12.2	29.1	0.8	4.5	13.8	29.6
Panel B. Mother's education								
Below HS	9.3	27.3	9.6	4.0	4.8	22.8	17.1	5.2
HS/Voc	6.0	25.2	12.0	6.4	3.0	19.0	20.5	7.9
College	3.4	16.7	15.1	15.0	1.4	9.4	22.1	17.0
College+	1.4	8.3	12.1	30.2	0.6	3.6	13.1	30.8

Notes: Each row is the parent's highest completed education and reports the percentage distribution of the child's type; rows sum to 100 up to rounding. Panel A conditions on the father's education and Panel B on the mother's, so each row averages over the other parent's education. For each gender block, shaded cells denote the most common destination for sons and daughters of each parent group.

Table A-10: Sources of Flow-Utility Dispersion

Education	Wage utility	Amenities	Covariance term
Panel A. Parents			
Men			
Below high school	7.3	90.1	2.5
High school / vocational	15.4	74.7	9.9
College	10.9	79.2	10.0
Postgraduate	9.4	83.7	6.8
Women			
Below high school	22.5	79.8	−2.3
High school / vocational	17.2	73.4	9.4
College	18.4	71.3	10.3
Postgraduate	8.1	90.2	1.7
Panel B. Children			
Men			
Below high school	44.9	87.8	−32.7
High school / vocational	34.5	84.5	−19.0
College	22.8	85.8	−8.5
Postgraduate	10.1	93.5	−3.6
Women			
Below high school	48.7	75.0	−23.7
High school / vocational	41.2	79.5	−20.7
College	50.4	75.1	−25.6
Postgraduate	27.9	90.2	−18.1

Notes: Panel A refers to the parent generation in the 1990s and Panel B to the child generation in the 2010s. Entries report each component's share of the variance of flow utility, $v = \alpha_\ell u(w) + \phi_{\ell j}$, in percent. The columns report $\mathrm{Var}(\alpha_\ell u(w))$, $\mathrm{Var}(\phi_{\ell j})$, and $2\,\mathrm{Cov}(\alpha_\ell u(w), \phi_{\ell j})$, each divided by $\mathrm{Var}(v)$. Shares sum to 100 within each row, up to rounding.

Table A-11: Flow-Utility Dispersion Between and Within Jobs

Education	Between jobs	Within jobs
Panel A. Parents		
Men		
Below high school	96.0	4.0
High school / vocational	90.5	9.5
College	94.0	6.0
Postgraduate	94.6	5.4
Women		
Below high school	85.1	14.9
High school / vocational	88.5	11.5
College	88.3	11.7
Postgraduate	95.8	4.2
Panel B. Children		
Men		
Below high school	73.5	26.5
High school / vocational	79.5	20.5
College	87.7	12.3
Postgraduate	94.0	6.0
Women		
Below high school	68.4	31.6
High school / vocational	73.3	26.7
College	67.4	32.6
Postgraduate	83.1	16.9

Notes: Panel A refers to the parent generation in the 1990s and Panel B to the child generation in the 2010s. Entries are percentages of flow-utility variance attributable to differences between jobs and dispersion within jobs. Within worker type ℓ, the decomposition is $\mathrm{Var}(v \mid \ell) = \mathrm{Var}(\mathbb{E}[v \mid \ell, j] \mid \ell) + \mathbb{E}[\mathrm{Var}(v \mid \ell, j) \mid \ell]$. A job is an occupation–establishment-type pair. Because amenities are constant within type–job cells, within-job dispersion conditional on worker type reflects wage variation. Shares sum to 100 within each row, up to rounding.

Table A-12: Pearson and Spearman Correlations by Worker Type

	Parents		Children	
Education	Pearson	Spearman	Pearson	Spearman
Men				
Below high school	0.521	0.567	0.392	0.640
High school / vocational	0.606	0.596	0.641	0.697
College	0.394	0.578	0.587	0.706
Postgraduate	0.319	0.464	0.588	0.752
Women				
Below high school	0.649	0.562	0.568	0.597
High school / vocational	0.724	0.600	0.664	0.648
College	0.658	0.616	0.497	0.699
Postgraduate	0.302	0.599	0.650	0.782

Notes: Parents refers to the parent generation in the 1990s and Children to the child generation in the 2010s. Each entry is the correlation, across the jobs held by one worker type, between a job's value and its average log wage. Both are averages over the job's wage bins, weighted by person-months, and the values are those recovered from worker flows. The Pearson correlation weights each job by its person-months; the Spearman rank correlation weights all jobs equally.

Table A-13: Decomposition of Pooled Flow-Utility Variance into Wage Utility and Amenities

	Log wage	
	Level (1)	Share (2)
Panel A. Parents		
$\mathrm{Var}(v)$	3.819	1.000
$\mathrm{Var}(u(w))$	0.307	0.080
$\mathrm{Var}(\phi)$	3.791	0.993
$2\,\mathrm{Cov}(u(w), \phi)$	−0.279	−0.073
Panel B. Children		
$\mathrm{Var}(v)$	0.617	1.000
$\mathrm{Var}(u(w))$	0.198	0.320
$\mathrm{Var}(\phi)$	0.508	0.824
$2\,\mathrm{Cov}(u(w), \phi)$	−0.089	−0.145

Notes: Parents refers to the parent generation in the 1990s and Children to the child generation in the 2010s. The table decomposes the variance of flow utility v, pooled across worker types, into the variance of wage utility $u(w)$, the variance of amenities ϕ, and twice their covariance. Wage utility is measured by the log wage. Flow utility and amenities are expressed in log-wage units (A34): $v = \log w + \phi$, with $\phi = \phi^{c}_{\ell j} - \bar{x}_{\ell} = (\widehat{\phi}_{\ell j} + \beta\gamma_{\mathrm{E}})/\widehat{\alpha}_{\ell}$. Variances and the covariance are computed across the job–wage pairs of all worker types, weighted by person-months. The level column reports variances, and the share column reports them as shares of $\mathrm{Var}(v)$; the three components sum to $\mathrm{Var}(v)$, up to rounding.

D.4.3 Reliability of Estimated Job Values

Split-sample correlation. Because job values are estimated, they contain sampling error, which biases our rank-rank slopes toward zero. To gauge the size of this bias, we estimate our model separately on two disjoint, randomly drawn halves of the workers in each generation. For each parent-child pair, we then construct the child's average job value over 2010–2019 and the parents' average job value over 1991–2000 twice, once with each half's estimates.

Table A-14: Split-Sample Correlation of Job Value Ranks

	Children	Parents
Split-sample correlation	0.971	0.944
Observations	75,283	75,775

Notes: This table reports the correlation between two estimates of the job-value rank, obtained by estimating the model separately on two disjoint subsamples of the estimation sample. Children refers to the rank of the child's job value in 2010–2019 and Parents to the rank of the family-average job value of the parents in 1991–2000. Observations are those with both estimates.

We find that the split-sample correlations of the resulting ranks are high for both generations, 0.971 for children and 0.944 for parents (Table A-14), which indicates that sampling error attenuates our rank-rank slopes only slightly.

Bootstrap standard errors. The rank-rank slopes are computed in a second step from estimated job values, so their sampling error has two sources: which families enter the linked sample, and estimation error in the job values.

Following the two-step logic of Murphy and Topel (1985), we add the two variances,

$$\widehat{\text{se}}(\hat{\beta})^2 = \widehat{\text{se}}_{\text{conv}}(\hat{\beta})^2 + \widehat{\text{se}}_{\text{boot}}(\hat{\beta})^2$$

The conventional part is the standard error of the rank-rank regression run once at the point estimates, treating job values as data.

We compute bootstrap standard errors as follows. We draw 100 bootstrap samples. For each draw, we sample N workers with replacement from the N workers in each generation's estimation sample. We retain each drawn worker's entire employment history. We re-estimate the model, applying the estimation procedure described in Section 5 to the resampled panel. In each draw, we repeat every step of the main specification: we attach values to jobs, average over the measurement windows, rank within each generation, and run the corresponding rank-rank regressions on the same parent-child pairs. Our bootstrap standard error is the standard

deviation of the resulting slopes across the 100 draws.

Table A-15: Bootstrap Standard Errors of the Rank-Rank Estimates

	Estimate	Conventional SE	Bootstrap SE	Overall SE
Job value (heterogeneous)	0.111	0.0036	0.0011	0.0038
Wage income	0.175	0.0036	0	0.0036
Job flow value $\alpha_\ell u(w) + \phi_{\ell j}$	0.038	0.0037	0.0016	0.0040
Continuation value $\mathbb{E}$(cont.)	0.113	0.0036	–	0.0036
Flow amenity $\phi_{\ell j}$	0.109	0.0036	0.0020	0.0041
Flow wage utility $\alpha_\ell u(w)$	0.160	0.0036	–	0.0036
Observations	76,187			

Notes: Rank-rank slopes of the child's rank on the rank of the average family measure, 1980-81 birth cohorts. The conventional SE treats the estimated job values as data; the bootstrap SE is the standard deviation of the slope across 100 worker-level bootstrap draws of the job-value estimator with the parent-child sample held fixed; the overall SE is the square root of the sum of the two squared SEs. Wage income is not estimated, so it has no bootstrap part; a dash marks components whose bootstrap SE has not been computed.

Table A-15 shows that this part is small. For the job-value slope of 0.111, it raises the standard error from 0.0036 to 0.0038.

E Main Results I: Mobility in Job Value vs. Mobility in Earnings

E.1 Income Mobility

Table A-16: Rank-Rank Slope Estimates

	Rank–Rank			
	(1)	(2)	(3)	(4)
Wage Income	0.175***			
	(0.004)			
Income w. Transfers		0.174***		
		(0.004)		
Income w/o Transfers			0.209***	
			(0.004)	
Disposable Income				0.156***
				(0.004)
Constant	41.644***	41.728***	39.968***	42.624***
	(0.209)	(0.208)	(0.206)	(0.209)
Observations	76,187	76,187	76,187	76,187
R^2	0.031	0.030	0.043	0.024

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

E.2 Intergenerational Transmission in Job Value

Table A-17: Intergenerational Mobility in Job Value

	Dependent Variable: Child Job Value (Heterogeneous)		
	(1)	(2)	(3)
Average Family Job Value	0.111***		
	(0.004)		
Sum Family Job Value		0.122***	
		(0.004)	
Max Family Job Value			0.120***
			(0.004)
Constant	0.445***	0.439***	0.440***
	(0.002)	(0.002)	(0.002)
Observations	76,187	76,187	76,187
R^2	0.012	0.015	0.014

Notes: Standard errors in parentheses. Parent and child job values are estimated from the heterogeneous model and measured as ranks. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A-18: Intergenerational Job Value Transmission by Component

	(1) Job Flow Value $\alpha_\ell u(w) + \phi_{\ell j}$	(2) Continuation $\mathbb{E}$(cont.)	(3) Flow Amenity $\phi_{\ell j}$	(4) Flow Wage Utility $\alpha_\ell u(w)$
Parent component rank	0.038***	0.113***	0.109***	0.160***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	76,187	76,187	76,187	76,187
R^2	0.001	0.013	0.012	0.026

Notes: Standard errors in parentheses. Parent and child job-value components are estimated from the heterogeneous model and measured as ranks. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

F Main Results II: Understanding Differences in Value and Earnings Transmission

F.1 Relation to Existing Evidence on Family Background and Job Attributes

This appendix relates our findings in Section 7.1 to existing evidence on how non-wage job attributes vary with family background.

Evidence from the United States. Boar and Lashkari (2025) score occupations in the United States on a survey-based index of "intrinsic quality," which summarizes attributes such as respectful treatment, opportunities to learn, and the absence of heavy lifting. They show that the children of higher-income parents choose occupations of higher intrinsic quality.[84] We find the same pattern for observed attributes of this kind. In our data, too, the children of higher-earning parents work in occupations with less handling and moving of objects, more freedom to make decisions, and a lower risk of injury: the slopes of these attributes on parental earnings rank are -0.120, 0.100, and -0.103.

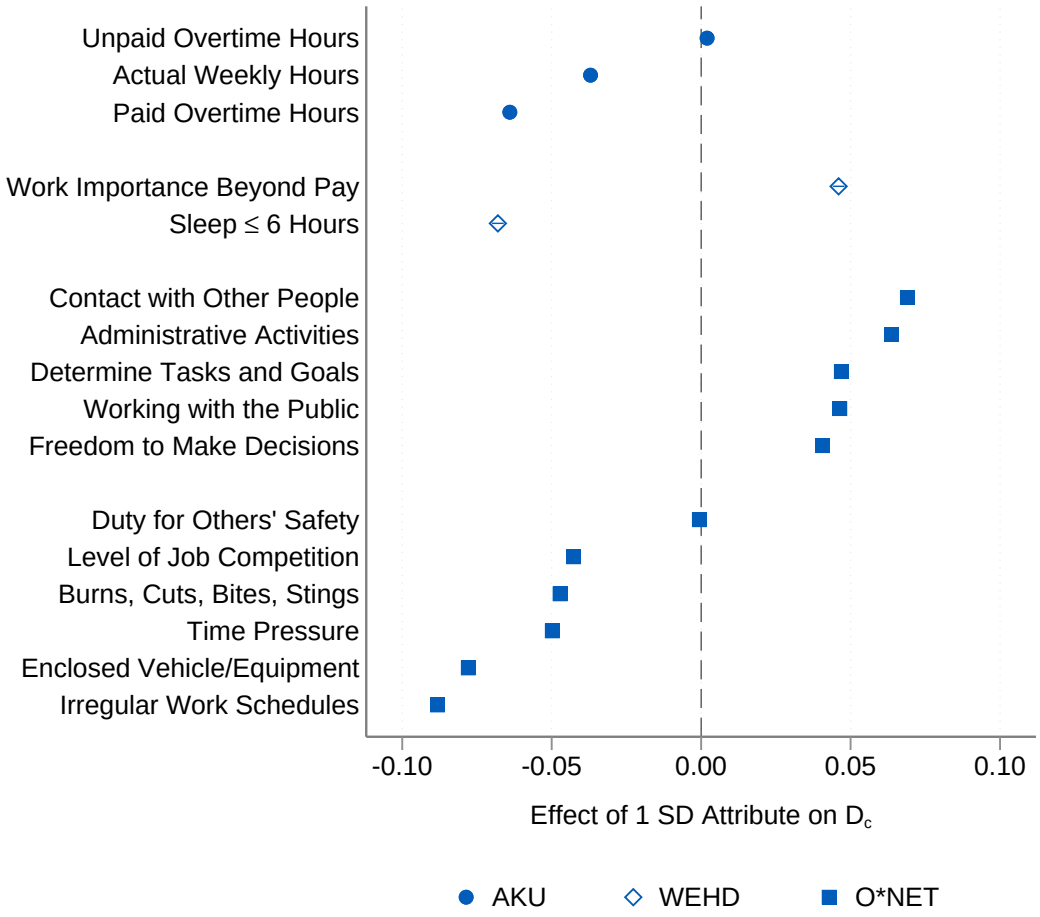
Valuing intrinsic quality in a model of occupational choice, Boar and Lashkari (2025) conclude that the welfare of children is more strongly related to parental resources than their earnings are. With parents ranked by their earnings, we find a slope of 0.131 for the job value of children and 0.175 for their earnings. We view the two sets of results as complementary, because they measure different objects in different settings. First, our measure of job value is inferred from the voluntary moves of workers across jobs. It therefore reflects the entire bundle of job attributes, including job security and attributes that surveys do not measure, whereas intrinsic quality summarizes a set of measured attributes. Second, we study Denmark rather than the United States. Third, we define jobs more finely (a three-digit occupation in one of twelve types of establishment, against 54 occupations in their analysis). Fourth, we measure earnings in administrative registers rather than in a household survey.

Evidence from Sweden. Our findings are consistent with recent evidence from Sweden. Forsberg et al. (2026) use the PageRank approach of Sorkin (2018) to infer the value of firms from the moves of workers. They find that the value of the child's firm is less strongly related to the father's income than the firm's pay premium is (R^2 of 0.019 against 0.031).

[84] Haeck and Laliberté (2025) document the same pattern in Canada.

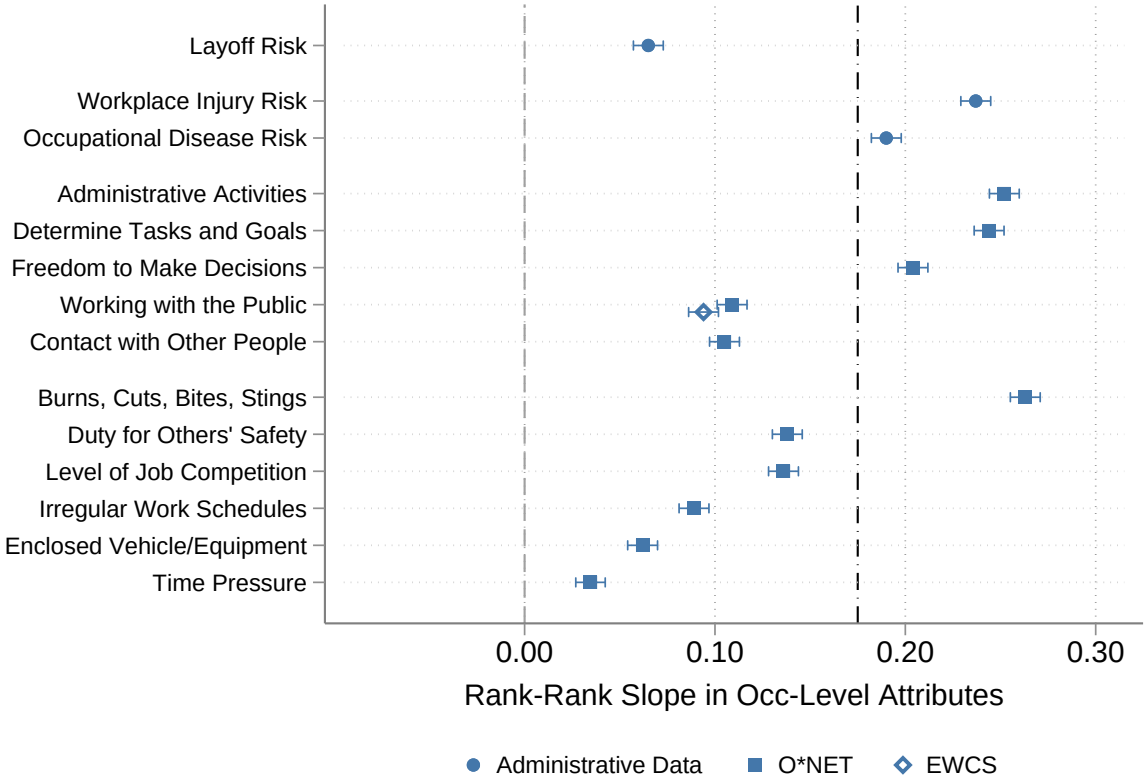
F.2 Relating Model Estimates to Observables

Figure A-3: Job Attributes and the Value–Earnings Rank Wedge: Additional Attributes



Notes: Each marker shows the coefficient from a separate regression of the child's rank wedge on one standardized occupation-level attribute, as in Figure 11.

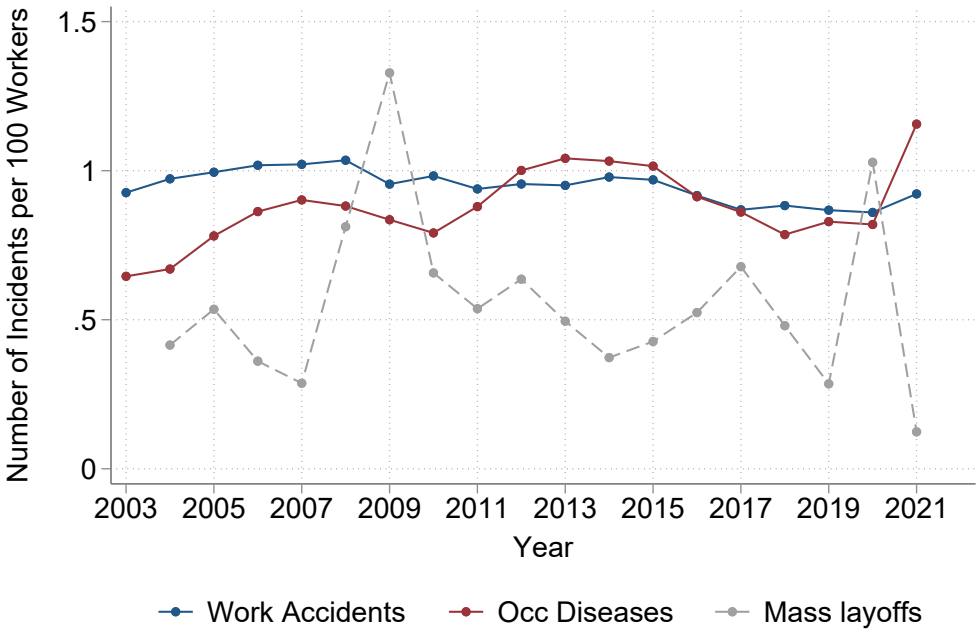
Figure A-4: Intergenerational Transmission of Job Attributes: Additional Attributes



Notes: This figure adds attributes to Figure 13. Each marker shows the rank-rank slope from regressing the child's rank in an occupation-level attribute on the parents' rank in the same attribute. Horizontal bars represent 95% confidence intervals, and the dashed line marks the rank-rank slope in earnings.

In Denmark, 0.6% of workers are injured in a work accident each year. From the injury claims described in Section 4, we construct the injury risk of an occupation as the number of reported injuries in the occupation divided by its number of full-time employees. We do so separately for work accidents, sudden and unexpected events during work that cause an injury, and for occupational diseases, which develop through prolonged exposure to harmful conditions at work. Figure A-5 compares the incidence of workplace accidents with that of mass layoffs.

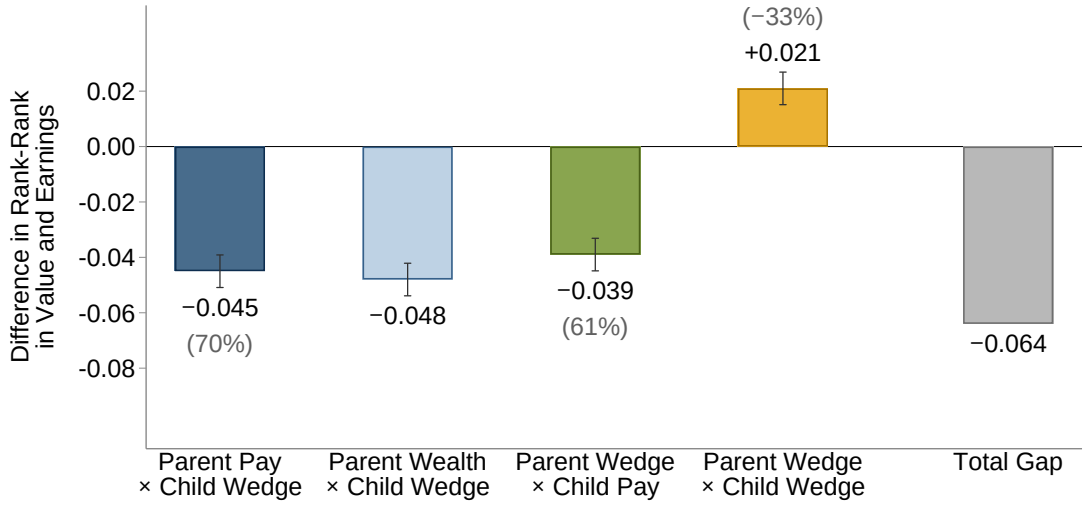
Figure A-5: Workplace Accidents Are as Common as Mass Layoffs



G Mechanisms

G.1 Is It About Parental Resources *per se*?

Figure A-6: Decomposition of the Difference between Value and Earnings Transmission, with Parental Wealth



Notes: This figure adds to Figure 9 the slope from a regression of the child's rank wedge on the rank of parental net worth (second bar). Table A-19 reports the regressions behind the first two bars. Error bars represent 95% confidence intervals.

Table A-19: Parental Resources and Child Wedge

	Child Wedge: Value Rank − Earnings Rank	
	(1)	(2)
Parental Pay	−0.045***	
	[0.003]	
Parental Net Worth		−0.048***
		[0.003]
R^2	0.002	0.003
Observations	76,187	76,187

Notes: Each column reports a separate regression of the child's wedge, the child's job value rank minus the child's earnings rank, on a measure of parental resources: the rank of average family wage income in column (1) and the rank of family net worth in column (2). Job values are estimated from the heterogeneous model. Standard errors in brackets. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

G.2 Exogenous Wealth Shock from Sudden Death

A natural hypothesis emerges from models of job search with consumption-saving decisions.[85] 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 death of the last unmarried parent, following Druedahl and Martinello (2022). Large, unexpected inheritances provide a test: if the wages-amenities trade-off is governed by asset positions, substantial wealth shocks should induce workers to re-optimize their job choices, moving to positions with higher amenities and lower wages.

As Druedahl and Martinello (2022) discuss, estimating the causal effect of an inheritance 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, so that the comparison comes from the timing of parental death. Second, we restrict the sample 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.[86] For net worth and liquid assets, this comparison isolates the wealth effect from any direct effects of parental death itself.

Figure A-7 presents event-study estimates of the effect of a large inheritance on job value (panel a) and the flow amenity (panel b). The vertical dashed line at year 0 marks the timing of parental death. Despite substantial increases in an heir's net worth following the parental death, we find no statistically significant effects on job value or the flow amenity.[87] The point estimates for both the job value rank and the amenity rank remain close to zero up to six years after parental death, with tight confidence intervals ruling out economically meaningful effects.

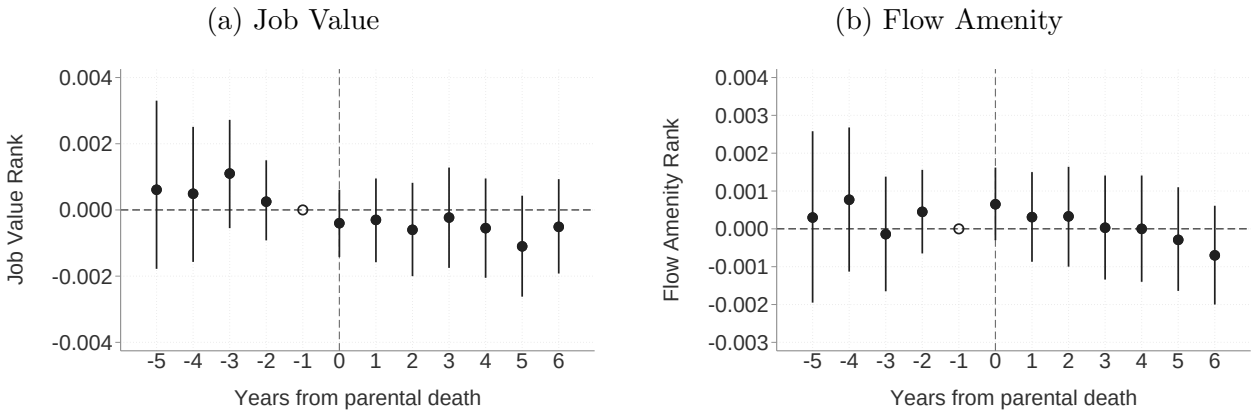
The absence of direct wealth effects on job value and the flow amenity suggests that the negative relation between parental wealth and children's rank wedges does not primarily reflect the

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

[86] Details on the definition of permanent income, the calculation of potential inheritance in the Danish context, the event-study specification, the sudden death timeline, and descriptive statistics for the heirs are provided in the next section.

[87] As shown in Figure A-9 and Figure A-10.

Figure A-7: The Effect of (Large) Inheritance on Job Value and the Flow Amenity



Notes: Estimates of δ_k from equation (A35) for heirs with a sizable potential inheritance. The outcomes are the rank of the heir's job value (panel a) and the rank of the flow amenity of the heir's job (panel b).

direct effect of wealth transfers *per se*. Large, unexpected wealth shocks, even those exceeding annual permanent income, fail to alter the value or the amenities of heirs' jobs.

G.3 Unexpected Inheritance Design Details

We define permanent income as a weighted average of the 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 Nielsen, 2011). This approximation suits Denmark, as Druedahl and Martinello (2022) note: few Danes write a will (Andersen and Nielsen, 2011), and the law reserves part of the estate for the children even when there is a will (Danish Inheritance Act No. 515 of 6 June 2007, Section 5).

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

$$Y_{i,t} = \delta_{<-5}\,\mathbf{1}[t-\tau_i<-5] + \sum_{k=-5}^{-2}\delta_k\mathbf{1}[t-\tau_i=k] + \sum_{k=0}^{7}\delta_k\mathbf{1}[t-\tau_i=k] + \alpha_i + \lambda_{c(i),t} + \varepsilon_{i,t} \quad \text{(A35)}$$

The dependent variable $Y_{i,t}$ represents wealth holdings and labor market outcomes. For wealth, we examine net worth and liquid assets. On the labor market side, we investigate job value and the flow amenity.

Our parameter of interest is δ_k; these coefficients trace out the dynamic treatment effects

relative to $k = -1$. As in Druedahl and Martinello (2022), we include individual fixed effects α_i and year-by-cohort fixed effects $\lambda_{c(i),t}$, where $c(i)$ is the birth cohort of heir i. The indicator $\mathbf{1}[t - \tau_i < -5]$ pools all years more than five years before the parental death, and we drop years more than seven years after it.

Figure A-8: Sudden Death Timeline

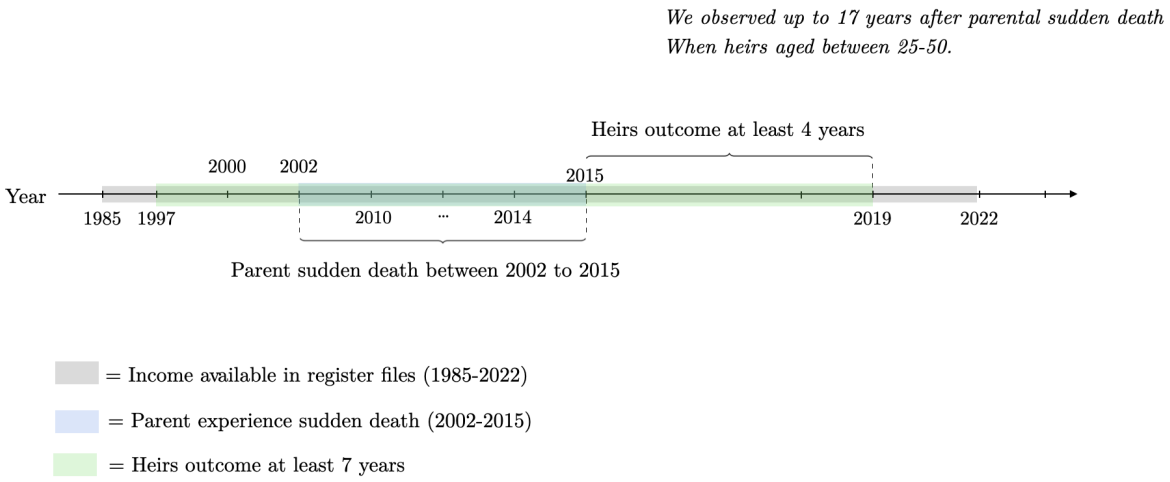
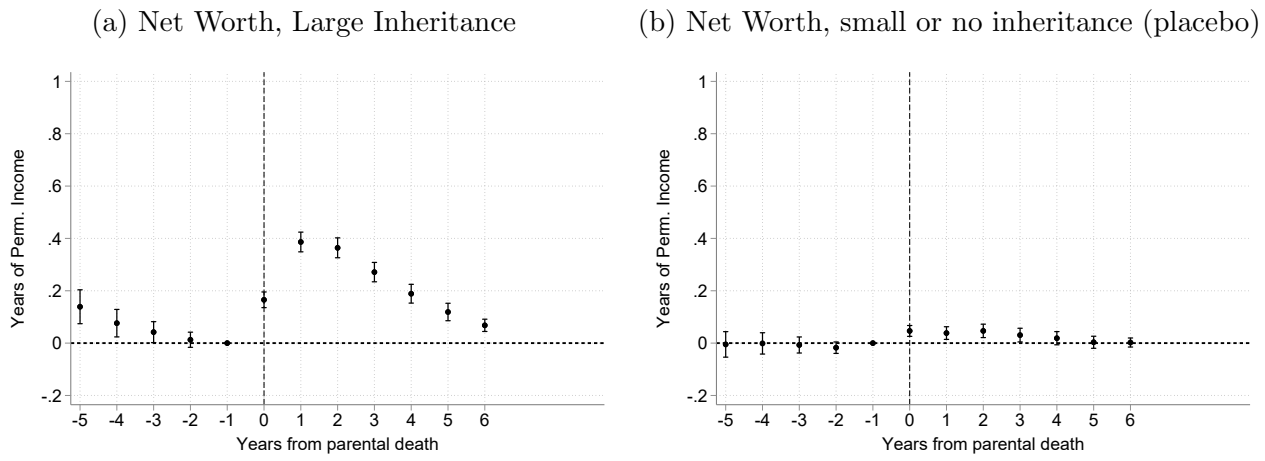


Table A-20: Characteristics of Heirs One Year before the Parent's Death

		Unexpected inheritance	
	All	All	Sizable pot. inheritance
Imputed inheritance, 1,000 DKK	27.998	29.077	675.730
Permanent income, 1,000 DKK	211.192	206.177	208.637
Potential inheritance, normalized	0.141	0.152	3.597
Net worth, normalized	0.246	0.222	0.557
Liquid assets, normalized	0.273	0.262	0.366
Uncollateralized debts, normalized	0.738	0.724	0.717
Financial investments, normalized	0.070	0.069	0.136
Housing equity, normalized	0.641	0.615	0.772
Housing value, normalized	2.389	2.303	2.638
Mortgage, normalized	1.748	1.688	1.866
Homeowner	0.554	0.548	0.581
Owner of 2+ units	0.055	0.053	0.045
Disposable income, 1,000 DKK	217.459	212.659	215.612
Married	0.499	0.490	0.490
Year of inheritance	2006.853	2006.346	2006.888
Age at inheritance	40.513	39.954	38.914
# episodes	368,308	32,527	1,262

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 of DKK. All wealth measures are normalized by permanent income.

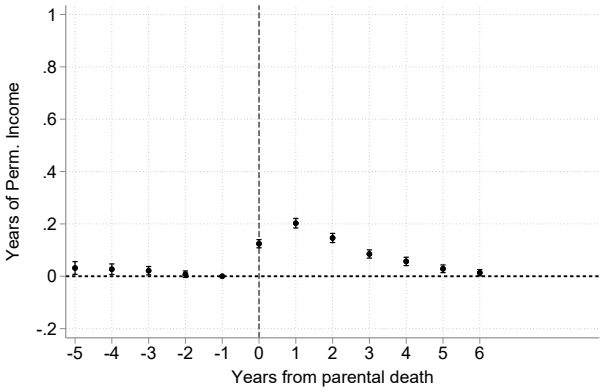
Figure A-9: The Effect of Inheritance on Net Worth



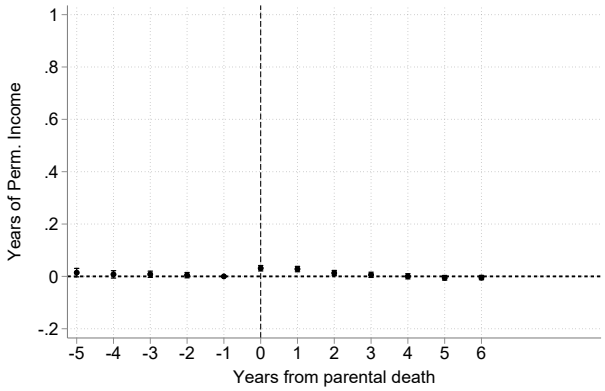
Notes: Estimates of δ_k from equation (A35) for heirs with a sizable potential inheritance (panel a) and for heirs whose potential inheritance is below one month of permanent income (panel b, placebo). Net worth is in years of the heir's permanent income. The hollow marker is the omitted period, $k = -1$. Vertical bars are 95% confidence intervals, with standard errors clustered by heir.

Figure A-10: The Effect of Inheritance on Liquid Assets

(a) Liquid Assets, Large Inheritance



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



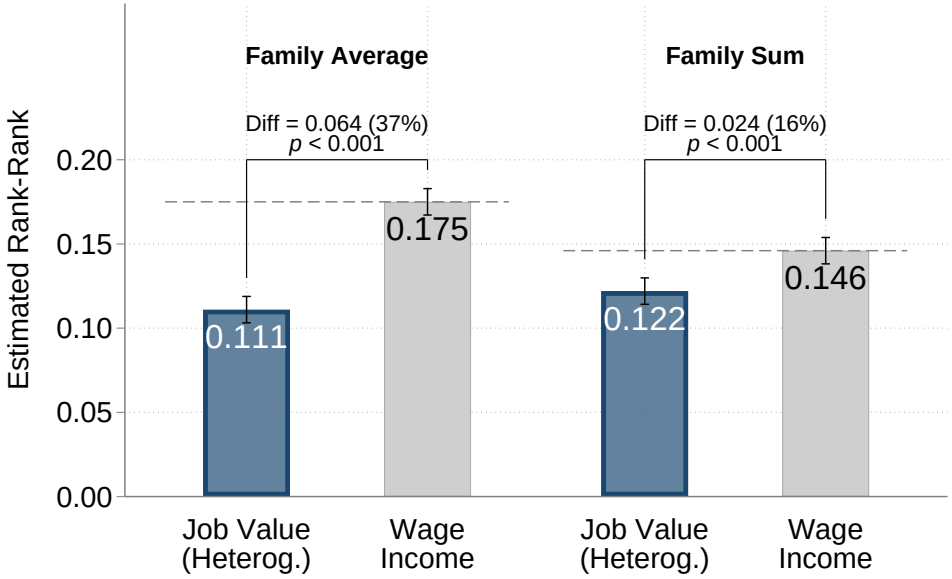
Notes: As Figure A-9, for liquid assets.

H Robustness and Additional Results

H.1 Robustness

H.1.1 Alternative Family Measure

Figure A-11: Rank-Rank Slopes in Job Value and in Earnings, by Family Measure



Notes: This figure compares the rank-rank slopes in job value and in earnings when parents are ranked by the average (left) or by the sum (right) of the mother's and the father's outcomes. Brackets report the difference between the two slopes, its percentage of the earnings slope, and its p-value. Dashed lines mark the earnings slopes. Error bars represent 95% confidence intervals.

H.1.2 Involuntary Job-to-Job Moves

This appendix presents the version of the model with Godfather shocks that we use in Section 8.1.4. We first lay out the model and then describe how we identify and estimate the probability of the shock, $\rho_{\ell j}$. In both parts, we follow Sorkin (2018) almost exactly.

The model. The only change from the baseline is the problem of an employed worker. At the start of each period, the job of a worker of type ℓ in job j is destroyed with probability $\delta_{\ell j}$, and the worker moves to nonemployment. If the job survives, the worker receives a Godfather shock with probability $\rho_{\ell j}$: she is reallocated to a job–wage pair (j', w') drawn from the distribution $\tilde{g}_\ell$, without the option to stay in job j. Otherwise, she faces the same choices as in the baseline. With probability λ_ℓ^1, she receives an outside offer (j', w'), drawn from G_ℓ, and chooses between the offer and her current job. With probability $1-\lambda_\ell^1$, she chooses between nonemployment and

her current job. Like the destruction probability, the probability of the shock is an attribute of the job that is fixed over time and does not vary with the wage. The value of employment at job j and wage w is therefore

$$V^e_{\ell j}(w) = \underbrace{\alpha_\ell u(w) + \phi_{\ell j}}_{\text{flow payoff}} + \beta\,\mathbb{E}\Big[\underbrace{\delta_{\ell j}\{V^n_\ell + \iota_1\}}_{\text{exogenous job destruction}} + \underbrace{(1-\delta_{\ell j})\,\rho_{\ell j}\sum_{(j',w')}\tilde{g}_\ell(j',w')\,\{V^e_{\ell j'}(w') + \iota_2\}}_{\text{Godfather shock: forced job-to-job move}}$$
$$+ (1-\delta_{\ell j})(1-\rho_{\ell j})\Big[\underbrace{\lambda^1_\ell \sum_{(j',w')} g_\ell(j',w')\,\max\{V^e_{\ell j'}(w') + \iota_3,\; V^e_{\ell j}(w) + \iota_4\}}_{\text{offer arrives: endogenous job-to-job}}$$
$$+ \underbrace{(1-\lambda^1_\ell)\,\max\{V^n_\ell + \iota_5,\; V^e_{\ell j}(w) + \iota_6\}}_{\text{no offer: worker chooses stay vs. quit}}\Big]\Big]. \tag{A36}$$

As in the model of Sorkin (2018), the Godfather term contains no max operator: a worker who receives the shock moves to (j', w') whatever its value relative to her current job, so the move reveals nothing about her preferences. When $\rho_{\ell j} = 0$ for all types and jobs, equation (A36) reduces to equation (2) of the baseline model. The problem of a nonemployed worker, equation (4), does not change.

Identification and estimation of $\rho_{\ell j}$. With Godfather shocks, some job-to-job moves are forced, so Step 1 must classify job-to-job moves as well as separations into nonemployment. We keep the baseline classification of separations into nonemployment, so the destruction probabilities $\delta_{\ell j}$ are those that we measure from benefit records, as described in Section 5.2.1. A move from one job to another leaves no benefit record. For these moves, we follow the approach of Sorkin (2018, Section V.B), who infers forced moves from the employment dynamics of employers. Unlike Sorkin, we do not use employment dynamics to recover $\delta_{\ell j}$.

The approach rests on two restrictions. First, a job-to-job move out of an establishment that is not contracting is a choice, and so is a change of occupation within an establishment. Second, at a contracting establishment, workers leave for other establishments by choice at the rate that the model predicts, and the moves in excess of this rate are forced. We classify establishments, and not jobs, as contracting, because a job is not an employer: employment in an occupation within an establishment type can fall when workers change occupation inside establishments that are growing. An establishment is contracting in month t if its headcount, summed over all worker types, is lower in month $t+1$ than in month t, and it is growing otherwise.[88] Each job-to-job move takes the status of its origin establishment in the month of the move.

[88]The departure of a worker lowers the headcount of her establishment by one. At a small establishment, a single voluntary departure could therefore make the establishment count as contracting. For workers who leave their establishment, we call it contracting only if its headcount falls by more than one.

The rate that the model predicts is the probability that a type-ℓ worker in job j at wage w moves by choice to another job-wage pair, the counterpart of equation (18) in Sorkin (2018):

$$\pi_{\ell j}(w) = \underbrace{(1-\delta_{\ell j})(1-\rho_{\ell j})}_{\text{no exogenous shock}} \underbrace{\lambda^1_\ell}_{\text{offer arrives}} \sum_{(j',w')\neq(j,w)} \underbrace{g_\ell(j',w')\,\mathbb{P}_{\ell,j'w'|jw}}_{\text{offer of } (j',w') \text{ is accepted}}, \tag{A37}$$

where $\mathbb{P}_{\ell,j'w'|jw}$ is the acceptance probability of equation (3). Let $\bar{\pi}_{\ell j}$ denote the average of $\pi_{\ell j}(w)$ over the wage bins of job j, weighted by person-months.[89] For each month t, let $G^c_{\ell jt}$ be the number of type-ℓ person-months in job j at contracting establishments, and let $s_{\ell jt}$ be the share of these person-months that end in a job-to-job move to another establishment. The probability that such a move is forced, and the probability of the Godfather shock, are then

$$\chi_{\ell jt} = \max\left\{0,\ 1 - \frac{\bar{\pi}_{\ell j}}{s_{\ell jt}}\right\}, \qquad \rho_{\ell j} = \frac{1}{G_{\ell j}} \sum_t \chi_{\ell jt}\, s_{\ell jt}\, G^c_{\ell jt}, \tag{A38}$$

where $G_{\ell j}$ is the number of type-ℓ person-months in job j, as in equation (A6). The first expression is one minus equation (19) in Sorkin (2018), and the second follows his definition of the probability of the reallocation shock. If workers leave contracting establishments no more often than the benchmark predicts, none of their moves counts as forced. We do not know which moves are forced. Each job-to-job move out of a contracting establishment therefore enters the endogenous mobility matrix M_ℓ with weight $1-\chi_{\ell jt}$, the probability that it is a choice, and every other job-to-job move enters with weight one. The probability $\rho_{\ell j}$ counts the forced moves that these weights imply, per person-month in job j.

As Sorkin (2018, Online Appendix G) does, we therefore iterate. We start with a benchmark equal to the rate at which type-ℓ workers in job j leave growing establishments for other establishments, pooled over months. In each round, we compute the weights and $\rho_{\ell j}$, recover the job values, the offer shares and λ^1_ℓ as in Steps 2 and 3, and update the benchmark with equation (A37). We stop when the correlation between the job values of two successive rounds reaches 0.999, or after 20 rounds.

Given $\rho_{\ell j}$ and M_ℓ, the remaining steps follow the baseline with two changes. First, a worker can receive an outside offer or quit only if her job survives both shocks. The factor $(1-\delta_{\ell j})(1-\rho_{\ell j})$ therefore takes the place of $(1-\delta_{\ell j})$ in the flow equations (6) and (8), and with it in the PageRank score (9), the job values (14), the aggregate job-to-job transition rate (16) and the model's quit probability (A33). Second, the continuation value in Step 4 is the one implied by

[89] We also scale $\bar{\pi}_{\ell j}$ by a factor that is common to all jobs of type ℓ, so that its person-month-weighted average across jobs equals the corresponding average of the rates at which type-ℓ workers leave growing establishments for other establishments. The scaling makes the benchmark comparable to the rates $s_{\ell jt}$ below, which count only moves to another establishment, while $\pi_{\ell j}(w)$ counts every move between jobs. The model thus determines how the benchmark varies across jobs, and growing establishments determine its level. Sorkin (2018) averages the benchmark and the shock probabilities within 20 sectors; we average both within jobs.

equation (A36). It includes the expected value after a Godfather shock, which depends on $\tilde{g}_\ell$, a distribution that Steps 2 and 3 do not recover. Following Sorkin (2018, Online Appendix K), we set $\tilde{g}_\ell = g_\ell$, so that a forced move leads to a job–wage pair drawn from the offer distribution.

H.1.3 PageRank

This appendix presents the PageRank approach of Sorkin (2018). The approach starts from a static discrete choice. When worker i makes a voluntary job-to-job move and chooses between jobs j and k, she compares the value of the two jobs. The utility of worker i from job j is

$$U_{ij} = \underbrace{V_j^{\mathrm{PR}}}_{\text{common value}} + \epsilon_{ij}, \tag{A39}$$

where V_j^{PR} is the value of job j that is common to all workers (the superscript distinguishes it from the value of employment in our model, $V_{\ell j}^e$), and ϵ_{ij} is an i.i.d. Type-I extreme-value preference shock with scale normalized to one. By the logit structure, the probability that a worker chooses job k over job j is

$$P(\text{choose } k \text{ over } j) = \frac{\exp(V_k^{\mathrm{PR}})}{\exp(V_k^{\mathrm{PR}}) + \exp(V_j^{\mathrm{PR}})} = \frac{M_{kj}}{N_{kj}}, \tag{A40}$$

where N_{kj} is the number of workers who choose between jobs k and j, M_{kj} is the number who choose k over j, and M_{jk} is the number who choose j over k. Abstracting from the size of jobs, the relative value of two jobs follows from the bilateral flows between them:

$$V_k^{\mathrm{PR}} - V_j^{\mathrm{PR}} = \ln\left(\frac{M_{kj}}{M_{jk}}\right). \tag{A41}$$

Equation (A41) cannot be applied pair by pair in practice. Many pairs of jobs have no flows in one direction or no flows at all, and even when flows exist, the pairwise comparisons need not be consistent with one another: they may imply $V_A^{\mathrm{PR}} > V_B^{\mathrm{PR}}$, $V_B^{\mathrm{PR}} > V_C^{\mathrm{PR}}$ and $V_C^{\mathrm{PR}} > V_A^{\mathrm{PR}}$. Sorkin (2018) resolves both problems by imposing $M_{kj}/M_{jk} = \exp(V_k^{\mathrm{PR}})/\exp(V_j^{\mathrm{PR}})$ for all pairs simultaneously and aggregating the conditions into one equation per job. Cross-multiplying and summing over j, the value of each job k is the fixed point of

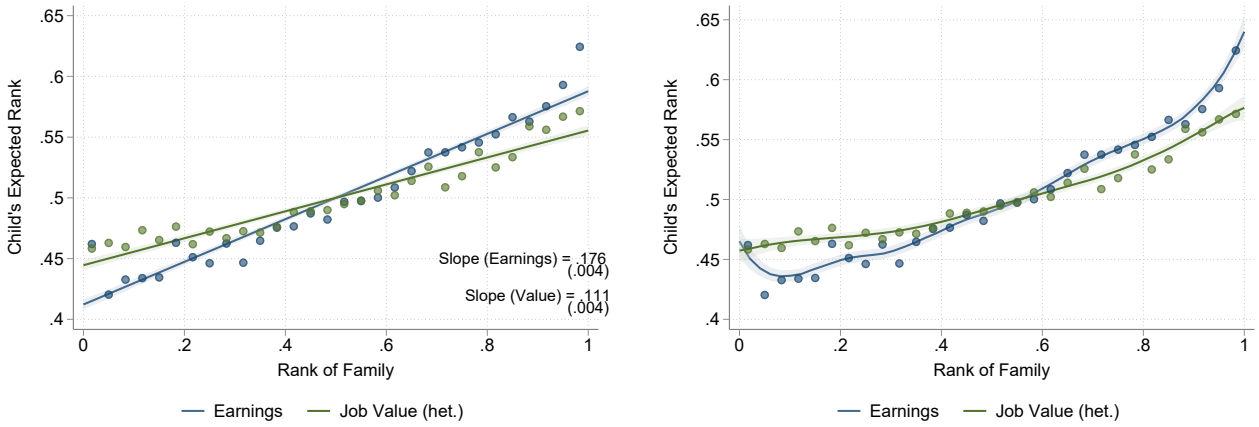
$$\exp(V_k^{\mathrm{PR}}) = \frac{\overbrace{\sum_{j\in\mathcal{J}} M_{kj}\exp(V_j^{\mathrm{PR}})}^{\text{value-weighted entry}}}{\underbrace{\sum_{j\in\mathcal{J}} M_{jk}}_{\text{exits}}}, \qquad \forall k \in \mathcal{J}, \tag{A42}$$

where $\mathcal{J}$ is the set of all jobs. Equation (A42) defines the value of a job recursively: a good job attracts workers from other good jobs and loses few workers. The numerator weights the inflow of workers into job k by the value of the jobs that they leave, and the denominator penalizes jobs with many departures. We solve equation (A42) on the voluntary job-to-job moves of all workers together, which yields a single ranking of jobs, and rank children and parents by the resulting values as in the baseline.

H.2 Additional Results

H.2.1 Absolute Mobility with Binned Means

Figure A-12: Absolute Mobility in Value-Value Specification, with Binned Means



(a) Linear Comparison

(b) Non-linear Comparison

Notes: This figure repeats Figure 15. Markers show the mean rank of children within bins of family rank, when both generations are ranked by earnings (blue) or by job value (green). Lines show linear fits (panel a) and local linear regression fits (panel b).

H.2.2 Amenity–Earnings Transmission

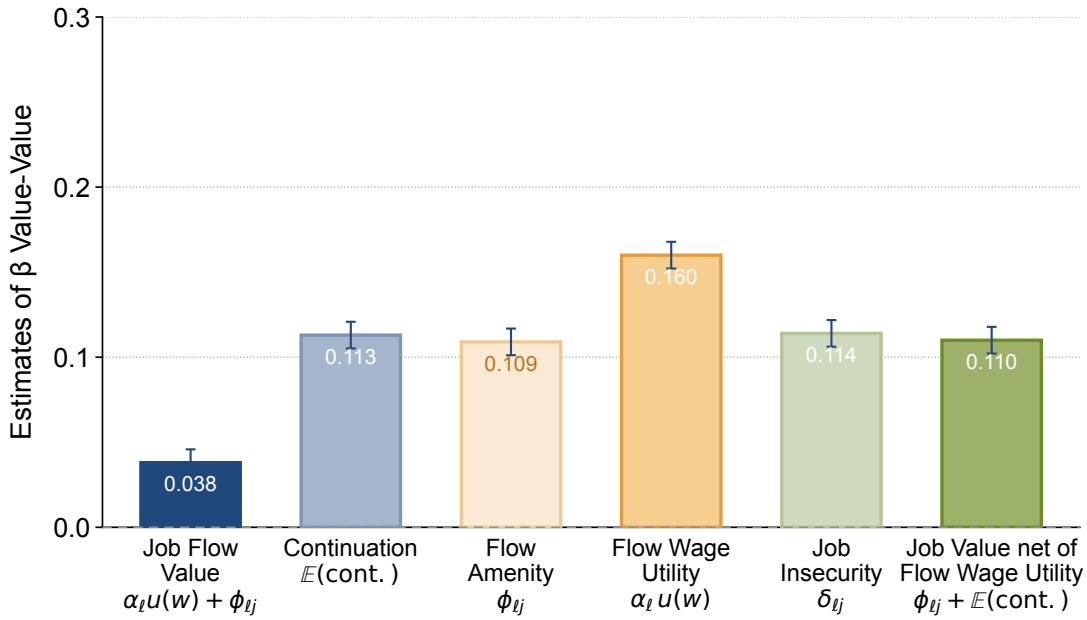
Table A-21: Amenity–Earnings Transmission

	Dependent Variable: Child Job-Value Component (Heterogeneous)			
	Flow Wage Utility (1)	Flow Amenity (2)	Continuation Value (3)	Job Value net of Flow Wage Utility (4)
Average Family Earnings	0.143***	−0.100***	0.112***	0.111***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.428***	0.550***	0.444***	0.445***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	76,187	76,187	76,187	76,187
R^2	0.021	0.010	0.013	0.012

Notes: Standard errors in parentheses. Child job-value components are estimated from the heterogeneous model and measured as ranks; families are ranked by the average of their parents' earnings. Job value net of flow wage utility is the sum of the flow amenity and the continuation value. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

H.2.3 Components of Intergenerational Transmission in Job Value

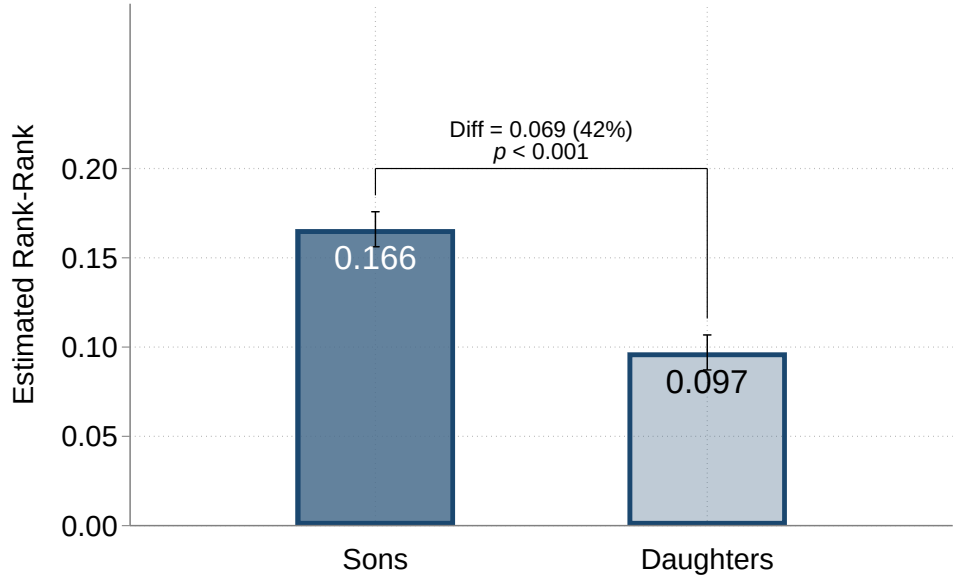
Figure A-13: Intergenerational Transmission of Job Value Components



Notes: The figure reports rank–rank slopes of each child job-value component on the corresponding family component. Families are ranked by the average of their parents' components. Components are from the model with heterogeneous preferences. Whiskers show 95 percent confidence intervals.

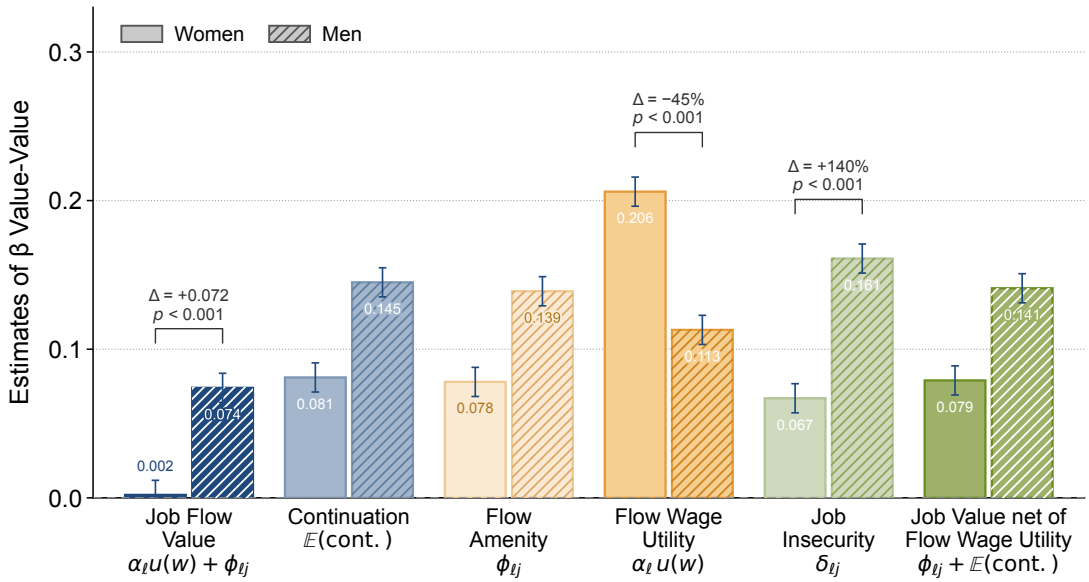
H.2.4 Gender Differences

Figure A-14: Value–Earnings Transmission, Sons and Daughters



Notes: The figure reports rank–rank slopes of the child's job value on the family's earnings rank, separately for sons and daughters. Families are ranked by the average of their parents' earnings. Whiskers show 95 percent confidence intervals. The p-value is from a two-sample z-test.

Figure A-15: Intergenerational Transmission of Job Value Components, Sons and Daughters



Notes: The figure reports rank–rank slopes of each child job-value component on the corresponding family component, separately for sons (hatched) and daughters (solid). Families are ranked by the average of their parents' components. Components are from the model with heterogeneous preferences. Whiskers show 95 percent confidence intervals.

H.2.5 Job Value Transmission Within and Across Worker Types

We next examine how educational attainment relates to intergenerational persistence in earnings and job-value ranks.

Our analysis relates to the literature on educational mobility in Denmark. Karlson and Landersø (2025) document substantial expansion of higher education among cohorts born in the 1970s and 1980s, alongside declining intergenerational educational mobility. Landersø and Heckman (2017) likewise document a persistent relationship between family background and educational attainment. These findings distinguish increases in educational attainment across generations from reductions in the dependence of children's education on parental background.

Table 1, Panel D, documents the generational shift in educational attainment in our sample. In the IGM-Job sample, 50 percent of children have college or postgraduate qualifications, compared with 24 percent of fathers and 31 percent of mothers. Conversely, approximately 76 percent of fathers and 69 percent of mothers fall below the college education group. Children are therefore substantially more likely than their parents to have completed higher education.

There is a clear association between the educational attainment of parents and that of their children. Among children whose fathers did not complete high school, 36 percent have a college or postgraduate education.[90] This share rises to 47, 71 and 85 percent among children whose fathers have a high school or vocational education, a college education and a postgraduate education, respectively. The corresponding shares by the education of mothers are almost identical: 36, 47, 69 and 86 percent.

To assess how persistence in earnings and job-value ranks changes after accounting for observed types, we augment the baseline rank–rank specifications with discrete type controls:

$$R_i^{c,k} = a_k + \widetilde{\beta}_k R_i^{p,k} + \boldsymbol{D}_i'\boldsymbol{\theta}_k + \varepsilon_i^k, \qquad k \in \{\text{Value}, \text{Earnings}\}. \tag{A43}$$

Here, $R_i^{c,k}$ is the child's rank in outcome k, $R_i^{p,k}$ is the corresponding parental-rank measure, and $\boldsymbol{D}_i$ collects indicators for each combination of the child's education–gender type, the father's educational attainment, and the mother's educational attainment.

Let $\widehat{\beta}_k$ denote the parental-rank coefficient without type controls and $\widehat{\widetilde{\beta}}_k$ the coefficient from equation (A43). We summarize the change using

$$\widehat{\Delta}_k = \widehat{\beta}_k - \widehat{\widetilde{\beta}}_k, \qquad \widehat{s}_k = \frac{\widehat{\Delta}_k}{\widehat{\beta}_k}. \tag{A44}$$

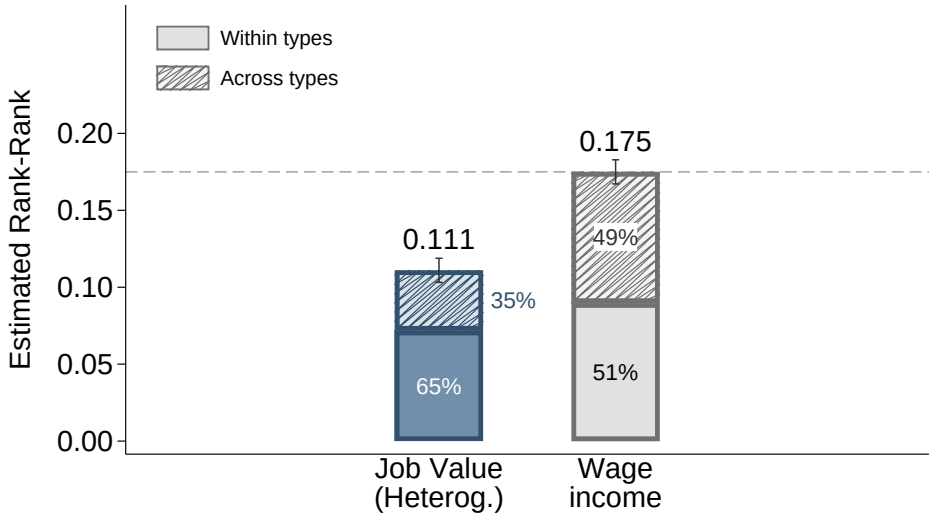
Thus, $\widehat{s}_k$ measures the proportional reduction in the rank–rank coefficient associated with

[90] These shares add the "College" and "College+" columns of Appendix Table A-8.

adding type controls.

Figure A-16 reports the estimates. For earnings, adding the type controls lowers the rank–rank coefficient from 0.175 to 0.090, so that 49 percent of the coefficient is associated with transmission across types. For job value, it lowers the coefficient from 0.111 to 0.072, so that 35 percent is associated with transmission across types.

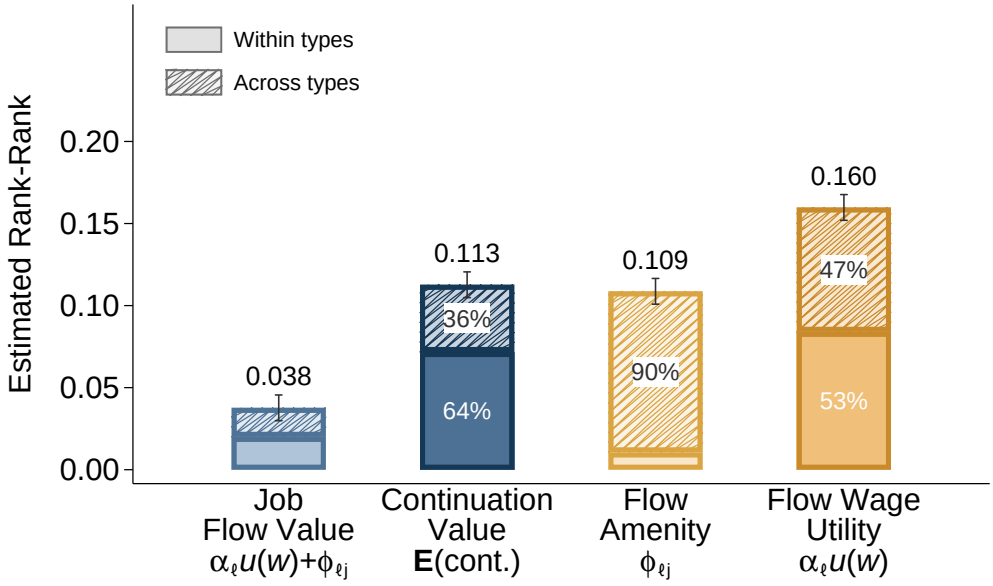
Figure A-16: Job Value Transmission Within and Across Worker Types



Notes: The figure compares rank–rank persistence in job value and earnings. Within Types reports the coefficient after adding the type controls in equation (A43), $\widehat{\widetilde{\beta}}_k$. Across Types reports the difference between these coefficients, $\widehat{\beta}_k - \widehat{\widetilde{\beta}}_k$. Percentages express each displayed component relative to the corresponding coefficient without type controls.

Figure A-17 repeats the decomposition for the components of job value. Most of the transmission of flow amenities occurs across types (90 percent of the coefficient). By contrast, transmission within types accounts for 64 percent of the coefficient for the continuation value and 53 percent for flow wage utility.

Figure A-17: Job Value Components: Transmission Within and Across Worker Types

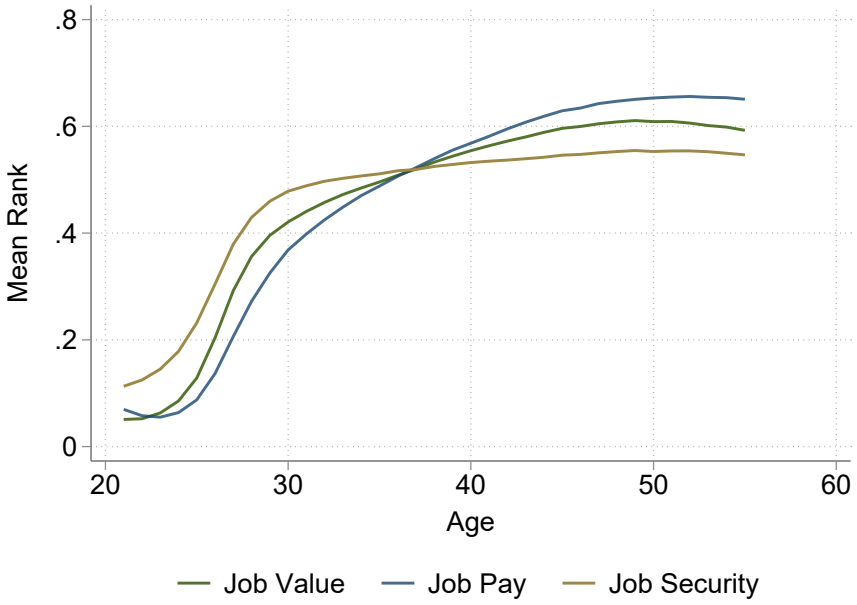


Notes: The figure repeats Figure A-16 for the components of job value. Each bar shows the rank–rank coefficient of a component without type controls. Within Types (solid) reports the coefficient after adding the type controls in equation (A43); Across Types (hatched) reports the difference. Percentages are relative to the coefficient without type controls.

H.2.6 Job Value over the Life Cycle

Figure A-18 plots the mean rank of job value, job pay and job security by age. Ranks are computed in the pooled sample for 2010–2019, so the profiles show where workers of each age stand in the distribution of all workers. The figure is a cross-section: workers of different ages also belong to different birth cohorts.

Figure A-18: Job Value, Pay and Security over the Life Cycle



Notes: This figure plots the mean rank of job value, job pay and job security by age. Ranks are percentile ranks among all workers in the pooled sample for 2010–2019. Job values and their components are from the model with heterogeneous preferences.