NBER WORKING PAPER SERIES

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Working Paper 25786
http://www.nber.org/papers/w25786

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2019, Revised February 2024

We thank the IFAU for providing the data and supporting the project. We are grateful to participants in seminars at Chicago, Northwestern, SED, IFAU, NBER Summer Institute 2016, and the Conference in honor of Joe Altonji for valuable comments. We thank Joe Altonji, Peter Arcidiacono, Thibaut Lamadon, Anders Forslund, Greg Kaplan, Magne Mogstad, Emily Nix and five anonymous referees for comments. Costas Meghir thanks the Cowles Foundation and the ISPS for funding. All errors and interpretations are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 25786
April 2019, Revised February 2024
JEL No. I18,J24,J31,J63

ABSTRACT

We use matched employer-employee data from Sweden to study the role of the firm in affecting the stochastic properties of wages. Our model accounts for endogenous participation and mobility decisions. We find that firm-specific permanent productivity shocks transmit to individual wages, but the effect is mostly concentrated among the high-skilled workers. The pass-through of temporary shocks is smaller in magnitude and similar for high- and low-skilled workers. The updates to worker-firm specific match effects over the life of a firm-worker relationship are small. Substantial growth in earnings variance over the life cycle for high-skilled workers is driven by firms. In particular, cross-sectional wage variances by age 55 are roughly one-third higher relative to a scenario with no pass-through of firm shocks onto wages.

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1 Introduction

Workers face multiple sources of labor market risks. In the workhorse competitive labor market model, they only bear the risk of shocks to their *own* productivity, which they carry with them wherever they work, and they bear them fully. But labor and credit market frictions weaken this extreme view. A recent literature has argued that job search costs on the two sides of the labor market (or the presence of non-monetary components that workers or employers value, such as job amenities or employee loyalty), underscore a role for firms to affect both the levels and the dynamics of wages over an individual's career. This research agenda also reflects the growing availability of employer-employee data with detailed information on worker and firm characteristics, offering the opportunity to better understand the sources of inequality and of labor market risks that individuals face over the life cycle, and in particular how much of those risks are affected by who we work for.

Some papers have focused on the extent to which wages of individuals are related to the firm in which they are employed, with various mechanisms being proposed, such as sorting or rent sharing.[1] See, e.g., Abowd, Kramarz, and Margolis (1999) (AKM) as well as more recent papers such as Card, Heining, and Kline (2013) and Card et al. (2018), who provide an excellent review and interpretation of the literature. There is comparatively less research on the extent to which shocks to the firm's fortunes (such as product market or technology shocks) pass onto wages, partly because of more stringent data requirements. As an example, Lise, Meghir, and Robin (2016) do consider the transmission of productivity shocks to wages, but restrict themselves to the implications driven by a specific structural model with search frictions. Moreover, they do not have access to matched employer-employee data and consequently the actual shocks to the firm are not observed. Balke and Lamadon (2022) develop a structural model with directed job search that offers a theoretical framework for understanding the role of firm-level shocks for worker outcomes and tests some of its im-

[1] An earlier paper by Slichter (1950) argued that, in contrast to the predictions of competitive models, workers' wages appeared to move with their employer's profitability.

plications on Swedish administrative data. Besides job search frictions, the transmission of firm shocks onto wages is often interpreted as reflecting the extent that workers share rents with the firm, and an early study in this direction is Van Reenen (1996).

There have been two broad empirical approaches to measuring the role of firms in explaining wage dynamics. In one approach, researchers focus on specific events affecting firm profitability and test whether wages adjust in response to the implied firm-related shocks (see, e.g., Kline et al., 2019, Kroft et al., 2022, Hummels et al., 2014, Garin and Silvério, 2019, and the discussion in Section 4.2). A different approach, which is the one we use here, is to consider the theoretical restrictions that a model of wage and firm productivity dynamics imposes on the joint distribution of firm and worker data (see, e.g., Guiso, Pistaferri, and Schivardi, 2005, and Juhn et al., 2018).[2] For example, Guiso, Pistaferri, and Schivardi (2005) estimate the pass-through of firm-level shocks onto wages using Italian matched employer-employee data and interpret the results as estimates of the amount of partial insurance the firm provides, reflecting imperfections faced by workers in credit and insurance markets. For the US, Juhn et al. (2018) find that top employees' wages are more sensitive to firm shocks than those of rank-and-file workers, consistent with the idea that in certain occupations performance pay acts as a countervailing force to wage insurance.

A common limitation of papers in this literature is that they ignore job-to-job mobility and the transitions between employment and unemployment.[3] Such transitions may well hide the impact of firm-level shocks on wages because a worker may quit or switch jobs instead of suffering too large a pay cut, causing wage growth to be censored. Another element that is missing from these papers is a characterization of how much of the lifetime risk faced by a worker is explained by the firm, how it differs across different type of workers, and how it is affected by movements across employment states and across employers. The goal of our

[2]Another recent example is Lamadon, Mogstad, and Setzler (2022) who consider the role of firms for wages in the context of amenity pricing.

[3]Carlsson, Messina, and Skans (2016) distinguish between industry-level and firm-level shocks, but as in Guiso, Pistaferri, and Schivardi (2005) they maintain the focus on stayers at incumbent firms. Other recent papers on the pass through of firm-level shocks onto wages include Engbom, Moser, and Sauermann (2023) and Chan, Salgado, and Xu (2021).

paper is to fill these gaps. We start by presenting a series of descriptive facts about wages, firm productivity shocks, and job mobility. In particular, we show that: (a) separations are more likely to occur when the firm is doing poorly and that worker mobility rates remain higher for a few years after the firm-level shock; (b) wage growth rates of those who leave a shrinking firm are higher than those who don't, while no difference between movers and stayers exist if the incumbent firm is expanding; (c) there is strong homophily in the type of firms that workers transition to/from; and (d) wages grow when moving to better firms and decline when moving to less productive firms.

These empirical facts guide us in the buildup of the model, which relates closely to the literature on the stochastic structure of earnings.[4] Using matched employer-employee data, we consider a process for earnings that, in addition to individual productivity shocks, allows for match-specific and firm-level productivity shocks passing onto wages. This relates directly to the amount and sources of risk faced by individuals and to the competitiveness of the labor market, making it an issue of first order importance from a number of perspectives. With respect to most of the earlier literature on rent sharing, the key innovations are that we distinguish between the nature of the shocks to firms (permanent versus transitory) and whether they translate into permanent shocks to individual wages or just transitory adjustments, which would happen if the workers were to move to another firm or leave employment altogether. This consideration underscores another important element of our framework, which is to allow for endogenous mobility choices and moves between employment and unemployment spells. To further highlight the importance of the firm in shaping careers and to capture some of the key empirical regularities mentioned above, we allow the process of on-the-job offers to depend on the type of employer one is working for. These choices can have first-order implications for the measurement of the pass-through of shocks to wages and the identification of different sources of risk.[5]

[4]See Abowd and Card (1989), MaCurdy (1982), Meghir and Pistaferri (2004), Guvenen (2007) and more recently Altonji, Smith, and Vidangos (2013).

[5]Gregory (2021) offers an additional perspective on the role of the firm, arguing that it drives life cycle earnings inequality through heterogeneous learning environments. We focus here on wage volatility.

In a related paper, Low, Meghir, and Pistaferri (2010) find that making job mobility and employment choices endogenous reduces the estimated variance of permanent shocks compared to earlier studies. In their model, firms are represented as a fixed matched heterogeneity effect. However, because they do not observe firms they are not able to measure the impact of shocks to firms separately from worker productivity shocks. They do, however, infer indirectly the amount of heterogeneity that can be attributed to the workplace.[6] We use our statistical model to examine how wage risks evolve in counterfactual scenarios in which we shut down some sources of variation, such as firm risk or movements across jobs or employment states. While we do not wish to make excessive claims to generality, we avoid making too many structural restrictions linking transitions, wages and firm shocks, that would come from a specific structural model.

Our data are drawn from Swedish administrative employment records. We match these records with data on firm balance sheets. The result is the universe of workers and firms, matched to each other for the years 1997–2008. The data include earnings for each employment spell, detailed information of job histories, including the identity of the firm, and information on value added and total employment. It does not include hours, and hence our baseline analysis focuses on men, who rarely work part-time. In an extension of our main analysis, we use a smaller administrative database that includes information on actual hours worked to investigate whether our findings change once variation in hours worked is accounted for; reassuringly, they do not. We allocate individuals to two education groups: those with some college education and those with less. In a different extension, we consider additional sources of unobserved worker heterogeneity, which we measure using records from the Swedish military enlistment database, containing cognitive and non-cognitive scores from standardized tests and professional psychological assessments.

We specify a model of earnings, employment and job mobility, all of which are interre-

[6] A related paper is Altonji, Smith, and Vidangos (2013), who specify a model of employment, hours, wages and earnings in order to distinguish between different sources of risk. Selection into employment and between jobs is modeled in a similar way as in Low, Meghir, and Pistaferri (2010)

lated. Specifically, wage shocks drive entry and exit from work, while mobility is allowed to depend on wage improvements between the incumbent and the poaching firm. Firm productivity also affects the frequency and quality of outside offers. The stochastic structure of wages includes idiosyncratic effects, reflecting changes in individual productivity, and firm-specific effects. The latter consist in part of shocks to firm productivity (transitory and permanent) passing onto wages, as well as individual match effects originating from production complementarities. As such, it is a particularly rich framework that effectively nests most of the earlier specifications of the stochastic process of earnings.

We find that firm productivity is quite volatile and that this volatility transmits to wages of high-skill workers to a larger extent than for low-skill workers, particularly when it relates to permanent shocks. It thus turns out that the firm is responsible for a high fraction of cross sectional variance of wages attributable to unobserved components and interpreted as uncertainty. We also find that employment is related to wage shocks, consistent with self-selection into work and work incentives, although the implied elasticity is rather low. Finally, job mobility is sensitive to wage improvements, albeit other factors may lead to pay cuts when moving across workplaces.

To better understand the implications of our findings, we simulate the model in a number of counterfactual scenarios in which we change the nature of wage variability faced by workers over the life cycle. In one scenario, we eliminate any pass-through of firm shocks onto wages; in another, we shut down any form of firm influence on wages (match productivity effects, firm shocks pass-through, and origin of outside offers). We find that wage variances over the life cycle decline substantially when eliminating the impact of firm shocks (with the effect being particularly relevant for the high-skilled), while eliminating idiosyncratic match productivity shocks matters little. Specifically, eliminating transmission of firm-level shocks into wages would result in 32.5% lower cross-sectional wage variation among high-skill workers by age 55. In another set of counterfactual experiments, we eliminate selection by preventing job-to-job moves or moves into unemployment, whether voluntary or not.[7] If workers cannot move or never become unemployed (which are extreme forms of labor market frictions), shocks stay with them longer and cannot be avoided, resulting in higher variances over the life cycle. We show that, again, this is mostly due to pass-through of firm-specific shocks. Hence, workers' fluidity (becoming unemployed or moving to alternative employers) represents an implicit form of insurance against labor market risks.[8] We further use counterfactuals to illustrate that ignoring this insurance motive by only focusing on stayers (as in most of the literature following Guiso, Pistaferri, and Schivardi (2005)) understates the transmission of firm-level permanent shocks to workers and, especially for high skill workers, the role of the firm in explaining wage variability by age 55.

The paper proceeds as follows. Section 2 introduces the data and presents descriptive evidence. Section 3 presents the model of the income process. Section 4 presents the estimation and identification strategy. Section 5 shows the main results for the two-stage estimation procedure and their implications for our understanding of where labor market risks come from. Section 6 consider different extensions of the baseline model. Section 7 concludes.

2 Data

We start with an overview of the main data sources for our analysis. The Data Appendix A provides more details about the databases we use, the data cleaning and sample construction process, and the definition of the key variables.

2.1 Data sources

For our empirical analysis, we construct a matched employer-employee data set that combines information from four different administrative databases, compiled by Statistics Sweden.

[7] We cannot distinguish between quits and being fired. However, one can think of being fired as equivalent to a large pay-cut that the worker would rather avoid.

[8] Work by Davis and Haltiwanger (2014) documents a decline in labor market fluidity for the US, with important welfare implications.

Main data sources Specifically, we start from annual information on the entire working age population in Sweden from the Longitudinal Database on Education, Income and Employment (LOUISE). These data contain demographic and socioeconomic information, including age, gender, family characteristics, social benefits usage, and education level.

We then merge the Register-Based Labour Market Statistics (RAMS), covering the universe of employment spells in Sweden from 1985 onward. Most importantly, RAMS includes worker and firm identifiers, as well as the gross yearly earnings and the first and last remunerated month for each employment/firm spell. We further add daily-level information on all unemployment spells from the Unemployment Register to adjust employment spell duration and to measure transitions into and out of unemployment.

Finally, we merge the data with accounting and balance sheet information for all non-financial corporations in Sweden from 1997 onward from the Structural Business Statistics (SBS). Crucially, Statistics Sweden uses the accounting data to provide a measure of annual value added based on production value minus the cost of purchased inputs.

Main variables On the worker side, the key variables for our analysis are employment status and earnings. We use the data from RAMS together with unemployment spell data to define employment on a *quarterly* basis.[9] Using firm identifiers, we record for each quarter if an individual is a job mover, a job stayer, or an entrant from non-employment (which includes all periods of unemployment and non-participation, terms we use interchangeably in the analysis). We then use yearly earnings by employer and the exact length of employment spells to construct our earnings measure as average monthly earnings. On the firm side, we combine SBS data on firms' value added with their employment at the end of the previous year to define our core measure of firm productivity, value added per worker.[10]

[9]For individuals with multiple jobs during a quarter we keep the main employment, defined as the employment that accounts for the largest share of quarterly earnings, see Appendix A for full details on cleaning.

[10]Our focus is firms, since there are no balance sheet data at the establishment level. The share of single-establishment firms in our data is 91.9 percent. The share of employment at single-establishment firms is 52.5% for the low educated, 41.9% for the high educated, and 49.6% overall. In a recent paper Hazell et al. (2022) show that 40%-50% of a job's posted wages are identical across locations within a firm for the US.

Auxiliary data sources We complement the main data with two additional data sources. The first is the Wage Structure Statistics (WSS), which contains information on actual hours worked for all workers from a random sample of firms, usually for the month of September. It covers almost 50% of all employees in the private sector each year and oversamples large firms. We use this data source to analyze the relative importance of firm shock transmission to hours versus wages in Section 6.

Second, we use measures of cognitive and non-cognitive skills based on tests that Swedish males take at the point of military enlistment (typically at age 18). Cognitive skill assessments measure inductive skill, verbal comprehension, spatial ability, and technical understanding. Non-cognitive skills are assessed based on an interview with a certified psychologist who determines social skills as well as personality traits, including willingness to assume responsibility, emotional stability, persistence, and independence.[11] These cognitive and non-cognitive scores allow us to analyze worker heterogeneity within education groups.

2.2 Sample construction

Given the constraints on firm data from the SBS, we focus on non-financial limited-liability firms for the period 1997–2008.[12] This sample of firms represents 84 percent of value added and 86 percent of employment in the Swedish non-financial private sector over this period.

We include all individuals who work at firms in our sample at some point during the 1997–2008 period. We exclude individuals until they no longer receive public study grants for formal education, and as soon as they receive disability or pension benefits. We further exclude individuals when they move to a workplace that is not in the firm sample (typically, these are moves to the public sector, a financial corporation, or self-employment). Importantly, however, we keep all the records of non-employment that are in connection with

[11] See Lindqvist and Vestman (2011) and Edin et al. (2022) for more details on the enlistment data.

[12] The sample includes commercial or limited liability partnerships, limited liability companies, and co-operatives. This includes both private and publicly-listed companies. We exclude sole proprietors because data for these entities are not available for the entire period.

employment spells at the firms in our sample.[13]

In this paper we focus on men only. Results for women are much harder to interpret given that earnings variation reflects changes in both hours (especially at the extensive margin) and productivity (Friedrich, Laun, and Meghir, 2022). footnoteThe fraction of men in the WSS reported to have a part-time position was 2.8% for low educated and 2.0% for high educated during our sample period. The corresponding numbers for women were 29 percent for low educated and 21 percent for high educated. The average share moving between part-time and full-time contracts was 2.0% for low educated men and 1.6% for high educated men, compared to 6% for women in both groups and higher shares for women of child-bearing age.

Firm types and worker types We follow Bonhomme, Lamadon, and Manresa (2019) and group firms into four "types" $s = \{1, 2, 3, 4\}$ using k-means clustering. Specifically, we residualize worker wages (as we will explain in Section 4.3 below), determine average residual wages by education group for each firm-year in our sample and cluster on these residual wages. We allow firms to differ in their type for high-educated and low-educated workers in a given year and to change type over time.

Since different groups of individuals may be exposed to different types of shocks or contractual arrangements, we also consider heterogeneity across worker types. In the main analysis, we estimate the model separately by education. Specifically, we use the highest achieved level of education from LOUISE to group workers into two categories: low educated workers with at most high school education and high educated workers with at least some college education. We use low and high education or low-skill and high-skill interchangeably for these two groups. We take as given education choices and restrict our estimation sample to individuals age 26–55 for both education groups.

[13] The RAMS register and the unemployment register allow us to reconstruct the full employment history of individuals. When workers leave the sample, we know whether they are moving into unemployment or in alternative employment (public sector, self-employment, etc.); when they re-enter the sample, we know whether they came from unemployment or another employer, even when that employer is not in our firm sample. The missing spells do not prevent us from constructing the appropriate moments to compare to the simulated moments and there is no confusion between a missing spell and non-employment.

In addition, we further use the cognitive and non-cognitive scores from military enlistment tests to group workers within education into subgroups that differ by their cognitive and non-cognitive skills. Specifically, we use standardized cognitive and non-cognitive scores reported on an integer Stanine scale (from 1 up to 9, with mean 5 and standard deviation 2). We then apply a k-means clustering approach using these two-dimensional scores to categorize workers (within education) into four skill groups: low (cognitive skills)-low (non-cognitive skills), low-high, high-low, and high-high. This grouping reflects the separate roles that cognitive and non-cognitive skills play in workers' labor market outcomes (Edin et al., 2022).

2.3 Wage Setting in Sweden

Before we turn to our empirical analysis, we provide a short overview of wage setting institutions in the Swedish labor market.

Sweden does not have a legally binding minimum wage. Instead, industry-specific collective bargaining plays an important role in regulating the wage setting process throughout the Swedish economy. Union density is high at about 80% over our sample period, and since collective agreements usually extend to non-union workers, coverage is even higher (Skans, Edin, and Holmlund, 2009). Bargaining typically occurs at the industry level every three years. Collective agreements govern the wage setting process and often impose a wage floor, which may affect how shocks can be transmitted to wages.

Most importantly for our analysis, the wage bargaining process has been substantially decentralized starting in the early 1990s, extending the scope to negotiate wages at the firm level. Specifically, Fredriksson and Topel (2010) report that in 2004, wages for only 7% of workers were set by a central agreement. For the remaining vast majority of workers, wage negotiations happened at the local level, ranging from entirely local negotiations with firms (36% of workers) to varying degrees of discretion for the remaining share subject to guidelines from the central agreement. Restrictions by central agreements are more common in industries such as wood and paper, cleaning, retail and wholesale, transportation, and construction, with a large share of low-educated workers (National Mediation Office, 2004).

As a result of local discretion, only a small minority of workers faces a binding wage floor. Saez, Schoefer, and Seim (2019) argue that in Sweden union minimum wage floors mostly bind for new, young employees (see also the evidence in Skedinger, 2006, and Skedinger, 2015, for the hospitality and retail sectors). Based on these findings, we do not expect collective bargaining to introduce substantial asymmetries in firm shock transmission to wages.

2.4 Descriptive Evidence

Table 1 presents descriptive statistics for the firms in our main sample. The data include about 110,000 unique firms and 900,000 firm-year observations.[14]

Panel B presents characteristics of the firm types that we classify using the k-means approach explained above. Types are ordered by their average residual wages, from lowest-paying type 1 to highest-paying type 4. Since we allow firms to have different types for workers with low and high education, we present their characteristics separately.

The clustering algorithm generates groupings of unequal size. Residual wage differences across types are large, with a small group of the lowest-ranked firms (with 4–5% employment share) paying 40 and 47 log points below average, whereas a small group of top-ranked firms (with around 12% employment share) pay 47 and 61 log points above the market average, respectively for low and high educated workers. In contrast, a large majority of firms represented in types 2 and 3 on average pay a 0–25% premium. The average workforce monotonically increases for firm types 1 to 3, but the top group 4 has lower average employment. Interestingly, pay differences correlate strongly with firm productivity, such that higher paying firms have higher average value added per worker. Firm types are spread out similarly across industries, with somewhat higher shares of construction and retail firms in the bottom two types (especially for high educated workers), manufacturing over-represented

[14]Appendix Table A1 provides more information on the size and sectoral composition of the sample. The construction, manufacturing, retail and service sectors account for 15%, 18%, 27% and 40% of all firms in the sample, respectively.

Table 1: **Summary Statistics, Firms**

Panel A: Full Sample				
No. unique firms	109,493			
No. firm-year obs.	903,567			

Panel B: Firm Type Statistics	Type 1	Type 2	Type 3	Type 4
Low Education Workers				
Employment share	0.038	0.326	0.520	0.115
No. of employees	9.6	24.0	46.1	30.2
Log wages	9.532	9.930	10.095	10.358
Residual wages	–0.402	–0.012	0.184	0.471
Value added per worker	466,518	565,191	672,780	806,360
Residual, log V.A./worker	–0.245	–0.042	0.111	0.242
Growth, log V.A./worker	–0.037	–0.022	–0.016	–0.026
% Construction	0.173	0.208	0.191	0.096
% Manufacturing	0.143	0.245	0.227	0.128
% Retail	0.271	0.285	0.272	0.267
% Services	0.413	0.262	0.309	0.509
High Education Workers				
Employment share	0.051	0.267	0.561	0.121
No. of employees	21.1	41.4	82.0	44.1
Log wages	9.744	10.150	10.365	10.669
Residual wages	–0.472	–0.018	0.250	0.614
Value added per worker	560,915	682,034	856,493	950,061
Residual, log V.A./worker	–0.112	0.064	0.216	0.361
Growth, log V.A./worker	–0.032	–0.023	–0.020	–0.023
% Construction	0.114	0.107	0.087	0.067
% Manufacturing	0.189	0.239	0.230	0.152
% Retail	0.260	0.241	0.230	0.223
% Services	0.437	0.412	0.452	0.558

Note: Value added per worker is in real SEK for base year 2008.

in types 2 and 3, and service firms more common among type 4 for both education groups.

Table 2 presents summary statistics for each group of workers. Workers with low education are on average slightly older, which reflects changes in years of schooling across cohorts. Workers with lower education are also less likely to have children living at home. As expected, high educated workers have higher average monthly earnings. Employment rates are high for both groups and most workers stay at their current job each quarter. Still, the data indicate that job-to-job mobility and transitions between employment and non-employment are fairly common. Each quarter, 2–3 percent of employed workers change jobs and around

Table 2: **Summary Statistics, Workers**

	Low Education	High Education
No. unique workers	1,146,208	462,343
No. worker-quarter obs.	30,846,261	11,114,670
Monthly earnings	24,997	36,000
(2008 SEK)	(8,049)	(17,201)
Age	40.30	39.05
Married	0.5794	0.6108
Having children	0.4567	0.4982
Employed, of which:	0.8768	0.9044
Job stayer	0.9548	0.9493
Job mover	0.0235	0.0321
Re-entrant	0.0218	0.0187
Sectors		
Construction	0.1519	0.0598
Manufacturing	0.4084	0.3782
Retail Trade	0.1858	0.1355
Services	0.2540	0.4264
Wage Survey Data		
Share observed	0.4092	0.4626
Monthly hours worked (avg)	150.22	155.68
Monthly hours worked (sd)	(33.82)	(30.53)
Military Enlistment Data		
Share observed	0.7341	0.7582
Cognitive skill score	4.4437	6.5578
Non-cognitive skill score	4.7465	5.7772

2 percent enter employment after a period of non-employment. In particular, high educated workers are more likely to experience a job-to-job move. In Appendix A.4.1 we describe the life cycle evolution of earnings and labor market transitions. A key feature worth noting is that the variance of earnings increases over the life cycle for higher education workers, but remains flat for the lower education ones, a feature that our model will replicate.

The auxiliary data from the wage survey covers 41% and 46% of low and high educated workers in our main sample, respectively. For our analysis, the key measure we extract from the survey is monthly hours worked, and the average corresponds very closely to a typical work week of 37–40 hours. There is some variation around that average that we will account for in an extension in Section 6.

Finally, the military enlistment data covers around 75% of individuals in our sample. The average for the entire population is 5 (on a standardized integer scale ranging from one to nine), and high educated workers score higher than the average on both cognitive and non-cognitive skills. Appendix Table A2 stratifies further by reporting statistics by education and cognitive/non-cognitive skill groups. We find systematically higher average earnings for workers with higher cognitive and/or non-cognitive scores, consistent with significant returns on both skills in the labor market (Edin et al., 2022). In addition, we document that workers with higher skills are more likely employed at higher-ranked firms. We use these sorting patterns in an extension that allows for worker heterogeneity types.

Wage Dynamics for Movers Across Firms It is well documented that a substantial and increasing share of wage inequality is driven by differences across firms (see Card, Heining, and Kline (2013) for Germany, Song et al. (2018) for the U.S., and Akerman et al. (2013) for Sweden).This motivates the investigation of the role of firms for wage inequality and wage dynamics in our paper and suggests that understanding worker mobility across firms may be crucial for our analysis.

In Table 3 we describe – separately for low- and high-educated workers – the pattern of worker mobility between the four type of firms, and how (residual) wages change between jobs when mobility does not involve an unemployment spell in between jobs. We compare residual wage growth in the year that precedes and in the year that follows a job move, conditional on no other transition happening in this three-year window. Among job-to-job movers about 49% of low-skill workers and 52% of high-skill workers move to a firm of the same type (80% if we add adjacent firm types); in both groups, 26.5% of transitions are to a higher-paying firm, and the rest to a lower-paying firm.

On average, movers experience positive wage growth when moving to higher ranked firms, especially when leaving firms of the lowest type. In contrast, mobility to lower ranked firms goes along with zero or negative wage growth, and the decline is larger if the new firm

Table 3: **Data: Job Mobility and Residual Wage Growth across Firm Types**

		Low-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.006	.014	.010	.003	.159	.276	.392	.466	.346	.166	.132	.125
Departing	2	.020	.134	.123	.027	–.005	.031	.087	.146	.554	.455	.351	.272
firm type	3	.016	.124	.311	.088	–.067	–.043	–.001	.053	.631	.610	.529	.406
	4	.003	.023	.055	.043	–.164	–.123	–.073	–.015	.703	.700	.636	.535
		High-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.007	.010	.010	.003	.167	.279	.371	.417	.347	.231	.163	.173
Departing	2	.012	.079	.126	.028	.001	.044	.084	.169	.519	.436	.361	.251
firm type	3	.013	.113	.390	.088	–.075	–.027	.011	.091	.599	.568	.498	.361
	4	.003	.018	.063	.039	–.221	–.136	–.082	.017	.694	.671	.634	.470

ranks further below the previous employer. These patterns are consistent with the results from Portugal reported in Card et al. (2018). In general, these average changes mask wide dispersion in pay changes as evidenced by the share experiencing wage cuts when moving from one firm to another (the right transition matrix in Table 3). As expected, the share experiencing wage cuts is inversely related to the direction of the move and rank distance between the previous and new firm.[15] Our model allows for such wage cuts: the motive for changing jobs, expressed in equation (10), trades off wage improvements to other observed and unobserved reasons for mobility. Understanding the underlying theoretical model that would replicate such intricate patterns would be particularly interesting. Many search models do not allow for wage cuts: the basic Burdett-Mortensen wage posting model excludes them. On the other hand the model by Postel-Vinay and Robin (2002) does allow for wage cuts: the worker may choose to move to a firm where the match surplus is higher; they may wish to pay for this move in terms of a lower upfront wage because of the option value of future wage increases. Finally, in Lise, Meghir, and Robin (2016) wage movers are either improving their match or are moving away from a firm that has suffered a productivity shock.[16] This

[15]Note that residual wages are computed for the full sample of stayers and movers, so residual wage cuts are not mechanical. In addition, Appendix Table A3 shows that qualitatively similar patterns hold for *nominal* wages, with 10%–47% wage cuts that are systematically related to the type of transition to a firm that is lower, equally or higher ranked.

[16]Bonhomme and Jolivet (2009) and Sorkin (2018) consider search models in which amenities are valued in utility, also rationalizing the possibility of job-to-job transitions with wage cuts.

formulation allows for a much more flexible relationship between wage changes and mobility.

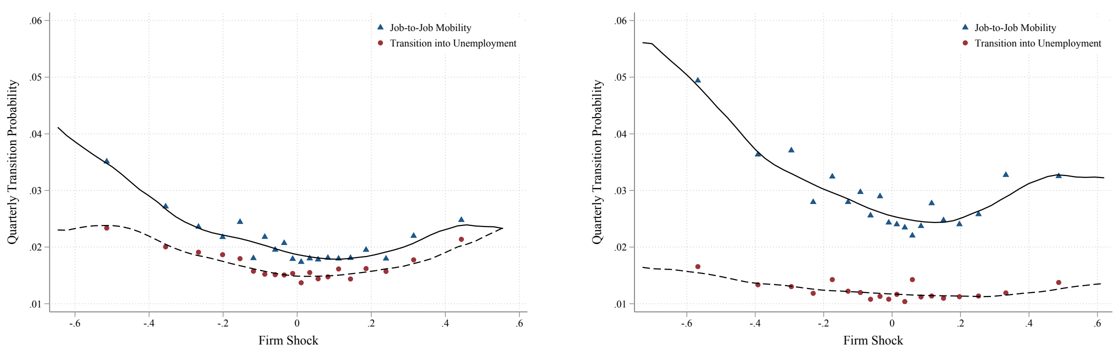
While wage cuts are not uncommon when a job-to-job move is recorded, they are also observed among stayers, as we document in Appendix Figure A4. These facts are indicators of the importance of firm-level shocks in determining wages and worker mobility, and we further explore this link below.

Firm Shocks, Mobility, and Wages To motivate our approach and the structure of the model, we now present descriptive evidence on how shocks to the firm relate to mobility and wages.[17] To improve readability, the focus is on the range of firm shocks between the 5-th and 95-th percentile of the firm shock distribution.

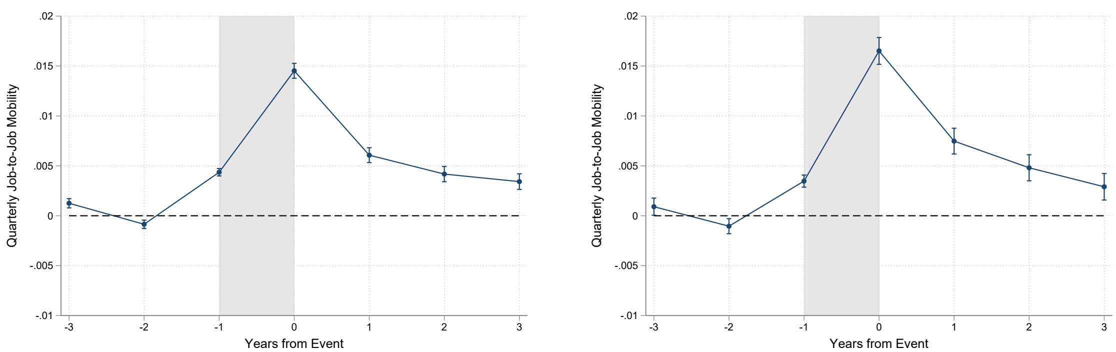
Figure 1: Firm Shocks and Worker Mobility

Low Education High Education

Concurrent Worker Mobility



Timing of Job-to-Job Mobility



[17]Firm shocks are the residuals of a regression of log value added per worker on year×county and year×industry (2-digit NACE) fixed effects.

First, we show evidence of increased worker mobility away from firms with negative shocks, both towards new firms as well as unemployment. The top panels of Figure 1 plot the average quarterly mobility rates for workers (on the y-axis) as a function of the magnitude of the contemporaneous shock at their incumbent firm (on the x-axis). While both education groups respond to firm shocks, there are important differences. The lower educated change jobs or move to unemployment at approximately similar rates in response to firm-level shocks. The higher educated move much more frequently between jobs than from work to unemployment.

Second, in a frictional labor market, mobility responses may not be limited to the period in which a particular firm shock occurs. Instead, mobility may be delayed based on the offer arrival process. We analyze the timing of job-to-job mobility in more detail in the bottom panel of Figure 1. We compare mobility rates at "exposed" firms (with a large negative shock in period 0, defined as a shock in the bottom tercile of the distribution) with mobility rates at all other firms. Since we can only measure firm shocks at an annual frequency, the figure shows a shaded area for the time span between -1 and 0, during which a firm shock measured at time 0 might have occurred.[18] On the vertical axis, we plot the difference in quarterly job-to-job mobility rates between exposed and non-exposed firms.[19] We document little difference in mobility rates before the differential shock occurs. We then find the largest mobility response in the year of the shock, but also significantly higher job mobility rates at exposed firms in subsequent years.[20] These responses are slightly stronger for high educated workers, but the patterns are similar across education.

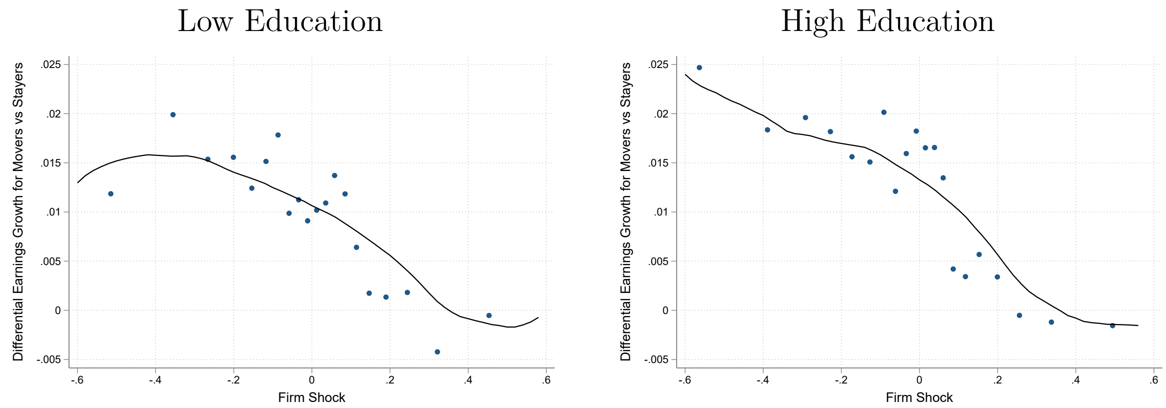
Finally, combining the insights from the previous discussion, Figure 2 analyzes differences in wage growth between job-to-job movers and stayers (on the y-axis) as a function of the magnitude of firm-level shocks (on the x-axis). For movers, these firm shocks refer to their

[18]For example, if a persistent firm shock occurs in the second half of year $t-1$, we will measure the majority of its impact in year t, but workers' responses may be visible before.

[19]For these stacked event studies, we residualize job mobility using a linear probability model that controls for calendar year$\times$quarter fixed effects. The confidence intervals use clustered standard errors by firm.

[20]As expected given the issue of time aggregation for firm productivity shocks, we also detect a smaller mobility response at time -1, consistent with some firm shocks already occurring then.

Figure 2: Firm Shocks, Mobility, and Wages



previous employer to meaningfully compare their wage growth to that of the workers who stay with the firm. We find a strong association of the wage growth gap between movers and stayers with firm shocks. Both groups experience similar wage growth only when the firm shock is sufficiently positive. For negative firm shocks, movers experience systematically larger wage growth than stayers, consistent with their strategic mobility to other firms to avoid the transmission of these negative firm shocks. This mover advantage is similar across education groups and only slightly more pronounced for highly educated workers.

While these figures do not allow causal conclusions to be drawn because of censoring issues, they nonetheless strongly support and motivate the underlying premise of our study, namely that shocks to firms pass through to wages, and worker mobility may hide the extent of this transmission. We next present a statistical model that builds on these facts.

3 The Stochastic Structure of Earnings

3.1 Overview

Our wage equation is specified separately for high and low educated workers. As discussed above, the distribution of wages (mean and variance) for these two groups evolve quite differently over the life cycle (see Figure A1). We allow for a stochastic structure of wages that depends on general productivity shocks, which follow the worker wherever he is employed; these shocks may reflect accumulation or depreciation of general skills and health shocks, for example. Wages also depend on match-specific effects (relating to the value of the specific worker/firm combination, e.g., including changes from both transitory bonuses and permanent promotions), and possibly on shocks to firm-level productivity passing onto wages, which is the central question of our paper. Our main administrative data do not measure hours of work and thus we do not distinguish between earnings and wages, terms we use interchangeably. We use the WSS, where hours worked are observed, to check whether this is an important limitation.

The descriptive evidence presented above points to mobility between employment and out-of-work as well as job-to-job moves as important features of careers. These transitions may be driven, at least in part, by shocks to wages. Ignoring this link may cause a serious bias in the measurement of the impact of firm-level shocks, since large adjustments are effectively censored by individual behavior: individuals who risk suffering large pay cuts as a result of negative productivity shocks may quit into unemployment or are more likely to accept alternative job offers. Moves to alternative employers are not costless, since they may reset one's career. We thus allow for endogenous employment and mobility and relate this directly to wage shocks.

We consider a quarterly model for firm productivity, wages, employment and job mobility. The quarterly frequency is designed to capture the effects of job mobility and the associated wage changes. If we were to focus on annual frequencies, there would be too few moves and the model would miss a key source of wage dynamics. In Section 6 we estimate the model using annual transitions and comment on the differences with the baseline.

3.2 The Statistical Model

Firm Productivity A potentially key source of wage variation is transmission of firm productivity shocks onto wages. Empirically, we measure firm productivity with value added per worker. We distinguish between permanent and transitory shocks because we can expect them to have very different impacts on wages. For example in a world with adjustment costs on either wages or employment we can expect the firm to smooth over transitory shocks but consider adjustments in response to a permanent change (see also Guiso, Pistaferri, and Schivardi, 2005). We thus assume that the stochastic process of log productivity for firm j observed in period t, denoted $a_{j,t}$, can be decomposed into permanent and transitory components,

$$a_{j,t} = a^P_{j,t} + \xi^T_{j,t} \tag{1}$$

$$a^P_{j,t} = a^P_{j,t-1} + \xi^P_{j,t} \tag{2}$$

We assume that the two ξ shocks are i.i.d. normal: $\xi^l \sim N\left(0, \sigma^2_{\xi^l}\right)$, for $l = \{P, T\}$, and may pass through to wages differently.[21] We now turn to a description of the stochastic process for individual wages.

Wages The education-specific log wage equation for individual i who works at firm j in period t is given by:

$$\ln w_{i,j,t} = x'_{i,t}\gamma + P_{i,t} + \varepsilon_{i,t} + v_{i,j,t}, \tag{3}$$

where $x_{i,t}$ includes observable worker characteristics (such as age and industry-time effects).[22] The remaining terms include an individual component ($P_{i,t} + \varepsilon_{i,t}$) and a firm-related productivity component ($v_{i,j,t}$). We now describe them in detail. All parameters are education specific, but we leave this dependence implicit to avoid cumbersome notation.

Individual productivity is subject to transitory shocks $\varepsilon_{i,t} \sim N\left(0, \sigma^2_\varepsilon\right)$.[23] $P_{i,t}$ is the

[21] Equation (2) assumes that the persistent component of firm productivity follows a random walk process, an assumption we test and fail to reject. We also assume for simplicity that there is no feedback from workers' mobility choices to firm value added. Recent work by Bilal et al., 2022 develops a dynamic model of firm growth in the presence of job-to-job mobility.

[22] Industry-time effects capture fluctuations due to collective bargaining, which are typically industry-wide.

[23] Any classical measurement error affects only estimates of the variance of transitory shocks. Meghir and Pistaferri (2004) point out the inability to disentangle the variance of the transitory shock, the variance of the measurement error and the parameters of the transitory process in a similar setting. The distinction

accumulation of persistent idiosyncratic productivity shocks and is specified as:

$$P_{i,t} = \rho P_{i,t-1} + \zeta_{i,t}$$

This persistent productivity evolves starting from the initial productivity draw upon entry into the labor market, $P_{i,0} \equiv f_i^{init} \sim N\left(0, \sigma_f^2\right)$. If $\rho = 1$ we have the standard random walk assumption for the permanent component of wages. The productivity shock is denoted $\zeta_{i,t}$ and we make a flexible distributional assumption:

$$\zeta_{i,t} \sim \text{mixture of Normals}\left(\{\mu_{\zeta_1}, \sigma_{\zeta_1}\}; \{\mu_{\zeta_2},\ \sigma_{\zeta_2}\}; \varsigma_m\right) \tag{4}$$

where $\{\mu_{\zeta_s},\ \sigma_{\zeta_s}\}$ $(s = 1, 2)$ represent the mean and standard deviation of each of the two normals in the mixture, and ς_m is the mixing parameter. By allowing for a mixture of normals we are able to fit higher order moments of the distribution of wage growth, such as the observed skewness and kurtosis (see Figure A4). The importance of higher order moments in earnings growth has been examined for the US by Guvenen et al. (2021). Earlier papers that consider a mixture of normals for income processes include Geweke and Keane (2000) and Bonhomme and Robin (2009). One interpretation of the mixture is that on occasion workers draw a large wage change, for example due to a promotion; another is that a non-negligible fraction of workers experience no wage growth from one period to the next. These features of the model turn out to be important empirically.

The identity of the firm affects wages through the composite term $v_{i,j,t}$. We assume that this component evolves stochastically as a result of firm- and idiosyncratic match-specific shocks. We also find it useful to distinguish between permanent (or at least long-run persistent) changes and transitory changes. For the periods following the date t_{ij} when

has economic implications, however, since measurement error is pure noise while transitory shocks reflect uncertainty that may give rise to economic responses. In practice, if some of the transitory variation in wages that we estimate reflects measurement error, the main effect will be an overstatement of transitory risk.

worker i joins firm j (and when the worker does not change jobs) we assume:

$$v_{i,j,t} = v_{i,j,t}^P + v_{i,j,t}^T \tag{5}$$

The permanent part of the firm-level component follows the law of motion:

$$\begin{aligned} v_{i,j,t}^P &= v_{i,j,t-1}^P + \kappa^P \xi_{j,t}^P + \psi_{i,j,t}^P \\ &= v_{i,j}^{init} + \kappa^P \sum_{s=t_{ij}+1}^{t} \xi_{j,s}^P + \sum_{s=t_{ij}+1}^{t} \psi_{i,j,s}^P \end{aligned} \tag{6}$$

Innovations to $v_{i,j,t}^P$ arise because of pass-through of permanent firm-level productivity shocks $\xi_{j,t}^P$ onto wages (where κ^P is the transmission coefficient) and because of innovations to the match component ($\psi_{i,j,t}^P$). The pass-through component induces spatial correlation of wages across all workers in a firm. This is the key observation that we exploit for identification of the pass-through coefficients. The term $v_{i,j}^{init}$ is the initial value of the permanent firm-level wage component;[24] we assume it is drawn from a firm-type specific distribution:

$$v_{i,j}^{init} \sim N\left(\tau_s, \sigma_{v^{init}}^2\right) \tag{7}$$

where τ_s can be interpreted as the average wage premium at firms of "type" s. As discussed in Section 2, we use a k-means clustering algorithm to allocate firms to four types (so that $s = \{1, 2, 3, 4\}$), and maintain this categorization in the model by keeping the size of the type distribution as in the data. Since firm-level shocks shift firm productivity over time, a firm may transition across types and hence change its wage premium as it moves up or down in the firm type ranking. This means that for a worker the initial value of a job depends on firm characteristics at the time of hiring.[25]

[24]An equivalent notation for $v_{i,j}^{init}$ is $v_{i,j,t_{i,j}}$.
[25]See Lachowska et al. (2023) for a study quantifying the role of time-varying firm pay policies in the US.

The transitory part of the firm-level wage component equals:

$$v_{i,j,t}^{T}=\kappa^{T}\xi_{j,t}^{T}+\psi_{i,j,t}^{T} \tag{8}$$

where κ^{T} is the transitory shock ($\xi_{j,t}^{T}$) pass-through rate and $\psi_{i,j,t}^{T}$ represents a transitory innovation to the match. Finally, we assume that the two ψ shocks are i.i.d. normal: $\psi^{l}\sim N\left(0,\sigma_{\psi^{l}}^{2}\right)$, for $l=\{P,T\}$.

Overall, the firm-level component of the wage $v_{i,j,t}$ reflects two important ways that firms may affect workers' pay: (a) systematic differences in the match quality, and (b) transmission of firm-level shocks to wages over time. Conceptually, firm shocks are shared by all workers within the firm (at least within a broad skill group) and are associated to changes in wage policy, contractual arrangements, etc. In contrast, match-specific shocks are idiosyncratic and are associated to changes in production complementarities, learning, individual performance evaluation, etc. By allowing for match specific shocks that are unrelated to firm-level productivity we guard against the possibility that the productivity shocks just proxy for worker-firm pair effects. Whether they matter in practice is an empirical question.[26]

One of the contributions of our work compared to earlier studies is that the evolution of the match component is not confused for rent sharing since the two are kept distinct. Our framework is general enough that it nests previous characterizations of the role of firms in wages. For example, if $\sigma_{\psi^{P}}^{2}=0$ the firm-level component would change only in response to firm-related permanent productivity shocks.

Employment and Job-to-Job Mobility For the dynamics of earnings a key issue is controlling for selection into work and for job mobility, both of which may truncate the

[26]The existence of a match-specific effect has been motivated theoretically within the search and matching framework by, among others, Topel and Ward (1992). Abowd, Kramarz, and Margolis (1999) use French employer-employee data to show that match-specific effects matter empirically. Most studies on earnings dynamics, however, have not explicitly modeled the firm side. Low, Meghir, and Pistaferri (2010) include a match-specific component in the wage process that remains unchanged over the duration of the match. As a result, in their model wage growth does not depend on the identity of the firm.

distributions of shocks. For example, if there is a large pass-through of firm-level shocks onto wages, the worker may actually quit the job rather than suffering the resulting pay cut, which may even be permanent (within the firm). Similarly, workers with large pay cuts in firms with bad productivity shocks may be more likely to accept alternative job offers, consistent with the evidence in Figure 1.[27]

We model employment E as:

$$E_{i,t} = \mathbb{1}\left\{z'_{i,t}\delta + \phi\left(P_{i,t} + \varepsilon_{i,t} + v_{i,j,t}\right) + u^{E}_{i,t} > 0\right\}. \tag{9}$$

The decision to work depends on the stochastic component of wages $(P_{i,t} + \varepsilon_{i,t} + v_{i,j,t})$.[28] The coefficient ϕ in part reflects the incentive effect of working but also the importance of unobserved heterogeneity in participation choices, including unobserved factors explaining persistence in the value of employment.[29] Other observable determinants of employment (such as age) are summarized in z.

Similarly, job-to-job mobility is defined as:

$$J_{i,t} = \mathbb{1}\left\{z'_{i,t}\theta + b\left(v^{init}_{i,j'} - v_{i,j,t}\right) + u^{J}_{i,t} > 0\right\}. \tag{10}$$

Job mobility depends on the difference between new (j') and incumbent (j) firm-level components $(v^{init}_{i,j'} - v_{i,j,t})$, and not on the remaining stochastic components, because permanent and transitory productivity shocks do not depend on a particular firm match but are portable characteristics of a worker across different jobs. The importance of wage differences as opposed to worker observable characteristics in determining mobility is captured by the parameter b. This setup relates closely to the descriptive evidence of Figure 1 (top panel) and

[27] Positive shocks may work in reverse, lowering quits and reducing the likelihood of a job-to-job move. We discuss below that allowing for asymmetric effects appears not to affect our findings much.

[28] A more general specification – not pursued here – would allow a different impact of the transitory and the permanent components because the former only causes substitution effects, while the latter also causes wealth effects (see Blundell, Pistaferri, and Saporta-Eksten (2016)).

[29] By participation we mean employment versus non-employment. We use the terms interchangeably.

Figure 2, showing that the incumbent firm's negative shocks drive both job separations and the wage growth premium experienced by movers relative to stayers. We further note that because mobility depends on the worker's match value at their current employer, a large permanent negative shock impacts workers' mobility decisions both today and in the future (if search frictions delay job mobility, see the evidence in the bottom panel of Figure 1).

Finally, both the employment and the mobility equation depend on stochastic shocks, respectively, $u^E \sim N(0,1)$ and $u^J \sim N(0,1)$. These shocks reflect exogenous job destruction and mobility (or lack thereof) due to unexplained random factors, in particular unobserved tastes for work or job mobility. In other words, workers may move to unemployment despite an attractive wage or may move to a job paying less than the current one for unobserved reasons, or indeed may not move despite an excellent alternative offer. As usual in this class of models, identification of parameters in (9) and (10) is only up to scale, and hence the variances of u^E and u^J are both normalized to 1. Finally, the observed characteristics in the two equations also reflect labor market attachment and employment and mobility costs.[30]

Sorting. In this paper, wages may depend on fixed individual and firm characteristics in a log-separable way as in Abowd, Kramarz, and Margolis (1999). We do not take a stand on whether there is assortative matching in the labor market (i.e., a correlation between these effects). But note that even if there is sorting based on permanent worker or firm characteristics (as some papers have found), we assume that the mechanism through which firm-level productivity shocks affect wages is common across all firms and hence there is no effect of sorting on wage growth. While this is restrictive, it is still more general than earlier models of wages estimated on matched data because of the richer structure of the shocks. Note also that Engbom, Moser, and Sauermann (2023) find a small role of sorting on wages in the same data we use here: while higher productivity workers tend to locate in higher

[30] Since this is not a structural dynamic model, we do not explicitly include option values of employment, moving or staying. However, our model includes much of what would be in the state space in such a structural model.

productivity firms, this sorting is not reflected much in wages.[31]

Labor Market Frictions and Job Offers Upon entry in the labor market, workers receive job offers at a rate λ_{entry}. In subsequent unemployment spells, job offers are received at an age-dependent rate $\lambda_U = \lambda_{U,0} + \lambda_{U,1} \cdot age$. The age dependency is, of course, testable. Job offers while employed are subsumed into age-dependent mobility preferences in equation (10), since the two cannot be separately identified.

These arrival rates create an asymmetry between the probability of entry and exit in employment. Given this flexibility we can interpret the employment equation (9) as reflecting both the decision to work or not and exogenous job destruction. Thus there is no presumption that exit from employment reflects purely endogenous individual decisions.

If a worker receives a job offer while employed, we model the origin of the offer as a function of the firm type s of the current employer:

$$\Pr\left(\text{offer from firm type } k \mid \text{current firm type } s\right) = \omega_s \cdot \frac{\exp(-\omega_{dist} \cdot |k - s|)}{\sum_g \exp(-\omega_{dist} \cdot |g - s|)}. \tag{11}$$

This functional form has two empirically relevant features. First, it allows for different offer arrival rates by firm type, ω_s.[32] Second, it allows for the possibility that workers face higher offer probabilities from firm types that are more "similar" to the current firm type (if the parameter $\omega_{dist} > 0$); this is done to match the empirical pattern from Table 3 that most job-to-job mobility occurs between similar firms. An interpretation of this is that workers have specific human capital or skills and that jobs requiring those specific skills are more likely to be available at firms of similar "type" (see also Caldwell and Danieli, 2022); ultimately, whether this is important will be determined empirically. Note that equation (11) provides a third channel for firms to affect worker careers, in addition to the firm premium and the

[31] In an extension to our baseline model, we allow for worker heterogeneity within education category based on cognitive and non-cognitive skills, and we use the empirical sorting between worker types and firm types in estimation.

[32] This is subject to a normalization because we also include a constant term in mobility preferences. We choose to define ω_s relative to always receiving an offer at the highest ranked firms.

transmission of shocks: The identity of the current employer and their performance over time also affect the frequency and quality of outside offers for their employees and will hence affect workers' ability to switch to alternative positions and accumulate search capital over the life cycle. If there is some "homophily" in the origin of offers, being in a growing firm may increase the frequency and quality of outside offers, while being in a shrinking firm worsens both.

4 Estimation Strategy

The estimation of the model is complex because of the combination of dynamics, endogenous selection into work and mobility, and the unobserved factor structure. To address these complexities, we proceed in three steps. First, we estimate the stochastic process of firm-level productivity and treat the results as an input into the model estimation. Second, we estimate wage residuals based on a model that accounts for quarterly selection into employment. Finally, we estimate the remaining parameters of the full model using the simulated method of moments (McFadden, 1989; Pakes and Pollard, 1989) based on the wage residuals, quarterly transition rates, and firm-level shocks.

4.1 Frequency and Time Aggregation

The timing of the model is crucial for the accurate understanding of the role of shocks. We need to map the complex reality of the model to the data we have, preserving both richness and tractability. Mobility in and out of work and between jobs is recorded very accurately in the data and can happen at any point in the year. Shocks to workers' earnings and shocks to the firm's value added, induced by events in the markets for their products and their inputs, are also likely to occur at high frequency. However, our measurements are at a lower frequency: firm performance is recorded annually and earnings either annually for non-movers or more frequently for movers.[33] In order to keep the various processes consistent with each other and preserve the richness of the data, while keeping the model tractable, we assume that all variables operate at a *quarterly* frequency. As a consequence, we need time aggregation of earnings and firm value added, which we discuss next.[34]

Our estimation approach treats consistently all data based on a quarterly frequency of the model. The identifying assumption is that the stochastic process remains the same from quarter to quarter, which means that within-year serial correlation can be picked up by the cross-year serial dependence. Subject to this assumption, we simulate the model at a quarterly frequency, and then time-aggregate the simulated data for wages and firm value added to obtain moments at an annual level (which is what we observe in the data). We then search for the parameters of the underlying quarterly processes that generate model moments at the annual level that match the annual level moments in the data. In Appendix Table B.1 we illustrate the success of this method in correctly estimating the parameters of the quarterly process. We also show the bias in the estimation of the annualized variances that would arise if we were to ignore time aggregation and treat the model as operating on an annual frequency. For completeness we also present estimates of the model at an annual frequency (see Section 6). As we shall see, the difference is rather moderate.

4.2 Firm Productivity Shocks

Our measure of firm productivity is log value added (VA) per worker. We interpret unexplained variation in value added per worker (i.e., variation not attributable to a rich set of observables or firm fixed effects) as "productivity shocks", and use the dynamics implied by the model (equations (1)-(2)) to distinguish between permanent and transitory ones. An alternative approach would be to identify unanticipated firm-specific events that shift firm

[33]Note that the earnings of a worker are never aggregated across his employers to form an annual earnings measure. If a worker moves out of a firm, say in March, we obtain an earnings record for the original firm up to the date of departure and an earnings record in the new firm from the start of employment up until December, or up until the end if the job ends before.

[34]Altonji, Martins, and Siow (2002) discuss the biases from ignoring these time aggregation issues.

productivity in the short- or long-term. These may include winning a procurement contract (Kroft et al., 2022), technological improvements reflected in patents (Kline et al., 2019), improvements in trade relevant to the firm (Hummels et al., 2014, Garin and Silvério, 2019) or improvements in infrastructure allowing better access to markets. This approach adds transparency and may be easier to interpret. However, it can only capture a limited (albeit important) set of shocks. Thus, it gives only a partial answer to the question which we set out to address, namely how important are shocks to the firm for the evolution of wages over the life cycle, their volatility, and the determination of inequality. Moreover, if the events affect other firms as well (for example, improvements in transport infrastructure) they will have general equilibrium effects and will not be suitable for isolating the impact of *idiosyncratic* firm effects. Explicit episodes may also blur the distinction between transitory and permanent productivity changes. For example, winning a public procurement auction may in some cases afford a firm a long-run advantage over competitors; but in other circumstances the positive effect may be transient, as when repeated contracts are auctioned and all firms "get a piece of the cake" eventually. This makes the interpretation of the pass-through difficult. Our approach captures all events that affect the firm in the current period.[35] These include both market level changes (like demand levels, opening up of new markets etc.) and technical change.

We consider a stochastic process for the firm's value added per worker at the quarterly level. Following equations (1) and (2), we write the log of value added per worker (y_{j,τ_q}) of firm j in period τ_q (where τ indexes the year and $q = \{1, 2, 3, 4\}$ the quarter) as:[36]

$$\begin{aligned} y_{j,\tau_q} &= f_j + x'_{j,\tau}\nu + a^P_{j,\tau_q} + \xi^T_{j,\tau_q} \qquad && \xi^T_{j,\tau_q} \sim N(0, \sigma^2_{\xi^T}) \\ a^P_{j,\tau_q} &= a^P_{j,t_{q-1}} + \xi^P_{j,\tau_q} && \xi^P_{j,\tau_q} \sim N(0, \sigma^2_{\xi^P}) \end{aligned} \tag{12}$$

where ξ^P_{j,τ_q} is the permanent shock and ξ^T_{j,τ_q} the transitory one. Vector $x_{j,\tau}$ includes county-

[35]In practice, we see the two approaches as complementing each other.

[36]We adopt the notational convention that $\tau_q = \tau_{q-1} + 1$ if $q \neq 1$ and $\tau_q = (\tau - 1)_{q+3} + 1$ otherwise.

by-year and industry-by-year interactions (so it does not vary at the quarterly level), and industry is measured at 2-digit NACE level. Controlling for the firm fixed effect f_j allows us to isolate the causal impact of shocks from other confounding factors, permanent in nature, determining firm performance.

To estimate the variances of the permanent and transitory shocks we use the residuals of value added per worker from the above regression and then apply the methods discussed in Meghir and Pistaferri (2004) adapted to this context with time aggregation. For this purpose we use the variance and first-order autocovariance of annual changes in firm log productivity as auxiliary moments. We then simulate the model at the quarterly level, annualize the results and construct the corresponding moments with the simulated data. Finally, we find the variances of the underlying shocks that are consistent with the covariance structure of the time-aggregated data. In Appendix B.3, we show how the linear structure for quarterly productivity implies tractable expressions for annual productivity growth.

In Panel A of Table 4, we show the empirical autocovariance structure of firm productivity. The results indicate that a random walk with an i.i.d. transitory component (1)–(2) is a good approximation of the stochastic structure of VA per worker because the second and third-order autocovariances for productivity growth in the data are close to zero.[37]

Panel B of Table 4 reports the estimation results for the standard deviations of shocks on a quarterly basis. The implied process for quarterly value added per worker shows sizable transitory shocks, which suggest considerable mean reversion. However, the permanent shocks are also substantial, implying quite volatile firm-level productivity. This in itself is an important result and consistent with Guiso, Pistaferri, and Schivardi (2005) and others.[38] These estimates will be used to draw firm shocks in the simulation estimation below.

[37]While some of these autocovariances are statistically significant, they are economically negligible (in all cases considered, second- and third-order autocovariances are an order of magnitude smaller than first-order autocovariances). An alternative to the random walk model is one in which the persistent component a^P follows an AR(1) process. However, we failed to reject the null that the AR(1) coefficient is equal to 1 (an estimate of 0.9998 with a s.e. of 0.0001).

[38]If we shut down the transitory shock, the annualized standard deviation of the permanent shock is 21.6%. Similarly, the annualized standard deviation of the transitory shock is 28%.

Table 4: **Estimating the Firm Productivity Process: Data and Estimates**

Panel A: Empirical Autocovariance of (residualized) growth in Value Added per Worker			
Var (Δa_τ)	Cov $(\Delta a_\tau, \Delta a_{\tau-1})$	Cov $(\Delta a_\tau, \Delta a_{\tau-2})$	Cov $(\Delta a_\tau, \Delta a_{\tau-3})$
0.2265	–0.0630	–0.0050	–0.0022
(0.0008)	(0.0004)	(0.0004)	(0.0004)
Panel B: Structural Estimates of Quarterly Productivity Process			
σ_{ξ^T}	0.5329	σ_{ξ^P}	0.158
	(0.0012)		(0.0006)

Note: $\Delta a_\tau = \Delta y_\tau - \Delta x'_\tau \nu$ denotes the unexplained growth in annual productivity in year τ. See Appendix section B.3 for details about estimation the underlying quarterly process from the time-aggregated data.

One issue concerns measurement error. It is not possible to distinguish measurement error from the variance of the transitory shock. This means that we may well be overstating the variance of the transitory component. This will understate the transmission of the transitory shocks to wages. Under the assumption of orthogonality of transitory and permanent shocks however, the pass-through coefficient for permanent shocks is unaffected.[39]

4.3 Wage Residuals

Next, we estimate the effects of individual characteristics (γ) in the wage equation (3). We estimate this part "outside" of the indirect inference step because there are many more sources of heterogeneity in wage data than we can hope to replicate in simulations of wage profiles by age or education. Based on this first stage, we can then use the wage residuals as the relevant input into the model estimation.

Equation (3) is estimated separately for workers with high and low education. As discussed in Section 2, our wage measure is determined as the total earnings at a firm divided by the employment duration in this job over the year. These employment decisions are endogenous and we consider quarterly choices in the model and the data. To account for endogenous selection into work, we apply the familiar Heckman selection correction (see

[39]To limit the implications for the estimated variances we eliminate observations with log changes from one year to the next outside the [–2,2] range. Note that firm survivorship bias in the estimation of the productivity shock variances is mitigated since we observe the firm up to the year in which it exits (if any).

Appendix B.2 for full details).

In the absence of credible exclusion restrictions, we use the same set of control variables for participation and wages, thus relying on functional form and the fundamental non-linearity in employment probabilities to identify the selection effects through the Mills ratio.[40] Specifically, we control for a fourth-order polynomial in age, as well as marital status, dummies for children in different age groups, parental leave and sickness benefits usage, and county-by-year effects.[41] In the wage equation, we add 2-digit-industry×year effects to control for industry trends. In particular, this implies that we consider impacts of the firm beyond industry-level collective bargaining agreements.

The estimates of the effects of individual characteristics on wages (γ) are presented in Appendix Table B2. We use these estimates to compute the wage residuals ($\tilde{e}$) in (3), which we use to construct key moments for identification (as detailed next).

4.4 Full Model Estimation

4.4.1 Simulation

We estimate the remaining parameters defining individual careers and wages using the simulated method of moments (McFadden, 1989; Pakes and Pollard, 1989). Each set of parameters is estimated for the lower and higher education groups separately.[42] The approach requires us to simulate wages and career paths, including transitions between employment

[40]In previous drafts we used as exclusion restrictions the interaction of time and region of residence, to capture differential changes in taxes across locations and over time. This produced similar results.

[41]Including controls for parental leave and sickness leave benefits in the wage equation is important to prevent biased selection effects from misclassified workers. It is quite common for individuals in Sweden to receive some payments from their employers while on leave. Those individuals may be falsely considered employed and will appear as low-productivity types selecting into work in the data even though they should be considered "not employed". Note that the familiar result of consistent estimates despite measurement error in the dependent variable does not apply for the participation equation because we estimate a nonlinear model, see Hausman (2001).

[42]We list these here for convenience: the parameters determining labor market participation (δ and ϕ), job-to-job mobility (θ and b), the transmission of firm-related shocks (κ^P and κ^T), the parameters of the stochastic processes determining wage dynamics ($\rho,\ \sigma^2_f,\ \mu_{\zeta_1},\ \sigma^2_{\zeta_1},\ \mu_{\zeta_2},\ \sigma^2_{\zeta_2},\ \varsigma_m,\ \sigma^2_{\varepsilon},\ \sigma^2_{\psi^P},\ \sigma^2_{\psi^T},\ \sigma^2_{\psi^{init}}$), average wage premia by firm type (τ_s, with $s = \{1, 2, 3, 4\}$), the job arrival rate coefficients ($\lambda_{entry},\ \lambda_{U,0},\ \lambda_{U,1}$), and the coefficients determining the source of outside offers by firm type ($\omega_s,\ \omega_{dist}$).

and unemployment and between jobs. Conditional on a guess for the parameter vector, we simulate life-cycle behavior and wages for overlapping cohorts of workers and a fixed number of firms in the model.[43]

Once we simulate these career paths we compute moments from the simulated data to match them to those from the actual matched employer-employee dataset. In doing this we aggregate data from a quarterly to an annual frequency whenever needed to match the observed data. The wages in the data are the residuals we constructed earlier.[44]

The moments simulated from the model mimic the moments we compute from the data and hence any sample selection is controlled for. In order to exactly replicate the data structure in the simulation, we use the empirical age distribution by education group as weights to compute the simulated moments from the model. The full set of moments is described in the section below.

4.4.2 Data Moments and Identification

This section describes the choice and computation of the data moments that we use to estimate the model (summarized in Table 5). Since different moments simultaneously contribute to pin down the structural parameters, the identification discussion in this section is naturally informal.

The first set of moments we use are quarterly employment shares and job-to-job mobility rates by age group.[45] These help identify the deterministic part of the participation and job-to-job transition equations (the parameters δ and θ in equation (9)), which we model as a second-order polynomial in age. The shift over the life cycle of mobility rates is also crucial for estimating the impact of differences in the value of firm-related components on the probability of a job-to-job move (the parameter b in equation (10)). The second set of

[43]A simulated economy consists of 4 overlapping cohorts with 6,000 individuals per cohort followed over their entire life cycle and who are matched with 80 firms. We repeat this simulation procedure for 5 independent samples of workers and firms to further increase precision.

[44]This aggregation step requires aggregating in levels and then taking logs to maintain the properties of the wage shock process.

[45]The age groups we use are 26–30, 31–35, 36–40, 41–45, 46–50, 51–55.

moments includes quarterly job creation rates (fractions moving into work from unemployment) and job separation rates (fractions moving from employment to unemployment) for the same age groups as above. The job creation rate relates to the arrival rate of offers by age ($\lambda_{U,0}$ and $\lambda_{U,1}$) and the distribution of initial offers (λ_{enter}). Moreover, we use job-to-job flows by firm type (see the left panels in Table 3) to characterize the offer arrival process as a function of the current employer's characteristics (ω_s and ω_{dist}). Separation rates by age groups relate to participation preferences and shock variances (see equation (9)), but also partly reflect the lack of available outside offers to switch jobs in the event of adverse shocks. Another set of moments we use is the covariance between wage residuals (obtained as described in section 4.3) and participation residuals (obtained from estimating a simple linear probability model for employment), which pins down the association between wages and work decisions (ϕ).[46]

Finally, we explicitly introduce moments that link firm shocks to separations (job-to-job and job-to-unemployment rates), which is the key distinguishing feature of our framework (see Figure 1). These moments further help identify sensitivity of employment and mobility decisions to wages (ϕ and b), as well as the firm-shock transmission coefficients κ that we discuss more below.

Quarterly job separations are endogenous and directly relate to transitory and permanent wage shocks. To distinguish "general" from "match-specific" wage shocks, we add annual moments related to wages, both levels and growth rates.[47] A first set of wage moments are the variances of wage residuals at selected points of the life cycle (age 26, 30, 35, 40, 45, 50, and 55; see Figure 3). The level of residual wage variance at the beginning of the life cycle depends on the variances of initial productivity (σ_f^2) and the variance of the initial

[46]This coefficient will be a function of both the causal impact of wages on participation and of the covariance of the errors, reflecting a composition effect on employment. Without exclusion restrictions these two effects cannot be disentangled. However, it does allow us to deal with censoring due to employment, whatever the interpretation of the coefficient.

[47]Since the model assumes quarterly processes for all shocks, all simulation outcomes are quarterly as well. As a result, we need to aggregate simulated outcomes such as firm shocks and wages within each year to make the simulation comparable to the observed moments.

Table 5: **Moments used in estimation**

	Quarterly moments		Annual moments
(a)	Employment shares (by age group)	(a)	Residual wage level variances (by age)
(b)	Job-to-job mobility rates (by age group)	(b)	Residual wage growth variance (stayers)
(c)	Job creation rates (by age group)	(c)	Residual wage growth autocov. (stayers)
(d)	Job separation rates (by age group)	(d)	Residual wage growth skewness (stayers)
(e)	Job-to-job mobility rates (by firm type)	(e)	Residual wage growth kurtosis (stayers)
(f)	Change in job-to-job mob. rates (by firm shock)	(f)	Average wage growth (movers)
(g)	Change in job-to-unempl. rates (by firm shock)	(g)	Variance residual wage growth (movers)
		(h)	Cov. wage growth and empl. residuals (stayers)
		(i)	Cov. wage growth and empl. residuals (movers)
		(j)	Spatial correlation (stayers)
		(k)	Autocov. average wage growth (stayers)
		(l)	Average wage growth for job movers (by firm type)

Note: Quarterly sets (a)–(d) each includes 6 moments (for age groups 26–30, 31–35, 36–40, 41–45, 46–50, 51–55); set (e) includes 10 moments (corresponding to the main diagonal and first off-diagonal components of the 4×4 transition matrix across firm types); sets (f)–(g) a single moment each. Moving to annual moments, set (a) includes 7 moments (at ages 26, 30, 35, 40, 45, 50, and 55); set (l) includes 10 moments (corresponding to the main diagonal and first off-diagonal components of the 4×4 transition matrix across firm types); the remaining annual moments include a single element. In total, we target 63 moments.

firm-related productivity component ($\sigma^2_{v^{init}}$). To distinguish between the two we use the variance of residual wage growth for movers, which pins down the variance of firm-specific initial values ($\sigma^2_{v^{init}}$) since initial (portable) productivity is differenced out.[48]

Variance and autocovariance of wage growth for stayers help identify the other individual productivity parameters. In particular, the AR(1) parameter in permanent productivity (ρ) is identified through the life-cycle pattern of the variance of residual wages. The first-order autocovariance pins down the contribution of transitory fluctuations, leaving the variance, skewness and kurtosis of wage growth to identify the contribution of more persistent shocks (including the parameters characterizing the mixture of normals).

Average wage growth for job movers pins down the mobility premium parameter b. Moreover, we target average wage growth by type of job transition, defined as pairs of firm types of the previous and new employer (see the middle panels in Table 3). These differences in wage growth closely relate to differences in wage premia τ_s that different firm types offer.

[48]Note that wage information in transition years is not very reliable because we often do not know the exact timing of a job-to-job move (only the month in which it took place). We therefore choose not to use wage information for these years and instead use mover information by looking at residual wage growth across years before and after the switch occurred. We focus on workers with only one job move between periods $t-1$ and $t+1$, i.e., we compute $(\tilde{e}_{t+1} - \tilde{e}_{t-1})$. We then use this residual wage growth measure to determine the variance of wage growth for movers.

Some of the key structural parameters are the pass-through coefficients of firm-level shocks onto wages. To identify these parameters, we measure the share of variation in wage growth that is due to variation across firms, i.e., the share of wage growth explained by a common factor, firm affiliation. This intra-class (or spatial) correlation of wage growth is defined as:

$$\rho_{\Delta\tilde{e}} = \frac{\sum_{\text{firm } j} \sum_{\text{worker } k \in j} \sum_{\text{worker } l \in j, k \neq l} (\Delta\tilde{e}_{kt} - \Delta\bar{e})(\Delta\tilde{e}_{lt} - \Delta\bar{e})}{\sum_{\text{firm } j} \sum_{\text{worker } k \in j} (\Delta\tilde{e}_{kt} - \Delta\bar{e})^2} \tag{13}$$

where $\Delta\tilde{e}$ is residual wage growth and $\Delta\bar{e}$ is average residual wage growth across all firms and workers. We complement this moment with the autocovariance of average wage growth among stayers to capture the mean reversion of transitory firm-level shocks. These two moments are closely related to the structural pass-through parameters κ^P and κ^T because (as long as there is a pass-through of firm shocks onto wages) the firm shock is the only common component in the wage growth of workers employed at the same firm.[49]

4.4.3 MCMC Estimation

We use a Markov-Chain Monte Carlo method (MCMC) to estimate the model. This derivative-free estimation method only requires many evaluations of the objective function at different parameter guesses. This is computationally attractive because the simulated moments may not be smooth. The method can deal with large parameter spaces and multiple local minima quite well; see also the discussion in Chernozhukov and Hong (2003). We describe our procedure in detail in Appendix B.5.

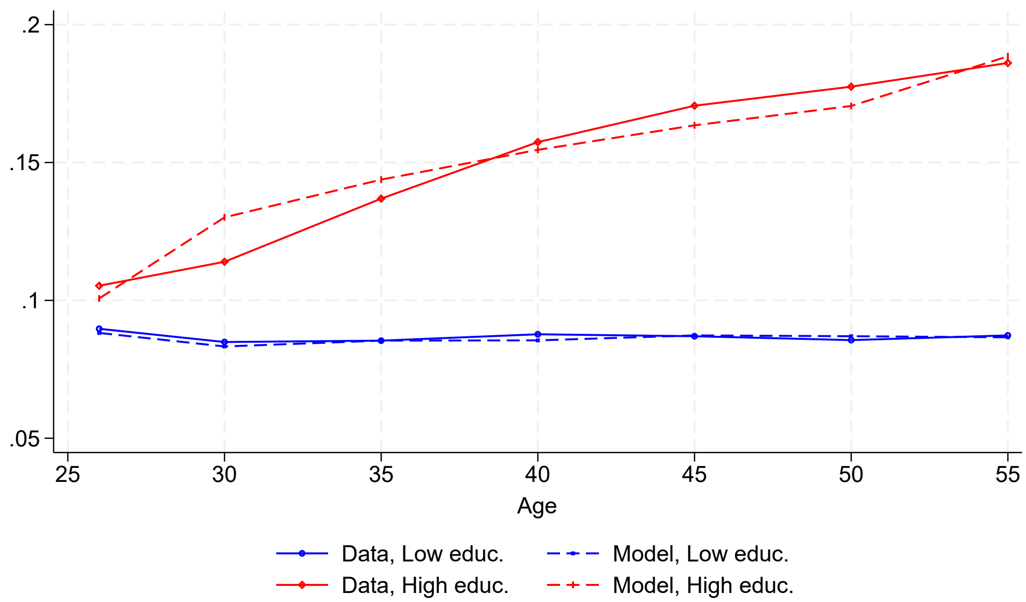
[49]Neglecting for simplicity selection issues, one can notice that – among stayers – $\rho_{\Delta\tilde{e}} \times \text{Var}(\Delta\tilde{e}_{kt}) = (\kappa^P)^2\sigma^2_{\xi^P} + 2(\kappa^T)^2\sigma^2_{\xi^T}$, and that the autocovariance of average wage growth is: $\text{Cov}(\Delta\tilde{e}, \Delta\tilde{e}_{-1}) = -(\kappa^T)^2\sigma^2_{\xi^T}$. Since firm data are used to identify the variance of firm shocks, $\sigma^2_{\xi^P}$ and $\sigma^2_{\xi^T}$, these two moments form a system of two equations in two unknowns that can be used to identify the pass-through coefficients κ^P and κ^T. Identification is predicated on having eliminated sources of spatial correlation in wage growth other than being exposed to common firm shocks (which is accomplished by appropriate controls in the wage equation), and on the absence of other reasons for observing a spatial correlation in wage growth (i.e., peer effects in labor supply, etc.).

5 Results

5.1 Model Fit

Our model is overidentified and consequently considering the fit of targeted moments can be informative about its performance. In Figure 3 we plot the actual and fitted cross sectional variance of (residual) wages. The variances are replicated extremely well by the model, showing a growing dispersion of wages over the life cycle for the high-education group and little to no age effects for the low-education group.

Figure 3: **Model Fit for Cross sectional variance by education over the life cycle**



In Table 6 we show the most salient moments. The overall fit for moments involving the dynamics of wage growth is very good. Some autocovariances show sign reversals, but they are all very close to zero and this is inconsequential.[50] When it comes to the moments relating to job movers ($J = 1$), we only consider the growth in wages that occurs between the year before the move and the year after the move, as explained above. This eliminates the effects

[50] All units are in logs.

Table 6: **Model Fit for Selected Wage Dynamics Moments**

	Low Education		High Education	
	Data	Model	Data	Model
Residual wage growth moments for job stayers				
$\text{Var}(\Delta\tilde{e}_t \mid E_{t-1} = E_t = 1, J_t = 0)$	0.0267	0.0262	0.0364	0.0290
$\text{Cov}(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1} \mid J_t = 0)$	–0.0039	–0.0004	–0.0050	0.0015
$Skewness(\Delta\tilde{e}_t \mid E_{t-1} = E_t = 1, J_t = 0)$	0.1863	0.1869	0.0287	0.0266
$Kurtosis(\Delta\tilde{e}_t \mid E_{t-1} = E_t = 1, J_t = 0)$	6.2154	6.1949	5.8351	5.8302
Residual wage growth moments for job movers				
$\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1} \mid E_{t-1} = E_{t+1} = 1, J_t = 1)$	0.0177	0.0234	0.0262	0.0304
$\text{Var}(\tilde{e}_{t+1} - \tilde{e}_{t-1} \mid E_{t-1} = E_{t+1} = 1, J_t = 1)$	0.0597	0.0615	0.0770	0.0712
Covariance between wage growth and employment residuals				
$\text{Cov}(\tilde{u}_t, \tilde{e}_t \mid E_t = E_{t-1} = 1, J_t = 0)$	–0.0001	–0.0001	0.0002	–0.0002
$\text{Cov}(\tilde{u}_t, \tilde{e}_t \mid E_t = E_{t-1} = 1, J_t = 1)$	0.0001	0.0066	0.0130	0.0180
Common shocks at the firm level				
Spatial correlation coefficient (for stayers)	0.1837	0.1816	0.1918	0.1900
$\text{Cov}(\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}] \mid J_t = 0)$	–0.0012	–0.0020	–0.0016	–0.0006
Worker mobility in response to firm-level shocks				
$\Delta \Pr(J2J_{\tau_q})/\Delta a_{j,\tau}$	–0.0111	–0.0074	–0.0132	–0.0123
$\Delta \Pr(E2U_{\tau_q})/\Delta a_{j,\tau}$	–0.0040	–0.0010	–0.0027	–0.0016

Var: Variance, Cov: Covariance, $\mathbb{E}$: average, $\mathbb{E}_j$: average within firm j. $\tilde{e}_t$ is the estimated wage residual at age t. $\tilde{u}_t$ is a residual from a linear probability regression for employment. $E_t = 1$ indicates employment, $J_t = 1$ denotes a job mover between period $t-1$ and t. Kurtosis and Skewness are computed excluding the top and bottom 1% of wage growth observations. $J2J_{\tau_q}$ denotes job-to-job transitions in quarter q of year τ, and analogously for transitions into unemployment, $E2U$. $\Delta a_{j,\tau}$ denotes the change in firm j's productivity in year τ.

of measurement error in the exact date of the transition and the associated measurement error in earnings changes between jobs.[51] The relevant statistics (the conditional mean $\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1} \mid E_{t-1} = E_{t+1} = 1, J_t = 1)$, and the conditional variance $\text{Var}(\tilde{e}_{t+1} - \tilde{e}_{t-1} \mid E_{t-1} = E_{t+1} = 1, J_t = 1)$) are reproduced accurately by the model. For the covariance between employment residuals and wage residuals for stayers and movers, the only moment that is economically relevant is for high-skilled movers. We match the positive relationship that suggests the opportunity cost of leisure is higher when wages grow substantially upon moving.

The skewness and kurtosis of wage growth for stayers capture the possibility of non-normality, one interpretation of which is that most wage adjustments are small but occasionally we see big changes, say because of a promotion or an important adverse effect on productivity. We will discuss this below when we look at the estimated parameters. Skew-

[51] No bias arises from this process because the model and the data moments are constructed using the same rules.

ness is close to zero (especially for workers with high education), but kurtosis is relatively high. Both these moments are fitted extremely well by the model.

In the penultimate panel of Table 6 we show two moments designed to capture the co-movement of wage growth among stayers in a firm; these moments identify the transmission coefficients and are thus of central importance. These are the spatial correlation of wage shocks and the autocovariance of average wage growth. Since we measure these moments using residual wage *growth*, they are unlikely to reflect correlation in wages due to sorting of similar workers into a firm. Rather, they reflect how changes in wages are correlated across individuals within a firm, which we interpret as the influence of firm-level shocks. This spatial correlation is quite high: 0.18 and 0.19 for low and high education groups, respectively, and this is closely reproduced by the model. Similarly, the model matches the autocovariance of average wage growth within firms ($\text{Cov}(\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}]|J_t = 0)$). In sum, the model captures rather well the way wages of workers in the same workplace move together from period to period.

The last two rows of Table 6 are designed to capture the association between firm shocks and separations (towards other firms or into unemployment). They replicate the evidence from Figure 1 and the model matches the moments of interest well. The estimates suggest that separation probabilities decline when the firm is growing and *vice versa* when the firm is shrinking. Labor market frictions admittedly attenuate the sensitivity of workers' separation behavior in response to firm shocks. Note also that the sensitivity is larger for job-to-job moves than for moves into unemployment: intuitively, it is less costly to separate when there is an outside job offer than when there is none.

Table C1 in the Appendix reports the fit of the model for employment rates and various labor market transitions. The model reproduces these moments quite well: It replicates the increasing participation over the life cycle, including the slowing down in the late 50s among the high educated; it fits accurately the age profiles of job creation, job separation, and job-to-job mobility (including the heterogeneity by education). The model, however, suggests slightly higher mobility rates among the high educated than seen in the data and overpredicts separations for the same group at young ages. Since we allow job offer arrival rates to differ by firm type, we further target transition frequencies and average wage growth for movers across firm types (the first two transition matrices reported in Table 3). The model captures extremely well these transition moments as we document in Table C3 in the Appendix.

Finally, the model replicates well features that we do not target explicitly: the share of workers experiencing pay cuts when moving across firms with different levels of productivity (the right transition matrix in Table 3). This is shown in the corresponding transition matrix of Table C3 in the Appendix.

5.2 Parameter estimates

Transitions We start by presenting results in Table 7 for the decisions to work and to move to another firm. Starting with employment, we find the expected increasing concave pattern in age (the δ parameters). The association of wages with participation is given by the coefficient ϕ in the table. The coefficient is positive and significant, with a notably higher value for high-skill workers.[52]

To interpret the size of the coefficient, we report at the bottom of the table the marginal effect of a 10 percent wage increase on employment for workers aged 40. This turns out to be higher for higher educated workers than the rest, implying a stronger combined effect of self-selection and incentives for the higher skilled group.

In the bottom part of Table 7 we look at the determinants of job-to-job mobility. We find that transitions across firms are decreasing in age, matching what we see in the data (e.g., the top-right panel of Figure A3). The coefficient b is estimated to be large and positive for both education levels, which shows that mobility choices are influenced by the wage difference between the incumbent and poaching firm. This sensitivity (which is particularly

[52] As noted earlier, this is a mix of a selection and an incentive effect and in this context we cannot distinguish the two since we do not have appropriate exclusion restrictions. Nevertheless this is not a threat to the identification of the stochastic process of wages, which is the central focus of this study.

Table 7: **Results: Participation and job mobility**

	Parameter	Low Education		High Education	
		Estimate	s.e.	Estimate	s.e.
		Employment			
δ_0	Constant	2.120	(0.005)	0.305	(0.007)
δ_{age}	Age	–0.163	(0.001)	0.813	(0.006)
δ_{age^2}	Age squared	0.035	0.000	–0.086	(0.001)
ϕ	Wage residual	0.275	(0.005)	0.636	(0.015)
Marginal effect of 10% wage increase (%)		0.139		0.233	
		Job-to-Job Mobility			
θ_0	Constant	–1.869	(0.008)	–0.946	(0.021)
θ_{age}	Age	0.070	(0.001)	–0.254	(0.006)
θ_{age^2}	Age squared	–0.022	(0.000)	0.018	(0.001)
b	Wage improvement	3.608	(0.020)	3.502	(0.051)
Marginal effect of 10% wage increase (%)		2.159		3.466	

relevant for the higher skilled, who have 50% larger marginal effects than the lower skilled) limits the ability of the incumbent firm to lower wages as a result of shocks (conditioning on the flow of outside offers received). However, mobility is not driven by wages only. Mobility costs that vary by age also matter, as do random exogenous shocks. This is important when we consider structural models of mobility because it suggests that wage concerns are only a part of the story driving job changes.

Table 8 presents the results on job offer arrival rates. High-skilled workers have a higher probability of job offers at labor market entry, λ_{entry}, implying a faster integration in the labor market post education. The arrival rate of job offers over the life cycle implies that at age 30, one job is sampled approximately every 4.4 quarters for the high-skilled and every 5.4 quarters for lower skill workers.[53] These rates moderately decrease as workers age.

In the bottom half of Table 8, the coefficients ω_s ($s = \{1, 2, 3\}$) show the probability of on-the-job offers from different firm types (defined using the k-means algorithm described above which clusters firms according to productivity). We normalize the offer rate for the highest-ranked firms (type 4) to 1 because we cannot separately identify overall arrival frequency

[53]This is calculated as $\frac{1}{\lambda_{U,0}+\lambda_{U,1}\times age}$.

Table 8: **Results: Arrival Rate of Offers**

		Low Education	High Education
Parameter	Description	Estimate (s.e.)	Estimate (s.e.)
	Job arrival rate		
λ_{entry}	Arr. rate at entry	0.709	0.868
		(0.0001)	(0.0002)
$\lambda_{U,0}$	Arr. rate, subs. spells	0.244	0.345
		(0.0000)	(0.0000)
$\lambda_{U,1}$	Arr. rate, subs. spells (age shift)	–0.002	–0.004
		(0.0000)	(0.0001)
	Origin of offer		
ω_1	Offer rate of type 1 firms	0.997	0.005
		(0.0029)	(0.0000)
ω_2	Offer rate of type 2 firms	0.531	0.261
		(0.0010)	(0.0003)
ω_3	Offer rate of type 3 firms	0.961	0.972
		(0.0001)	(0.0003)
ω_{dist}	Relative frequency of offers by type distance	4.532	1.961
		(0.0590)	(0.0303)

and mobility preferences. For high educated workers, the results suggest monotonically lower offer rates at lower ranked firms. The large ω_{dist} implies that when job offers are received, they typically originate from similar firms (81% of all offers on average, but higher (lower) for firms in the tails (middle) of the distribution). This implies that high educated workers who sample lower-ranked firms early in their career face the risk of being "stuck" in that segment of the economy, which may make a separation efficient in terms of their career prospects. Symmetrically, workers who sample high-ranked firms early in the life cycle face much better career prospects (see also Arellano-Bover, 2024). For the lower skilled the evidence is even starker: the estimate for the ω_{dist} suggests that only 1–2% of offers originate from firms of different type than the current firm. Overall, this implies that the fortunes of the firm are a key driver for workers' offer distribution, since firms with large positive shocks may move into a higher firm bin and this improvement will in turn generate new offers from this higher-paying firm group.

Stochastic process of individual productivity The stochastic process of wages contains the contribution of firm-specific components as well as components unrelated to firms and which the worker carries from job to job. The latter are shown in Table 9. There are clear similarities across education groups, but also some important differences as we would expect when considering the life-cycle patterns of log earnings dispersion in Figure A2.

Table 9: **Results: The stochastic process of individual productivity**

		Low Education		High Education	
Parameter		Estimate	s.e.	Estimate	s.e.
σ_f	Initial perm. productivity, wages	0.265	(0.0025)	0.305	(0.0068)
ρ	AR(1) coefficient	0.946	(0.0001)	0.965	(0.0007)
σ_ϵ	Transitory shock, wages	0.029	(0.0001)	0.063	(0.0004)
	Mixture of normals for persistent productivity shocks				
μ_{ζ_1}	mean of distribution 1	0.001	(0.0002)	–0.001	(0.0001)
σ_{ζ_1}	standard dev. of distribution 1	0.011	(0.0000)	0.010	(0.0000)
μ_{ζ_2}	mean of distribution 2	–0.013	–	0.005	–
σ_{ζ_2}	standard dev. of distribution 2	0.294	(0.0015)	0.288	(0.0070)
ς_m	Probability of distribution 1	0.911	(0.0000)	0.906	(0.0000)

Wages at labor market entry show a remarkable amount of dispersion (as measured by σ_f). Compared to the variance of wages at age 26 (see Figure 3 and Table C1), this means that the initial productivity component represents 77% and 88% of the variance of wages at the point of entry in the labor market, respectively for the low- and high-educated. Thereafter the shocks are quite persistent. However, recall that the AR(1) coefficient ρ is quarterly, which implies that the individual productivity process is not a random walk for either of the two groups. For example, after 10 years only 24% (11%) of a shock to high (low) education workers remains.

A feature of the wage data is heavy tails; one interpretation of this is that workers occasionally obtain large wage increases, possibly reflecting promotions, or large negative productivity shocks reflecting, say, a health shock, while otherwise there are small fluctuations reflecting small adjustments to pay. To capture this we allow the distribution of individual productivity shocks to be a mixture of Normals, which allows for a very general structure of moments. As we showed in Table 6, we are indeed able to match the observed kurtosis of wages. In Table 9 we show the estimated parameters of the mixture (μ_{ζ_s}, σ_{ζ_s}, s={1,2}, and the mixing parameter ς_m). The key feature here is that occasionally the individual draws a shock from a distribution with a very high standard deviation. Thus for the higher education group there is a 9.4% probability $(1 - \varsigma_m)$ that the idiosyncratic productivity shock would be drawn from a distribution with a standard deviation of 0.29; while in the vast majority of circumstances the draw is from a distribution with a much smaller standard deviation (0.010). The findings are qualitatively similar for the lower education group. Individual productivity shocks are only a part of the story driving wage fluctuations. The next key component are firm-level shocks, to which we now turn.

Table 10: **Results: Shocks and their transmission**

		Low Education		High Education	
Parameter	Description	Estimate	s.e.	Estimate	s.e.
τ_4	Wage premium, type-4 firms	0.150	(0.002)	0.102	(0.001)
τ_3	Wage premium, type-3 firms	0.046	(0.001)	0.024	(0.002)
τ_2	Wage premium, type-2 firms	–0.024	(0.001)	0.062	(0.004)
τ_1	Wage premium, type-1 firms	–0.798	(–)	–0.168	(–)
$\sigma_{\psi^{init}}$	Permanent initial shock, match value	0.006	(0.000)	0.022	(0.000)
σ_{ψ^T}	Transitory idiosyncratic shock, match value	0.043	(0.000)	0.020	(0.000)
σ_{ψ^P}	Permanent idiosyncratic shock, match value	0.004	(0.000)	0.016	(0.000)
κ^T	Transitory firm shock, match value	0.181	(0.001)	0.139	(0.004)
κ^P	Permanent firm shock, match value	0.111	(0.000)	0.222	(0.001)

Note: The standard deviation of the transitory firm-level shock is 0.5329; the standard deviation of the permanent firm-level shock is 0.158. See Table 4.

Match value and transmission of shocks In Table 10 we show the key parameters for our study, related to the impact of firms onto wages.

The initial value of the firm-related wage component is quite dispersed across firm types, with the average premium of joining the highest productivity firm ranging from 10 percentage points for the high-skilled to 15 percentage points for the low-skilled (relative to the mean, which we normalize to 0). In contrast, individuals who work for the lowest-type firms suffer large penalties (again, relative to the mean). These premia or penalties tend to persist over time (absent separations or shocks to the match) because, as discussed above, workers are more likely to receive outside offers from similar firm types.

The next set of coefficients in Table 10 ($\sigma_{\psi^{init}}$, σ_{ψ^P}, σ_{ψ^T}) relates to the idiosyncratic match value. This is a component of wage variation that relates to the specific worker-firm match, but is purely idiosyncratic to the pair and is not shared in equal measure by similar workers within the firm (unlike the "rent sharing" component we discuss below). In settings where information on firm performance is missing, this distinction is lost, while it plays an important role here and can be separately identified from the impact of firm-level shocks.[54]

For high-skill workers, we find a non-negligible role for idiosyncratic match effects. Note, for example, that the standard deviation of permanent shocks to the initial match effect (σ_{ψ^P}) is larger than the standard deviation of the typical shock to permanent idiosyncratic productivity in Table 9 and about half the size of the variation in wages explained by permanent firm shock transmission. Hence, it can generate heterogeneity in workers' participation and mobility responses to a common firm shock: some workers may decide to stay despite large negative common firm shocks because of mitigating update to their idiosyncratic match-specific effects. When we turn to lower skill workers, idiosyncratic transitory changes in the match effect over time are more important than permanent ones.

While match effects reflect learning or wage improvements due to between-firm competition for workers, another important source of variation for wages associated with the firm is shocks to firm productivity. Thus, the final set of parameters in Table 10 relate to the transmission of firm-related shocks onto wages. For workers with higher education 14% of a transitory shock is transmitted to workers. This is not large but still substantial and given the size of our data set the impact is highly significant. Permanent shocks, on the other hand, are transmitted to a much larger extent, with a 22% pass-through coefficient. Thus when the fortunes of firms change permanently, they change the wages of high-skill workers permanently (or at least until job separation), implying a high degree of rent sharing. This result is qualitatively consistent with Guiso, Pistaferri, and Schivardi (2005) (see below for

[54] Although we cannot rule out the possibility that these idiosyncratic match effects reflect heterogeneity in the pass-through of firm-related shocks.

a more quantitative comparison highlighting the importance of accounting for job mobility and periods out of work). It points to considerable firm-level market power, allowing the firm to adjust wages to reflect its fortunes.

The story is quite different for lower skill workers. Their wages fluctuate slightly more in response to transitory shocks in the firm's value added (18% transmission coefficient), but at the same time we find a substantially lower transmission of permanent shocks (11% transmission) than for high-skilled workers. This may indicate a stronger level of competition in the lower skill market as well as more union protection against structural revisions in pay. These findings are also consistent with a lower share of variable compensation compared to high-skilled workers (see also Juhn et al., 2018). From an econometric point of view this result may be traced back to the fact that overall permanent shocks are less important for low-skill workers, as implied by the descriptive analysis of their life-cycle variance, which does not increase with age, in contrast to that of the higher skill workers.

Card et al. (2018) offer a comprehensive survey of earlier estimates of rent sharing elasticities. Our elasticities cannot be readily compared to those in the literature they cite both because we distinguish between permanent and transitory shocks (a distinction that is absent in most of the studies they cite, with the exception of Guiso, Pistaferri, and Schivardi (2005) and the studies that replicate their approach) and because we report estimates separately for high- and low-skill workers (while most studies ignore this form of heterogeneity). Nevertheless our elasticity to permanent shocks for workers with some college is in the top half of their list and indeed quite close to that reported by Van Reenen (1996), who finds an elasticity of wages with respect to firm profits of 0.29. Using French data, Dobbelaere and Mairesse (2018) estimate a rent sharing coefficient of between 0.17 and 0.10, but again without distinguishing between types of shock and education groups. In Sweden Carlsson, Messina, and Skans (2016), using a different methodology than the one used here and focusing on manufacturing firms only, find a pass-through elasticity of approximately 0.1 when considering a measure of productivity close to ours. Thus, while our estimates are comparable, they tend to be higher, especially for workers with some college education. Besides differences in samples and methodologies, a possible explanation for discrepancies in the results is that controlling for endogenous mobility increases the estimates, since large downward wage adjustments are likely to induce worker departures, either to unemployment or to other firms. We examine this explanation further in section 5.3.[55]

To summarize, our results are not driven by omitted match-specific effects, but by the firm-level shocks that are observed and by the spatial correlation of wages between workers in a firm. Allowing for idiosyncratic match value does not appear particularly important: match specificity mainly originates from productivity shocks and essentially relates to non-competitive behavior in the labor market that allows both for rent sharing and a pass-through of negative fluctuations. Such non-competitive behavior seems to be much more important for workers with higher education.

5.3 Interpreting the Results

The role of the firm for earnings dispersion The identity of the firm in which one works appears to have a substantial impact on the evolution of wages over the life cycle, pointing to non-competitive behavior. Given that we are looking at innovations to wages and productivity, our conclusion is that a substantial amount of uncertainty faced by individuals has its origins in the fluctuating fortunes of their firm. This is beyond the issue of sorting that other authors have identified and that relates to the *level* of wages and firm productivity. In order to better understand the implications of these results we carry out a number of simulations of actual and counterfactual life-cycle profiles. For simplicity, we report statistics for five selected points in the life cycle: age 26, 30, 35, 45 and 55.

In Figure 4 we plot the baseline variance of log earnings over the life cycle, as well as counterfactual profiles obtained ruling out (sequentially) the key aspects of the firm's

[55] Balke and Lamadon (2022) use a structural directed search model and find a pass-through coefficient for firm shocks of 0.1. Their paper, while ignoring differences by education, provides a possible theoretical framework for the transmission of shocks.

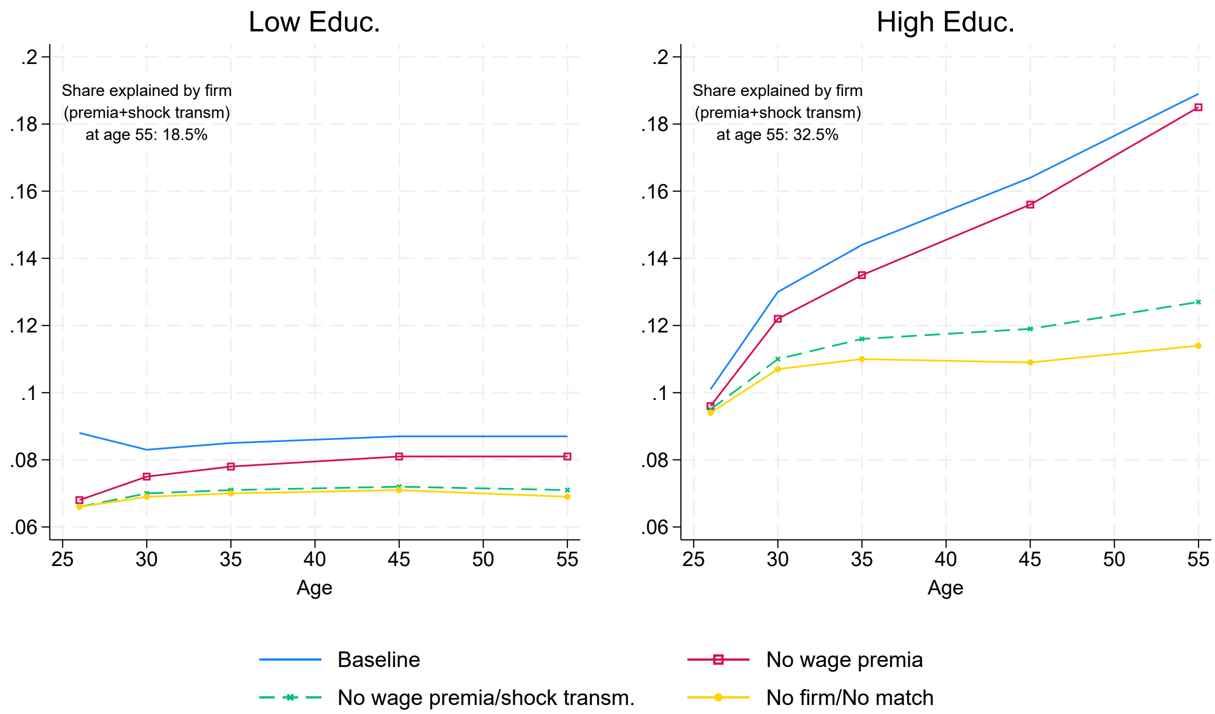
impact on careers: (a) initial wage premia, (b) transmission of firm productivity shocks, and (c) firm-worker pair specific shocks (together with "homophily" of outside wage offers). The left panel is for the low-skilled; the right panel for the high-skilled (with identical scale). Table C4 in the Appendix shows the actual numbers behind these pictures.

The "baseline" profile in Figure 4 is the life-cycle profile of variances of log wages for the full model, featuring endogenous participation and mobility choices. As we expect from the data (Figure A2), the predicted cross-sectional variance of earnings increases over time for the higher skilled while the growth for the low-skilled is minimal (despite starting values being in the same ballpark). We target these life-cycle patterns in the estimation, and the levels closely match the data as shown in Figure 3.

The first counterfactual experiment is to eliminate differences in initial pay across firm types (the lines labeled "No wage premia"). This induces an approximately 10% parallel shift in the cross-sectional variance of wages relative to the baseline. Note, however, that this channel only captures how firms' initial pay offers affect earnings dispersion. Any subsequent evolution in pay and career opportunities that depends on firm characteristics will further contribute to the overall role of the firm.

Hence, we next investigate the impact of firm shock transmission to workers' life-cycle earnings variance. In the next experiment (lines labeled "No wage premia/shock transm.") we switch off both initial differences in wage premia and the contribution of firm-level shocks (i.e., set the pass-through parameters $\kappa^P = \kappa^T = 0$). We now find larger effects as well as substantial differences across groups. While the decline in the variance of log earnings at young ages is almost entirely attributable to shutting down firm wage premia, the much reduced growth over the life cycle is primarily due to the transmission of permanent firm shocks onto wages. By age 55 the cross sectional variance for the high-skilled is only 0.127, compared to the full variance of 0.189. In other words, permanent firm-level shocks, which are transmitted to wages, increase the cross-sectional dispersion of wages for 55-year-old workers with at least some college education by about 32.5% relative to a world where there

Figure 4: **The variance of log earnings over the life cycle**



is no shock pass-through onto wages. This effect is important because, as documented in Table 10, it is the permanent shocks that are transmitted, and these accumulate over the life-cycle to a much larger extent than transitory ones (at least so long as people stay with the firm). Models that ignore the firm and this shock transmission structure will estimate a variance of permanent shocks that aggregates firm- and person-specific components and hence, to the extent that transmission of firm shocks can be avoided by moves out of work or into new firms, exaggerate the extent of economic risk faced by workers. For the lower skill workers, switching off transmission has a smaller effect, but again in the same direction: wages would be 18.5% less dispersed at age 55 in the absence of transmission of firm-level shocks. Taken together, initial wage premia and firm shock transmission account for 32.5% (18.5%) of earnings dispersion at age 55 among the high (low) skilled, with the lion's share of the decline accounted for by ruling out transmission of firm productivity shocks to wages.

Yet these channels still ignore the impact of firms on career opportunities of workers through job mobility and that of shocks to the idiosyncratic match effects. The final counterfactual experiment rules out these channels as well (on top of eliminating initial heterogeneity in wage premia and transmission of firm shocks). This is achieved by (a) assuming equal offer frequency for workers at all firm types, and (b) imposing that $\sigma_{\psi^T} = \sigma_{\psi^P} = 0$ in the wage model. Since these counterfactuals effectively eliminate any role for firms to influence the variance of wages and its growth over the life cycle, we label the line in Figure 4 that represent them the "No firm/No match" case.[56] Idiosyncratic match effects and differences in offer distributions across firms account for a stable but small share of earnings variation for the low skill group. For the high skill group these forces are quantitatively less important than the pass-through of shocks, but not entirely negligible. Indeed, combining the role of pay premia, shock transmission, match effects and offer differences, the firm accounts for 40% of total earnings dispersion for the high educated by age 55.

Participation and mobility as insurance mechanisms Building on the previous insights, we now shed further light on how participation and mobility choices allow workers to avoid being stuck at a firm going through bad times.[57] We consider three counterfactual scenarios in which we: (i) exclude the option of non-participation and instead assume full employment, (ii) rule out the arrival of new job offers while employed (OTJ offers), and (iii) combine restrictions (i) and (ii).

Intuitively, while scenario (i) eliminates the option of leaving the current job into non-participation in response to large negative shocks (or if matched with a low firm type), scenario (ii) rules out job-to-job mobility (implying that workers can join new firms only after an unemployment spell). The effect of no on-the-job offers on earnings dispersion is *a priori* ambiguous because it prevents both shock mitigation and accumulating search

[56]For completeness, in Table C4 in the Appendix we look at the impact of the four channels (wage premia, shock transmission, "homophily" of offers, and idiosyncratic match shocks) separately instead of sequentially. These exercises confirm that the quantitatively most relevant channel is the ruling out of firm shock transmission.

[57]We note that some of the separations especially into unemployment are involuntary and therefore do not necessarily represent insurance.

Table 11: **Simulations: Participation and Mobility as Insurance**

	Low Education		High Education	
Scenario	Variance at age 55	Share explained by firms	Variance at age 55	Share explained by firms
Baseline	0.087	18.5%	0.189	32.5%
Panel A: Limiting separations				
Full participation	0.091	21.7%	0.224	39.0%
No OTJ Offers	0.110	35.8%	0.206	37.4%
Full part., No OTJ Offers	0.133	45.7%	0.323	53.2%
Panel B: Limiting the nature of job offers				
No offer decline with age	0.086	17.7%	0.191	32.3%
More offers from better firms	0.085	17.1%	0.175	27.8%
No offer diff. across firms	0.085	17.6%	0.179	30.9%

Panel A shows simulation results for life-cycle earnings variance by comparing four mobility and participation scenarios: "Baseline" allows for both endogenous choices; "Full Participation" rules out non-participation; "No OTJ Offers" rules out job-to-job mobility by excluding on-the-job offers; "Full Part, No OTJ Offers" excludes mobility and non-participation. The share explained by firms is determined by simulating each scenario without heterogeneous firm premia and transmission of firm-level shocks and comparing the resulting earnings variance to the version with all firm channels reported in the table. Panel B shows analogous results for three additional scenarios that change the job offer distribution, by keeping offer rates constant over the career, increasing offers from higher-ranked firms while reducing offers from lower-ranked firms, and by removing differences in the frequency of offers across firms. Full results are in Appendix Tables C5 and C6.

capital through moving to opportunity. Finally, the combination of these constraints on participation and mobility implies that workers are fully tied to the fortunes of their first employer.

For each of these scenarios, we simulate the full model and a counterfactual without firm premia and firm-level shock transmission which eliminates systematic pay differences across firms (the equivalents of the top solid line and the dashed line of Figure 4). The resulting difference between the profiles of earnings variance over the life cycle will shed light on the role that the firm plays in overall earnings dispersion when excluding specific "insurance" mechanisms.

Panel A of Table 11 presents the results. We find that the impact of the firm on life cycle earnings dispersion increases substantially in the absence of the option to leave a sinking ship. Starting with higher skill workers, losing the options of choosing non-participation or that of moving to a different firm increases the cross-sectional earnings variation substantially, with shutting down non-participation being relatively more important. In particular, by age 55 the variance of log wages (0.189 in the baseline) is higher if separations into unemployment are ruled out (an increase to 0.224) or if job-to-job mobility is (an increase to 0.206).

The interaction between firm shock transmission and the insurance role of labor market transitions becomes clear when we consider shutting down transitions *and* transmission of firm shocks. In both cases, the role of the firm in explaining the higher variance increases, to 39% under full participation and to 37.4% without job-to-job mobility, respectively. Ruling out both "insurance" mechanisms in the third counterfactual increases the cross-sectional variance by age 55 to 0.323, largely driven by the role of firms which now account for 53% of earnings variation. This finding implies important substitution effects between the two types of decisions. However, without either of the two transition options, workers' fate in the third scenario is tied to whatever firm they join early in their career, resulting in more volatile wages over the life cycle due to firm shock transmission becoming, effectively, uninsurable through labor market transitions.

For low skilled workers the effects are qualitatively similar, but driven largely by shutting down the job mobility channel, which leads to an increase in earnings variance at age 55 from 0.087 to 0.11, of which 36% is accounted for by the firm. Again, ruling out both job mobility and non-participation leads to the most drastic results, raising the cross-sectional variance by age 55 by almost a half compared to baseline, and the role of the firm increasing to 46%.

In sum, these results emphasize the key role that participation and mobility choices play in responding to firm-level shocks. Accounting for these endogenous responses is crucial not only in estimating the transmission of firm-level shocks to wages but also in assessing the extent of risk that different workers are exposed to through the fortunes of their firm.

The role of search frictions Finally, we complement the previous results by counterfactual scenarios that change the offer distribution. This sheds light on the extent to which the role of the firm can be mitigated by reducing the magnitude and the quality of search frictions (see Di Addario et al., 2023 for similar evidence).

Specifically, Panel B of Table 11 reports results for three scenarios. First, we remove the age penalty in the offer arrival process (see Table 8) and instead hold the frequency of offers fixed across the life cycle. Second, we modify the origin of job offers by reducing the relative frequency of offers from lower firm types and instead increasing offers from higher-ranked firms. In a final experiment, we remove differences in job offer rates across firms.

The results show that, for both education groups, increasing the relative share of offers from better firms yields the most promising results. This scenario reduces the overall earnings variance at age 55 the most, and at the same time yields the lowest share of variation accounted for by the firm. Intuitively, this scenario improves the insurance role of job mobility by providing more frequent high-quality outside offers. These offers not only represent a good option to climb the job ladder; they also offer switching opportunities when facing negative shocks at the incumbent employer.

6 Extensions

In this section we consider several extensions to the baseline results. In a first extension, we allow for additional worker heterogeneity within education groups, based on differences in cognitive and non-cognitive skills assessed at the point of military enlistment. In a second extension, we consider asymmetric transmission of positive versus negative firm shocks. Third, some of the earnings responses we find may come from labor supply, rather than impacting worker productivity. We leverage survey data for a sub-sample of workers to investigate the role of hours and wages. Finally, while our model is based on quarterly realization of events (shocks, transitions, etc.), we also estimate a model that takes the traditional annual frequency. This also gives us the opportunity to compare our findings to those of Guiso, Pistaferri, and Schivardi (2005) who use annual data. We summarize all extensions below and report detailed results for estimates and model fit in Appendix D.

Table 12: **Results for Extensions: The Role of Firms**

	Low Education				High Education			
	κ^P		κ^T		κ^P		κ^T	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Panel A: Baseline								
Transmission to earnings	0.111	(0.000)	0.181	(0.001)	0.222	(0.001)	0.139	(0.004)
Share of variance attributable to the firm - age 55	18.5%				32.5%			
Panel B: Worker Heterogeneity (cognitive score, non-cognitive score)								
Worker Type 1: high, high	0.109	(0.002)	0.218	(0.002)	0.235	(0.006)	0.150	(0.003)
Worker Type 2: high, low	0.133	(0.002)	0.203	(0.003)	0.222	(0.0010)	0.139	(0.0040)
Worker Type 3: low, high	0.111	(0.0000)	0.181	(0.0010)	0.201	(0.003)	0.156	(0.006)
Worker Type 4: low, low	0.087	(0.001)	0.186	(0.002)	0.218	(0.003)	0.138	(0.002)
Share of variance attributable to the firm - age 55	19.8%				44.4%			
Panel C: Asymmetric Shock Transmission								
negative shocks	0.114	(0.001)	0.181	(0.001)	0.215	(0.001)	0.140	(0.003)
positive shocks	0.119	(0.000)	0.182	(0.001)	0.222	(0.001)	0.151	(0.002)
Share of variance attributable to the firm - age 55	20.4%				35.4%			
Panel D: Wage Sample								
Transmission to wages	0.106	(0.001)	0.146	(0.001)	0.198	(0.002)	0.107	(0.002)
Share of variance attributable to the firm - age 55	28.6%				35.9%			
Panel E: Annual Frequency								
Transmission to earnings	0.119	(0.000)	0.203	(0.002)	0.238	(0.002)	0.108	(0.004)
Share of variance attributable to the firm - age 55	28.5%				37.0%			

*"Share of variance attributable to the firm - age 55" denotes the share of cross-sectional variance in log earnings that is explained by the firm among workers aged 55. This share is determined by comparing the baseline simulated model to a counterfactual without firm premia and firm shock transmission to wages.

Worker Heterogeneity: Using IQ Data Obtaining measures of worker skills (besides education) is notoriously difficult. A feature unique to Sweden is the collection of detailed measures of cognitive and non-cognitive skills from military enlistment tests (typically conducted at age 18).

Within each education group, we allocate workers to four groups: (a) high scores on both cognitive and non-cognitive tests; (b) high cognitive and low non-cognitive scores; (c) low cognitive and high non-cognitive scores; and (d) low scores on both. This categorization reflects the separate roles that cognitive and non-cognitive skills play in workers' labor market outcomes (Edin et al., 2022). We then re-estimate the model of Section 3 separately for the eight skill groups, thus allowing for flexible differences in offer rates, wage premia, and firm-shock transmission.

We present the results in Panel B of Table 12. Allowing for more worker skill heterogeneity provides some insight into the effect of such heterogeneity on the transmission of firm shocks, without fundamentally changing the overall picture. Specifically, among highly educated workers, 20.1 to 23.5% of permanent shocks are transmitted to wages (compared to the overall baseline estimate of 22%), while for low-educated workers the transmission rates range from 8.7% to 13.3% (baseline is 11%). Among highly educated workers, shock transmission is highest for workers with high cognitive and high non-cognitive skills, followed by the group with lower cognitive skills but still high non-cognitive skills, while the latter group experiences the highest pass-through among less educated workers.[58]

Using the relative size of the different worker groups (see Table A2) to simulate market-level wage dispersion, we find an even larger role for the firm than in the baseline, explaining 19.8% and 44.4% of the cross-sectional wage variance at age 55 for low and high educated workers (as opposed to 18.5% and 32.5%, respectively).

Asymmetric Transmission of Firm Shocks Next, we extend the baseline model to allow for asymmetric transmission of firm shocks. To do so, we extend equations (6) and (8) to distinguish pass-through of negative and positive shocks, κ_{neg} and κ_{pos} for transitory and permanent firm shocks respectively:

$$\begin{aligned} v^P_{i,j,t} &= v^P_{i,j,t-1} + \kappa^P_{neg}\xi^P_{j,t} \times \mathbb{1}\{\xi^P_{j,t} < 0\} + \kappa^P_{pos}\xi^P_{j,t} \times \mathbb{1}\{\xi^P_{j,t} > 0\} + \psi^P_{i,j,t} \\ v^T_{i,j,t} &= \kappa^T_{neg}\xi^T_{j,t} \times \mathbb{1}\{\xi^T_{j,t} < 0\} + \kappa^T_{pos}\xi^T_{j,t} \times \mathbb{1}\{\xi^T_{j,t} > 0\} + \psi^T_{i,j,t} \end{aligned}$$

To identify asymmetry in transmission rates, we replace the spatial correlation defined in equation (13) as a targeted moment by two analogous moments that compute the average spatial correlation of wage growth for firms with overall positive or negative productivity

[58]The average non-cognitive score is highest for the high-high group among highly educated workers at 7.6, while the score for the low-high group is 6.7. For less educated workers this order is reversed with average non-cognitive scores of 6.3 and 6.5 for the high-high and low-high groups, respectively.

growth in a given year, respectively.

Panel C of Table 12 shows the results. While transmission of positive shocks is estimated to be slightly higher for both transitory and permanent shocks for both education groups, the differences between negative and positive shocks are quantitatively small. Consequently, the role of the firm in explaining the cross-sectional variance of earnings is similar to the main findings. This is a strong result because it points to mechanisms of rent sharing, rather than just the results of credible renegotiation as in Lise, Meghir, and Robin (2016).[59]

Wage Sample Evidence To separate productivity responses from labor supply responses, we use the Wage Structure Statistics survey provided by Statistics Sweden. As discussed in Section 2, this survey can be matched with approximately 50 percent of the annual worker-firm matches observed in the administrative data.

We take advantage of survey information on actual hours worked and residualize monthly earnings by flexibly controlling for monthly hours.[60] We then re-estimate the model targeting wage moments for the sub-sample of firms covered by the survey.[61] The results are in Panel D of Table 12. The implication of these results is that wages are the main transmission channel of permanent shocks to earnings, rather than hours. For highly educated workers, the pass-through rate to wages is 19.8% compared to 22.2% for earnings; similarly, for less educated workers the wage transmission rate is 10.6% compared to 11.1% for earnings. The role of hours appears more relevant for transitory shocks. For both education groups the pass-through of temporary firm shocks onto wages is about two-thirds smaller). This is consistent with temporary overtime measures (or reduced hours) playing some role in response to transitory shocks, whereas permanent shocks always require some wage adjustments.

Given these high transmission rates and the smaller cross-sectional variance of wages, we

[59]In principle, we may even underestimate the amount of rent sharing for workers with executive-level positions, since they are more likely to have part of their compensation in the form of stock options or firm ownership shares, which induce an even tighter link with the firm's fortunes.

[60]In practice, we use fixed effects for 10-hour bins to capture persistent variation in labor supply while relying on information from a specific month (typically in the fall) in the survey.

[61]Since the survey over-samples large firms, we use inverse probability weighting to make the wage sample comparable to our baseline sample, see Appendix D.

find that firms explain an even larger share of wage variation over the life cycle than in the baseline. Specifically, at age 55, the firm explains 28.6% and 36% of wage variation for low and high educated workers, respectively.

Annual model Next, we compare our baseline results to a model where all labor market transitions and shock realizations occur at an annual frequency. As discussed in Section 4.1, high-frequency data on worker mobility allows us to capture worker responses to firm shocks that annual data might miss. Nevertheless, we provide the annual model estimates as a benchmark that allows easier comparison to the previous literature.

In this extension, we model all stochastic processes and decision margins at annual frequency, including firm productivity, the wage process, the offer arrival process, participation and mobility choices. In the data, we take an "annual snapshot" approach and use moments derived from the labor market status and earnings of individuals in the fourth quarter of each year. Based on this "end-of-year" status, we identify movers from comparison with the fourth quarter of the previous year. We continue to use the monthly earnings measure for the Q4 employment described in section 2 for all wage-related moments.

Panel E of Table 12 shows that the results on firm shock transmission rates remain similar to the baseline. If anything, the annual model yields slightly higher transmission of permanent shocks than the quarterly baseline model for both education groups. This result is reflected in a slightly larger role of the firm over the life cycle, especially for low-skilled workers. Specifically, we find that firms account for 28.5% of the cross-sectional variance of wages at age 55 for low educated workers, and for 37% among high educated workers, respectively.

Comparison with GPS Finally, we can compare our baseline estimates with those in the literature by replicating the estimation strategy of Guiso, Pistaferri, and Schivardi (2005) (GPS) for the sample of stayers. More details for this IV approach can be found in Appendix E.1. Table 13 shows the results for the transmission coefficients. We estimate transmission

Table 13: **GPS Comparison: The Role of Firms**

	Low Education				High Education			
	κ^P		κ^T		κ^P		κ^T	
	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
Transmission to earnings	0.061	(0.002)	0.047	(0.002)	0.071	(0.002)	0.033	(0.004)
	Share of $\text{Var}(\Delta\tilde{e}_t \mid J_t = 0)$ attributable to permanent firm shocks							
GPS	12%				12%			
Our Model	15%				25%			
	Share of $\text{Var}(\tilde{e}_t)$ at age 55 attributable to the firm							
GPS–LC (Life Cycle)	14%				14%			
GPS–LC + Our $\hat{\kappa}$ est.$^{(*)}$	13%				23%			
Our Model	19%				33%			

$^{(*)}$ We use the annual firm-shock transmission coefficients $\hat{\kappa}$ from Table 12, Panel E.

rates for transitory shocks of 3.3% and 4.7% for high and low educated workers, respectively, as well as 7.1% and 6.1% for permanent firm-level shocks (these estimates are close to the ones that GPS obtain for Italy).

The transmission coefficients are only part of the story, because the two models imply other differences, including shock variances. So to help interpret these results, we provide the share of the cross-sectional variance of wage growth among stayers that is accounted for by permanent firm-shock transmission (this is the most relevant component of firm variation). Based on the GPS estimates, permanent firm shocks explain slightly below 12% of cross-sectional variation in wage growth for both education groups. Using our baseline model, we instead find an implied role of the firm of 25% for high educated workers but a much more similar 15% for low educated workers.

Hence, our results point to a larger role of firm-shock transmission, particularly for the wages of workers with high education. Yet, ultimately our main interest is in the role of the firm over the life cycle. To assess how the differences in transmission coefficients map into differences in the role of the firm for earnings dispersion, we need to analyze residual wages in levels over workers' careers. This means we first need to "complete" the GPS model because their setting is only suitable for cross-sectional analysis of wage growth. Below, we provide a short overview of this procedure and refer the reader to Appendix E.2 for full details.

The key differences between GPS and our model are that we consider endogenous participation and mobility choices, and that we model a mixture of permanent productivity distributions as well as the stochastic evolution of the idiosyncratic match component. In contrast, GPS treat the sample of stayers as random and only allow for fixed match effects (which get differenced out in their specification) and a random walk for permanent firm productivity. To achieve the closest comparison between the two models, we apply our estimates for participation and mobility preferences to GPS and assume random mobility conditional on worker characteristics. We further impose our estimates for the job offer arrival process, for both frequency and direction of offers, and for the levels of wage premia across firms.[62]

Using the autocovariance structure of cross-sectional wage growth for stayers, we re-estimate the variance of idiosyncratic transitory and permanent worker productivity, conditional on previously estimated firm-shock transmission coefficients and firm shock process. Finally, we estimate the variance of initial productivity dispersion by matching the cross-sectional variance of wages at age 26 as in our main model, conditional on all other shock processes. The estimates for this exercise are reported in Table E1.

The goal of this GPS extension is to understand any differences in the role of the firm over the life cycle. The bottom part of Table 13 shows that in the most comparable specification, GPS implies that firms account for about 14% of cross-sectional variance of earnings at age 55 for both education groups. These shares are smaller than the magnitudes implied by our model (19% for the low educated and 33% for the high educated).

We can further decompose these differences by imposing our pass-through estimates, κ^P and κ^T, onto the GPS framework. Table 13 shows that this closes half of the gap for the high educated but does not affect much the implications for the low educated.

In sum, focusing on stayers gives the impression of a much lower transmission rate of firm shocks to wages for workers with high education in particular. This in turn implies a bias towards concluding that labor markets are more competitive than they actually are. The

[62]For compatibility with the annual setting of GPS, we use our annual estimates from Tables D7 and D8.

downward bias is particularly large for the high educated since for this group the transmission of permanent firm shocks is higher and these shocks have a cumulative effect on life cycle variances.

An intuition for these results is as follows: The impact of the firm on individual wages comes from three channels: the passthrough of the permanent shock, the passthrough of the transitory shock and the *idiosyncratic match effect*. By selecting on stayers, one censors the overall impact of the firm, meaning that we select on people who overall have a smaller decline of wages (because they obtained a better idiosyncratic shock). This censoring then forces the passthrough coefficient to be lower. The difference is much larger for higher education people where the mobility elasticity with respect to shocks was shown to be much larger and where the variance of the idiosyncratic match effect is also more substantial.

This has important considerations for an evaluation of life-cycle risks faced by workers, since most firm-level shocks are not under the control of the agent. Fagereng, Guiso, and Pistaferri (2017, 2018) use this insight to study how exogenous permanent firm shocks passing through wages impact household savings and portfolio choices, respectively.

7 Conclusion

The extent to which the firm in which individuals work matters for explaining the level and fluctuations of their wages is an important question, both from the perspective of understanding the degree of labor markets competitiveness as well as to better characterize the sources and nature of uncertainty that individuals face. In this paper we use rich matched employer-employee data from Sweden to estimate the stochastic properties of the wage process for individuals and the way it may be impacted by productivity shocks to the firm, directly addressing this question. Our model accounts for endogenous participation and mobility decisions and thus deals with the potential truncation in the impact of productivity shocks on wages that is induced by people quitting into unemployment or changing employer.

The key finding is that firm-specific permanent productivity shocks transmit to individual wages for high-skill workers: the elasticity of wages with respect to permanent firm productivity shocks is 0.22. In other words firms pass roughly one-fifth of permanent changes in their fortunes to wages. Transitory (i.i.d.) shocks have an impact on the wages of high-skill workers that is about half as large. For low-skill workers the transmission of firm shocks does not have a large impact on wage profiles, both because the largest elasticity is for shocks that last little and because the elasticity to permanent shocks is half as large as for the high educated (0.11). We find that for the high-skilled the variance of wages increases by 80% between age 25 and age 55. Eliminating firm premia and transmission of firm shocks would mitigate that growth by one-third. For lower skill workers the effects are qualitatively similar, but the role of the firm is much less relevant because the dispersion in wages increases very modestly over the life cycle (only about 5% overall). Besides firm-shock transmission common to all workers in the same firm, idiosyncratic match effects also contribute to the overall wage dispersion over the life cycle, although their role is quantitatively smaller. Nonetheless, they play an important role for individual job mobility decisions, by exacerbating or mitigating common firm-level shocks. We find that shocks to the match effect tend to be more permanent for high-educated workers, and more transitory for the low educated.

Overall, our paper emphasizes that there are three sources of stochastic variation in wages that are often confounded (mostly due to imperfect data). The first is purely idiosyncratic to the worker and is transferred across jobs. It varies over time due to transitory and permanent components – for example because of short-lived spells of sickness or long-lasting skill depreciation. The second is specific to the firm-worker pair and can potentially also vary over the life of the worker-firm relationship, due again to short-term or long-term developments (such as learning or between-firm competition for talents). Finally, there is a component (reflecting rent sharing or partial insurance) that depends on how much the fortunes of a firm make their way onto the workers' wages. By its very nature, this component induces correlation across wages of similar workers within the firm. It would be unimportant in settings in which labor markets were perfectly competitive. It would also be absent in settings in which institutional features (such as union contracts) prevent wages from absorbing firm-side fluctuations (while allowing for industry-wide developments to matter, say). Our results show that the firm-level component plays a crucial role and affects the wages of workers of different skills differently. Highly skilled workers partake of the structural changes occurring in the firm's fortunes, while low-skilled workers appear more insulated from them. This finding is consistent with union protection being more important for these workers. It may also be consistent with lower transmission of shocks to workers who have lower savings or higher risk aversion.

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Not For Publication Appendix

A Data Appendix

A.1 Data Sources

For our empirical analysis, we construct a matched employer-employee data set that combines information from four different data sources, compiled by Statistics Sweden.

The Longitudinal Database on Education, Income and Employment (LOUISE) LOUISE contains annual information for the full working age population in Sweden from 1990 onward. The data set contains demographic and socioeconomic variables, and we use information on age, gender, municipality of residence, number and ages of children, marital status, education level as well as the collection of public transfers such as disability, public pension, sickness, unemployment and parental leave benefits.

The Register-Based Labour Market Statistics (RAMS) RAMS contains information about the universe of employment spells in Sweden from 1985 onward. On the worker side, RAMS includes the gross yearly earnings and the first and last remunerated month for each employment/firm spell, as well as firm and plant identifiers. On the firm side, RAMS includes information about industry and the type of legal entity for all firms with employees. Industry is based on the Swedish Standard Industrial Classification (SNI), which closely follows the Euopean Union's NACE standards. Specifically, we use two-digit industries (main industry groups or "Huvudgrupp") throughout the analysis.

The Structural Business Statistics (SBS) SBS contains accounting and balance sheet information for all non-financial corporations in Sweden from 1997 onward, and for a subset of corporations during the 1990–1996 period. Sole proprietors were excluded entirely until 1996, and for agriculture, hunting, forestry and fishing industries they were excluded before 2001.

SBS is used by Statistics Sweden as the basis for calculating the gross national product (GDP). The SBS survey includes data from tax authorities. The main source is the administrative material submitted by enterprises in an appendix to the income tax declaration.[63]

[63]For a complete descrition, see the Quality Declaration of the Structural Business Statistics, available here: `https://www.scb.se/contentassets/9dd20ce462644cc19f6f04eb2edbbe28/nv0109_kd_`

The Unemployment Register This data set contains all spells of unemployment registered with the Public Employment Service.

The Wage Structure Statistics (WSS) WSS is an annual survey from 1985 onward, which contains records of wages and hours worked for workers at a random sample of firms. The information is measured at one time during the year, typically for one month in the fall. All firms in Sweden are divided in stratas depending on firm size and business sector, and about 11 000 firms per year are selected by random sampling within each strata. Large firms with more than 500 employees are always included, but only two percent of small firms with less than 9 employees are included. The data covers more than 40 percent of all employees in the private sector each year.

Swedish Enlistment Data The Swedish enlistment data from the Swedish War Archives contain military enlistment test scores for the universe of drafted men, collected when the individuals were aged 18 or 19. The data include enlistments between 1969 and 2005 and covers, e.g., 88–96 percent of men in the birth cohorts born between 1951 and 1975. The overall measure of cognitive skills is based on four subtests of inductive skill, verbal comprehension, spatial ability, and technical understanding. The overall measure of noncognitive ability is based on four subtests of social maturity, intensity, psychological energy and emotional stability obtained from a semi-structured interview with a certified psychologist. Cognitive and non-cognitive scores are standardized within test and reported on an integer Stanine scale from one to nine. See Lindqvist and Vestman (2011) and Edin et al. (2022) for a description of the data.

A.2 Constructing the Analysis Data Set

Sample Selection The sample includes all non-financial corporations with the legal entity of limited partnership or limited company (other than banking and insurance companies), excluding sole proprietors, during 1997–2008. We exclude firms that never employ at least five employees during this period. The final sample represents 84 percent of value added and 86 percent of employment in the Swedish non-financial private sector (i.e., of all firms in the SBS) over this period.

We include all individuals who work at firms in our sample at some point during 1997–2008. We exclude individuals until the last year that they receive public study grants (typically, young workers at the beginning of their working life who are still completing their formal

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education). We also exclude individuals from the first year that they receive disability benefits, occupational pension or public pension benefits (typically, workers at the end of their working life). We further exclude individuals when they move to a workplace that is not in the firm sample (typically, these are moves to the public sector, a financial corporation, or self-employment). Importantly, however, we fully capture participation and mobility choices by keeping track of all non-employment spells and job transitions that are adjacent to employment spells at the firms in our sample, even if the destination firm is outside the sample.

We focus on men only and estimate the model separately for each of two education groups: workers with at most high school education ("low education") and workers with at least some college education ("high education"). We take as given education choices and restrict our estimation sample to individuals age 26-55 for both education groups.

Cleaning the Employment and Earnings Data The RAMS data is the basis for constructing quarterly employment and earnings records for each worker. The data contain the gross yearly earnings and the first and last remunerated month from each employment during the year. We perform a series of cleaning steps to improve the quality of the duration of employment at a particular employer. An assumption we make is that an employee has one main employment at a time.

First, we combine employment spells at the same employer and drop short jobs (one month duration or less) or minor jobs (monthly earnings less than one twelfth of a price basic amount (3,400 SEK or about 340 USD per month in 2008).[64] We combine the annual records into a panel covering the entire period and drop jobs when there are other jobs with higher monthly earnings covering the same period.

Second, we adjust the start and end month of each employment. Since the month indicators are based on remunerations, they may not align entirely with when the individual actually worked. Individuals may receive a final payment a few months after the last employed month or vacation pay by the year-end. Furthermore, it is apparent in the data that January is over-represented as the first remunerated month and December as the last remunerated month. This may be caused by firms' reporting behavior. To account for this, we again make use of the panel of employment spells. For individuals with one employment ending and another employment starting in a year, the end month of the ending employment is adjusted to the month before the start month of the new employment, given that the start month of the new employment is not January. When the start month of the new

[64] The price basic amount is used for calculations in the Swedish social insurance system. It is politically decided but follows the Consumer Price Index (CPI) very closely. In 2008 the level of the PBA was 40,800 SEK.

employment is January, we adjust the start month as the month after the end month of the ending employment.

Third, we combine the employment spell data with daily registrations of unemployment at the Public Employment Service. For unemployment spells occurring at the start or end of an employment spell, we adjust the start or end month of the employment such that it does not overlap with the registered unemployment spell. For all employment spells, we define monthly earnings at the employer as the annual earnings at this job divided by the adjusted employment duration. For unemployment spells occurring in the middle of an employment spell, we adjust the wage record of the employment spell by removing the duration of unemployment when calculating monthly earnings.

To arrive at a quarterly data set, we take the cleaned, non-overlapping employment spell data and define an individual as employed in a particular quarter if an employment spell covers at least two months of that quarter. For employed workers, earnings is defined by the monthly earnings record for that employment, calculated as described above.

The Analysis Data Set We use the quarterly employment data for individuals in our sample working at firms in our sample (see above). In each quarter, we record if an individual is a job mover, a job stayer or an entrant from non-employment. An individual can go in and out of the sample when they work, e.g., in the public sector or in a financial corporation. However, we always know whether they work or not and at which employer since the cleaned employment spell data covers the entire labor market. Thus, there is no confusion between a missing employment spell and non-employment. Non-employment is defined by the lack of an employment spell lasting at least two months during the quarter.

As an additional precaution in measuring earnings dynamics of movers, we do not use their earnings records in the transition year. Instead, we compare earnings in the years before and after job mobility because earnings records from full-year employment are of the highest quality.

A.3 Definition of Key Variables

Education We define education by the maximum education level reported during 1997–2008, as constant within individual. We define low educated workers as those with a maximum of high school education, equivalent to 12 years of schooling. We define high educated workers as those with at least some college education.

Firm productivity Our measure of firm productivity is value added per worker. We use value added as defined in the SBS and divide by the number of full-time equivalent employees reported in the SBS in the previous year, to avoid endogeneity. Value added is not reported directly in firms' accounts but is constructed by Statistics Sweden based on the combined data in the SBS, as described below. After residualizing firm productivity as described in Section 4.2, we drop outliers in firm productivity growth outside the range of $[-2, 2]$. This corresponds to about 1.5% of the records.

Value added is a measure of the total value added produced by the enterprise (i.e., its contribution to gross domestic product) and is defined in the Structural Business Statistics as the production value minus the cost of purchased goods and services used as inputs in the production. This does not include wages, social security contributions and the purchase cost of goods sold without processing because only the trade margin is included for these in the production value. Production value refers to the value of the actual production carried out by the enterprises during the year. The value is based on sales, that is, net turnover adjusted for changes in inventories and work in progress, work performed for own account and capitalised, other operating income excluding contributions, foreign exchange gains and capital gains, and the purchase cost of goods sold without processing (so that only the trade margin is included for these goods).

Earnings We define earnings as the average monthly income from employment from a particular employer during the year. We divide the annual earnings by the number of months employed by the employer. We clean the number of months employed according to the description presented in the cleaning steps in Section A.2 above. We divide by the average annual CPI as provided by Statistics Sweden[65] to calculate real earnings and trim outliers by removing the top and bottom 0.5 percent of earnings in each year.

[65] `https://www.statistikdatabasen.scb.se/pxweb/en/ssd/START__PR__PR0101__PR0101A/KPISkuggAr/`

A.4 Additional Descriptive Evidence

Table A1: **Summary statistics, firms**

	Firm size: number of employees			
	5–20	20–50	50–100	100+
A. Construction				
No. unique firms	15,527	984	195	142
Value added per worker	486,027	528,201	558,381	576,954
Growth, log V.A./worker	0.0363	0.0372	0.0390	0.0247
B. Manufacturing				
No. unique firms	14,373	2,705	1,080	1,166
Value added per worker	515,661	577,966	621,752	1,018,796
Growth, log V.A./worker	0.0290	0.0208	0.0130	0.0123
C. Retail				
No. unique firms	27,013	2,245	554	403
Value added per worker	507,697	624,140	633,776	760,339
Growth, log V.A./worker	0.0291	0.0245	0.0260	0.0206
D. Services				
No. of unique firms	45,637	3,931	1,015	832
Value added per worker	553,601	654,343	841,577	771,384
Growth, log V.A./worker	0.0368	0.0399	0.0439	0.0327

Note: Value added per worker is in real SEK for base year 2008.

Table A2: **Summary statistics, Worker Types**

High Education	1: High-High	2: High-Low	3: Low-High	4: Low-Low
No. unique workers	68,670	101,553	82,679	89,908
No. worker-quarter obs.	1,864,972	2,781,431	2,060,110	2,078,350
Avg cognitive score	7.7821	7.7486	5.2969	5.0505
SD cognitive score	0.8207	0.7717	0.8655	1.1075
Avg non-cognitive score	7.5680	5.0236	6.7052	4.1786
SD non-cognitive score	0.7075	0.9955	0.7698	1.0176
Avg log monthly earnings	10.5339	10.4069	10.3810	10.2567
SD log monthly earnings	0.4269	0.3911	0.4094	0.3819
Employment shares by firm type				
Firm Type 1	0.0279	0.0330	0.0410	0.0553
Firm Type 2	0.2074	0.2425	0.2659	0.3045
Firm Type 3	0.5954	0.6050	0.5510	0.5354
Firm Type 4	0.1694	0.1194	0.1421	0.1048

Low Education	1: High-High	2: High-Low	3: Low-High	4: Low-Low
No. unique workers	111,318	264,146	148,619	210,917
No. worker-quarter obs.	3,447,213	8,183,092	4,511,883	6,272,346
Avg cognitive score	6.8750	5.1137	4.0656	2.5488
SD cognitive score	0.8829	0.8981	1.0234	0.9151
Avg non-cognitive score	6.2797	4.1888	6.5366	3.3811
SD non-cognitive score	1.1216	0.9282	0.7296	1.1714
Avg log monthly earnings	10.1878	10.0858	10.1145	10.0118
SD log monthly earnings	0.3420	0.2965	0.3114	0.2855
Employment shares by firm type				
Firm Type 1	0.0332	0.0344	0.0328	0.0409
Firm Type 2	0.2793	0.3181	0.3051	0.3630
Firm Type 3	0.5051	0.5273	0.5255	0.5114
Firm Type 4	0.1823	0.1202	0.1366	0.0847

A.4.1 Life-cycle earnings

Figure A1 shows log earnings over age for five-year birth cohort groups.[66] The youngest cohort group is born in 1977–1981 and the oldest in 1942–1946. The main features of these graphs is the increased level and growth rate of the higher education group relative to the lower one (see for example Gosling, Machin, and Meghir, 2000, for ways to interpret such cohort graphs).

Figure A1: Log real monthly earnings for five-year cohort groups against age, 1997–2008

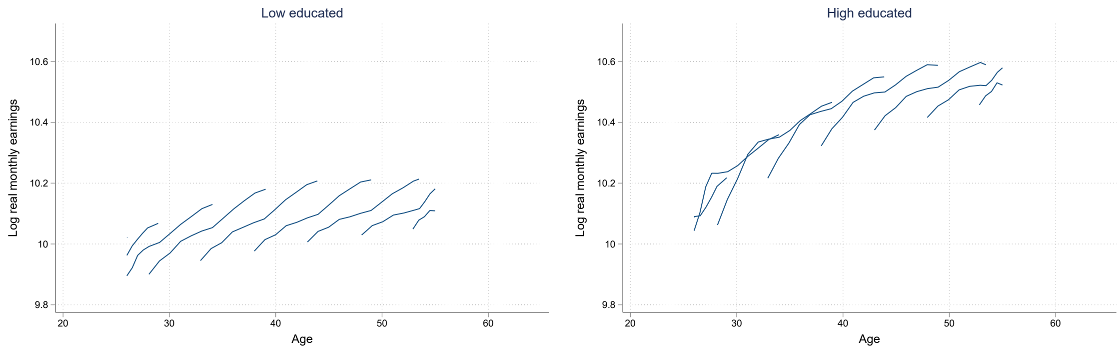


Figure A2 presents the evolution of the variance of residual log real earnings, obtained after removing year and age effects. While for the higher education group the variance increases by age, as has often been noted in US data (Meghir and Pistaferri, 2004), for lower education men the variance is either flat or increases at a very low rate. The lifecycle variance profile for those with some college is consistent with a random walk (or possibly heterogeneous age profiles). However the profile for those with high school or less is more consistent with stationary wages over the life cycle. Hence within-group inequality is increasing among the higher educated, but not among the lower educated.

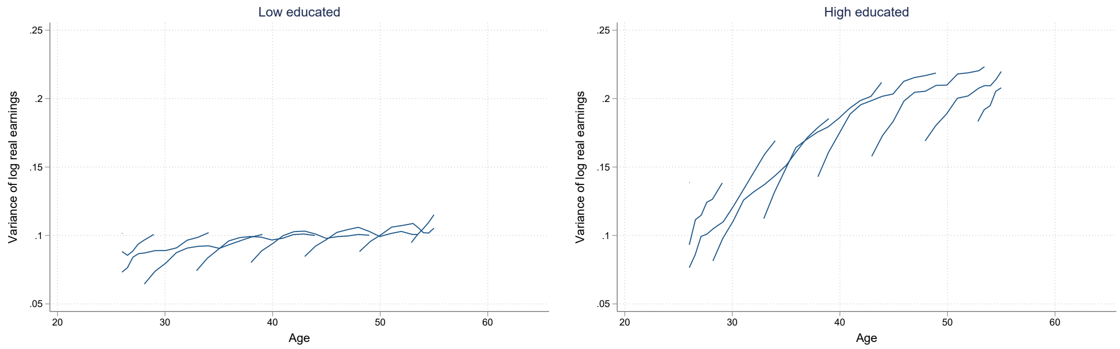
A.4.2 Participation and job transitions

The top-left graph in Figure A3 presents the employment rate in our sample by age for each education group. In our sample, employment rates are above 75% for all age groups. The lower the achieved level of education, the lower is participation at young ages. Interestingly, there is an increase in participation from the beginning of individuals' careers until their mid-50s for high-school graduates, whereas participation for workers with some college education quickly levels off at around 90%.

The bottom panels of Figure A3 shows that young workers across both education groups

[66]We use average monthly earnings, obtained dividing annual earnings by the number of months worked.

Figure A2: The variance of log real monthly earnings for five-year cohort groups against age, 1997–2008



have high quarterly job separation and re-entry rates when out-of-work. Low-educated workers face higher separation rates and lower re-entry rates at young ages. The entry rate from non-employment is rapidly falling with age and comparable across education groups around age 35, but the respective separation rates are higher for low-educated workers. As a result, the share of unemployed workers differs across groups.

As the employment, separation and re-entry rates illustrate, transitions in and out of employment are an important feature of the labor market. In addition, the top-right panel in Figure A3 presents substantial quarterly job-to-job transition rates by age for each education group, in particular at younger ages. Workers with at least some college switch employers more frequently than less educated workers.

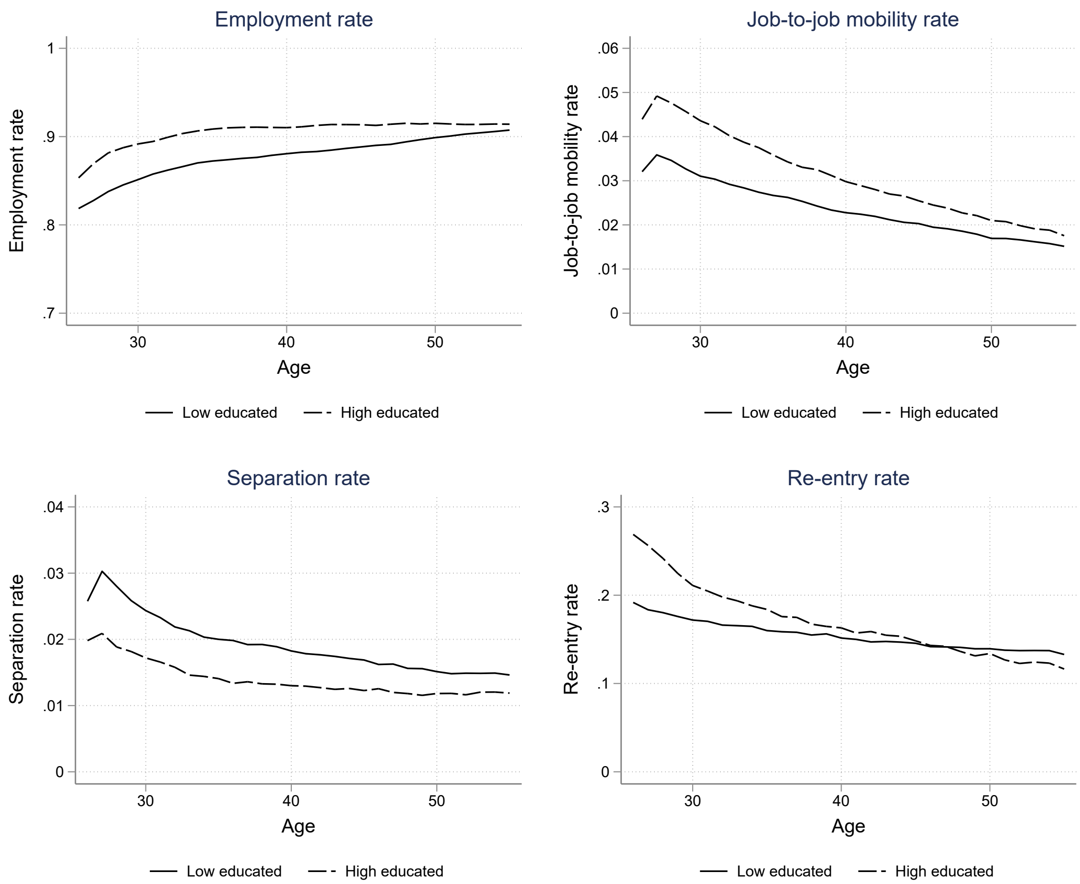
A.4.3 Wage dynamics for stayers

In the main text, we show evidence that wage cuts are not uncommon among movers. In fact, wage cuts are also visible among stayers, and one way of rationalizing this is exposure to firm-related shocks that workers find hard to avoid due to labor market frictions. Figure A4 shows a histogram of nominal wage growth by education group over a period where the worker has stayed in the firm for two full consecutive years. About a quarter of the low educated and 22% of the higher educated groups face declines in pay without changing firms. These results are consistent with Elsby and Solon (2019).

A.4.4 Job transitions across firm types and wage dynamics

Table A3 provides empirical patterns for job transitions across firm types analogous to Table 3 in the main text. The difference here is that results for average wage growth and the share of wage cuts are reported for log earnings rather than residualized earnings. The key takeaway

Figure A3: Quarterly employment and job transition rates by age and education



is that nominal wage cuts are common among movers, especially when moving to a lower ranked firm.

Finally, we also provide tables analogous to Table 3 by worker types within education groups. For each education group, we focus on the comparison between workers with high cognitive and high non-cognitive skills and workers with low skills on both dimensions. Table A4 provides results for low educated workers, while Table A5 shows the results for the high educated. For both education groups, we find that the high-high worker types have systematically higher frequency of mobility to and from the highest firm types 3 and 4. This is expected because their employment shares at these firm types is higher than for low-low types. We also document systematically larger average wage gains for upward mobility and smaller wage losses for downward mobility of high-high types compared to low-low types. Together this yields a smaller share of wage cuts for the high-high types as well.

Taken together, this evidence may suggest different job offer distributions, wage premia

Figure A4: Distribution of nominal and real wage growth by education

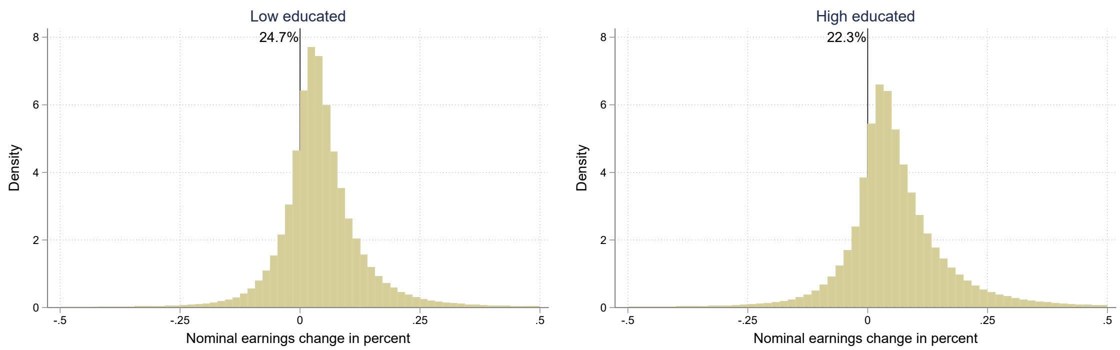


Table A3: **Data: Job Mobility and Log Wage Growth across Firm Types**

		Low-educated workers											
		Arriving firm type											
		Share of transitions				Log wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.006	.014	.010	.003	.191	.258	.432	.488	.288	.210	.108	.109
Departing	2	.020	.134	.123	.027	.060	.075	.134	.182	.343	.308	.235	.195
firm type	3	.016	.124	.311	.088	.011	.035	.060	.095	.422	.397	.323	.261
	4	.003	.023	.055	.043	−.046	−.017	.021	.066	.518	.474	.415	.329
		High-educated workers											
		Arriving firm type											
		Share of transitions				Log wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.007	.010	.010	.003	.180	.331	.421	.448	.301	.140	.100	.151
Departing	2	.012	.079	.126	.028	.099	.125	.158	.194	.299	.242	.199	.197
firm type	3	.013	.113	.390	.088	.043	.088	.113	.153	.362	.293	.240	.229
	4	.003	.018	.063	.039	−.038	.036	.075	.116	.466	.377	.329	.295

across firm types, and sensitivity to wage differences when deciding to change jobs across different worker types. We allow for these differences in the extension with worker heterogeneity within education groups in Section 6.

Table A4: **Data: Job Mobility and Residual Wage Growth across Firm Types**, Low Educated Workers by Type

		Low-low worker type											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	0.006	0.016	0.011	0.003	0.151	0.257	0.364	0.466	0.375	0.170	0.155	0.155
Departing	2	0.026	0.165	0.139	0.025	–0.023	0.026	0.080	0.138	0.584	0.456	0.365	0.298
firm type	3	0.016	0.135	0.301	0.070	–0.085	–0.055	–0.009	0.031	0.668	0.641	0.553	0.468
	4	0.003	0.018	0.040	0.025	–0.148	–0.162	–0.092	–0.036	0.737	0.763	0.673	0.597
		High-high worker type											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	0.003	0.008	0.008	0.003	0.198	0.300	0.409	0.496	0.276	0.163	0.125	0.128
Departing	2	0.014	0.093	0.106	0.033	–0.017	0.032	0.103	0.156	0.544	0.457	0.318	0.245
firm type	3	0.015	0.115	0.293	0.116	–0.053	–0.025	0.009	0.072	0.581	0.578	0.496	0.371
	4	0.004	0.032	0.078	0.078	–0.116	–0.117	–0.058	–0.008	0.624	0.693	0.609	0.504

Table A5: **Data: Job Mobility and Residual Wage Growth across Firm Types**, High Educated Workers by Type

		Low-low worker type											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	0.005	0.008	0.009	0.003	0.208	0.283	0.415	0.530	0.323	0.238	0.130	0.133
Departing	2	0.012	0.078	0.128	0.033	0.012	0.045	0.085	0.175	0.493	0.438	0.359	0.246
firm type	3	0.013	0.115	0.362	0.091	–0.062	–0.025	0.020	0.100	0.588	0.564	0.478	0.335
	3	0.003	0.021	0.071	0.049	–0.190	–0.126	–0.072	0.010	0.649	0.659	0.609	0.480
		High-high worker type											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	0.002	0.004	0.005	0.003	0.160	0.374	0.448	0.462	0.367	0.165	0.143	0.189
Departing	2	0.006	0.054	0.102	0.027	0.039	0.056	0.097	0.174	0.485	0.403	0.342	0.234
firm type	3	0.011	0.103	0.413	0.104	–0.029	–0.010	0.019	0.103	0.542	0.521	0.484	0.353
	4	0.003	0.019	0.085	0.059	–0.161	–0.125	–0.070	0.033	0.600	0.654	0.618	0.429

B Estimation Strategy

B.1 Time Aggregation

In this section we consider the bias from estimating a model that assumes that shocks to firm productivity happen at an annual frequency while in fact they occur at a quarterly frequency (as assumed in our baseline model).

In Table B.1, we report the results of Monte Carlo simulations for populations of 100,000 firms over 30 years (120 quarters). To set initial conditions, we simulate an additional burn-in period of 100 quarters. Each row in the table presents a separate simulation exercise for different combinations of "true" σ_ξ^T and σ_ξ^P.

For each combination of parameters, we simulate quarterly log value added per worker and then construct log annual VA/worker ($y_t = \log(\sum_q y_{\tau_q})$), see Appendix B.3 for details. We assume that the researcher has access only to the latter and is trying to recover estimates of quarterly σ_ξ^T and σ_ξ^P from these data.

Our estimation procedure recovers estimates of the parameters reported in the column labeled "Estimate Quarterly". They reproduce very closely the true parameters. The correct annualized standard deviations are reported in the column labeled "Annualized Quarterly". These are obtained by assuming that the firm process consists only of the transitory or permanent component, respectively. We then aggregate the simulated quarterly VA/worker to the annual level for each shock component ($y_t^K = \log(\sum_q a_{\tau_q}^K)$ for $K \in \{T, P\}$), and finally compute the standard deviations of y^K to yield the annualized dispersion.

A researcher that ignores the quarterly frequency of the data would assume that the stochastic process for firm productivity is $y_t = y_t^P + \xi_t^T$ with $y_t^P = y_{t-1}^P + \xi_t^P$, and use annual data moments to recover estimates of the variances. The estimates so obtained are reported in the column labeled "Estimate Annual". The bias of these estimates (the difference between the estimate and the correct annual variance implied by time aggregation) is reported in the last column, and shows that the bias can be substantial.

B.2 Wage Residuals

Derivation The stochastic model for quarterly wages is described by equation (3):

$$\ln w_{\tau_q} = x_\tau' \gamma + e_{\tau_q},$$

where we omit the i and j subscripts, take the x characteristics as constant within the year (for simplicity), and collect all the unobservables in the e_{τ_q} term. Wages are only observed

Table B1: Time Aggregation Bias in Firm Productivity: Monte Carlo Simulations

Transitory					Permanent				
True σ_ε	Estimate Quarterly	Annualized Quarterly	Estimate Annual	Bias	True σ_ζ	Estimate Quarterly	Annualized Quarterly	Estimate Annual	Bias
0.30	0.30	0.15	0.096	0.055	0.15	0.15	0.20	0.30	0.09
0.30	0.30	0.15	0.0003	0.15	0.30	0.30	0.41	0.55	0.13
0.15	0.15	0.075	0.0004	0.07	0.30	0.30	0.41	0.51	0.13
0.4	0.4	0.21	0.13	0.073	0.2	0.2	0.27	0.40	-0.13
0.2	0.2	0.10	0.06	0.04	0.1	0.1	0.14	0.20	-0.06
0.1	0.099	0.05	0.03	0.02	0.05	0.051	0.070	0.1	-0.031

if people work and consequently they are subject to selection, which we correct for using the Mills ratio under the assumption of normality ($\lambda^M(z'_{\tau_q}\delta)$), and we thus obtain,

$$\mathbb{E}\left(\ln w_{\tau_q}|E_{\tau_q}=1\right)=x'_\tau\gamma+\eta\lambda^M(z'_{\tau_q}\delta)$$

Assuming log-normality, this also implies that:

$$\mathbb{E}\left(w_{\tau_q}|E_{\tau_q}=1\right)=e^{x'_\tau\gamma+\eta\lambda^M(z'_{\tau_q}\delta)+\frac{\sigma^2_{u_w}}{2}} \tag{14}$$

What we observe in the data are average monthly earnings over the year, which can be written as the average across all quarters during which the person worked,

$$w_\tau=\frac{\sum_{q=1}^4 E_{\tau_q}\times E\left(w_{\tau_q}|E_{\tau_q}=1\right)}{\sum_{q=1}^4 E_{\tau_q}}.$$

Taking logs on both sides, and using (14), yields:

$$\log\mathbb{E}\left(w_\tau|\sum_{q=1}^4 E_{\tau_q}\geq 1\right)=x'_\tau\gamma+\log\left[\frac{\sum_{q=1}^4 E_{\tau_q}\times e^{\eta\lambda^M(z'_{\tau_q}\delta)}}{\sum_{q=1}^4 E_{\tau_q}}\right]+\frac{\sigma^2_{u_w}}{2}. \tag{15}$$

The additional variance term $\frac{\sigma^2_{u_w}}{2}$ shows the bias from aggregating individual wage information at annual frequency, even though wages are determined at a higher frequency. This aggregation bias term is reminiscent of the bias due to individual heterogeneity in Blundell, Reed, and Stoker (2003) when analyzing aggregate wages. Note that this term will be absorbed by the constant term in the regression. The second term is a nonlinear function of quarterly Mills ratios $\lambda^M\left(z'_{\tau_q}\delta\right)$. This term implies that seasonality of participation decisions can introduce a second bias when running a simple linear specification of log wages on individual characteristics, even when controlling for selection. If some of variables z_{t_q} affecting the decision to work change at quarterly frequency, a nonlinear specification is needed that accounts for seasonal changes in participation when aggregating employment choices to the annual level. The estimation approach based on equation (15) then controls for these two sources of aggregation bias that occur because of data availability and can be used to get consistent estimates of γ.

Finally, note that under the assumption that $z_{\tau_q} = z_\tau$ is constant across quarters within year, we can simplify the regression further, and the second term becomes the familiar expression $\eta\lambda^M(z_\tau'\delta)$. Finally, to relax the assumption of constant covariance of the errors in the wage and participation equation across age, we also include interactions of the Mills ratio with age in the wage regression, $\eta(age) = \eta_0 + \eta_1 \cdot age + \eta_2 \cdot age^2$.

Results The results for γ in equation (3) together with Probit estimates for participation are presented in Table B2 by education group. For readability, we suppress industry-time FE and county-time FE throughout.

First, consider the results for participation choices in Table B2. Column (1) and (3) report the results for workers with low and high education, respectively. The results are Probit estimates, and we focus on their sign patterns. For both groups, having children (with the exception of low-educated workers who have children up to three years of age) significantly increases the probability of participating in the labor market.

Temporary absence is facilitated by the Swedish system of parental leave benefits that offers 80% of previous wages for up to 13 months with a very generous cap. The full benefit period only applies if the father also stays with the child for some time, which is consistent with the lower participation probability for low-educated men with young children. Interestingly, married men are more likely to work in general.

The coefficients on parental leave and sickness benefits confirm the measurement problems in employment status described above. In particular, parental leave payments increase the probability of being employed. The reason is that men usually only take out parental leave benefits for a few months. Yet employers are likely to add some bonus payments during this time, which makes these fathers appear working at low wages. The coefficient for sickness benefits is negative and significant for both education groups, but a similar caveat applies: Short time sickness benefits will make individuals appear to be working nevertheless, but at a lower average wage.

Next, consider the results for wages in columns (2) and (4) of Table B2 respectively. The results confirm the familiar concave life-cycle profile of wages. The predicted wage profiles across the life-cycle are illustrated graphically in the top row of Figure B1. As we can see from the comparison with simple OLS wages profiles, the model predicts that selection has an effect on the slope of the wages profile. Positive selection into the labor market is stronger

Table B2: First-Stage Results: Participation and Log wages

	Low Education		High Education	
	Participation	Log wages	Participation	Log wages
age	0.4007	0.3217	0.6415	0.7427
	(0.019)	(0.004)	(0.033)	(0.010)
age^2	-0.3754	-0.2057	-0.7061	-0.4453
	(0.025)	(0.004)	(0.045)	(0.010)
age^3	0.1628	0.0673	0.2982	0.1419
	(0.013)	(0.002)	(0.023)	(0.005)
age^4	-0.0225	-0.0082	-0.0416	-0.0174
	(0.002)	(0.000)	(0.004)	(0.001)
child 0-3 yrs	-0.0491	-0.0358	0.0090	-0.0081
	(0.003)	(0.000)	(0.005)	(0.001)
child 4-6 yrs	0.0229	-0.0003	0.0628	0.0315
	(0.003)	(0.000)	(0.004)	(0.001)
child 7-10 yrs	0.0192	-0.0028	0.0608	0.0258
	(0.003)	(0.000)	(0.005)	(0.001)
child 11-17 yrs	0.0672	0.0154	0.1224	0.0478
	(0.003)	(0.000)	(0.005)	(0.001)
married	0.3244	0.1199	0.2085	0.1454
	(0.003)	(0.001)	(0.005)	(0.002)
parental leave	0.0185	-0.0373	0.0312	-0.0366
	(0.001)	(0.000)	(0.001)	(0.000)
sickness benefits	-0.0935	-0.0832	-0.1012	-0.1101
	(0.000)	(0.000)	(0.001)	(0.001)
Mills ratio		0.6829		1.2983
		(0.007)		(0.024)
Mills ratio * age		-0.1396		-0.3383
		(0.006)		(0.020)
Mills ratio * age^2		0.0361		0.0615
		(0.002)		(0.006)
Industry-Year FE	No	Yes	No	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Observations	30,846,261	7,016,743	11,114,670	2,616,595
R-squared		0.221		0.254

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: We use a Probit model for participation. Robust standard errors in parentheses.

at early ages, which means that without selection correction, wage growth at the beginning of the life-cycle will be underestimated by looking at cross-sectional worker data as lower ability individuals enter the labor force later. This is an important finding that needs to be taken into account for analyses of wage inequality for example. Furthermore, we find slightly increasing positive selection at the end of workers' careers again. One explanation could be early retirement based on disability, which is common in Sweden and more likely chosen by low-ability types. As a result, the wage decrease in the life-cycle of wages is underestimated.

To illustrate selection patterns across the life-cycle, we allow for a fairly flexible specification of the Mills ratio in the wage regression. The overall selection coefficients by age corresponding to the regression results in Table B2 can be found in the second row of Figure B1. For both education groups, selection is highest early in the life-cycle and decreases over time as lower-productivity types enter the labor market. Finally selection increases again as workers get closer to retirement age. These patterns directly mirror the results for wages profiles taking selection into account. Overall, the wage regression implies a positive and significant selection effect for both samples. As the average selection effects by age in the third row of Figure B1 suggest, wage differences because of selection are in the range of 0-20%, where these effects are higher for highly educated workers.

B.3 Firm Productivity Estimation

To derive the analytical expressions for annual productivity growth in the model, we proceed in two steps. First, we assume that firm productivity can be measured by value added per worker. Firm productivity (in levels) in year τ (omitting the j subscript from now on) is the sum of productivity in quarters $q = \{1, 2, 3, 4\}$ in that year:

$$Y_\tau = Y_{\tau_1} + Y_{\tau_2} + Y_{\tau_3} + Y_{\tau_4}$$

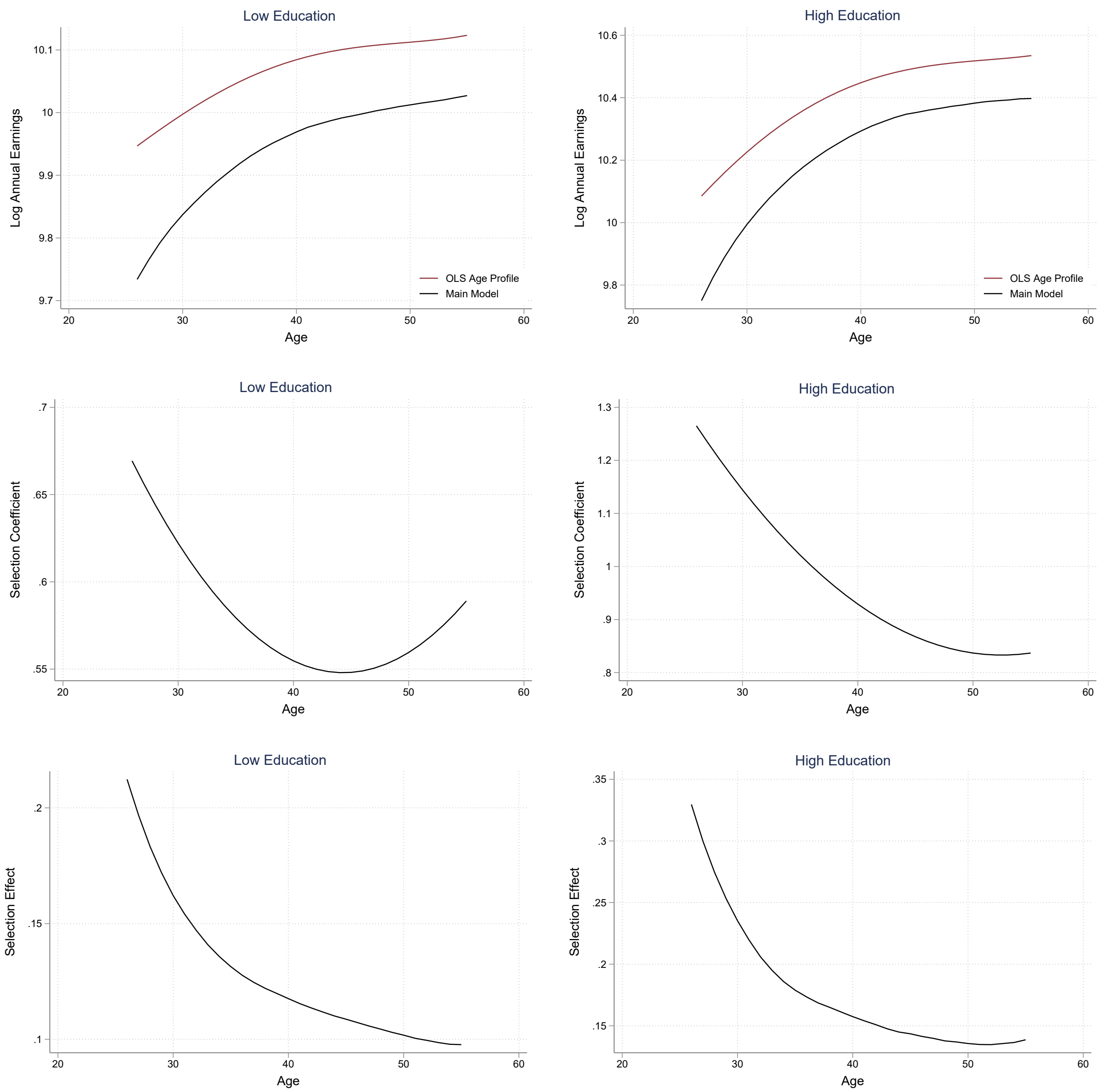
We consider a stochastic model for quarterly log productivity (equation (13)):

$$\begin{aligned} \log Y_{\tau_q} &\equiv y_{\tau_q} = x_t'\nu + f + a^P_{\tau_q} + \xi^T_{\tau_q} \\ a^P_{\tau_q} &= a^P_{\tau_q} + \xi^P_{\tau_q} \end{aligned}$$

Log annual productivity is therefore:

$$\begin{aligned} \log Y_\tau &\equiv y_\tau \\ &= \log\left(Y_{\tau_1} + Y_{\tau_2} + Y_{\tau_3} + Y_{\tau_4}\right) \\ &= \log\left(e^{y_{\tau_1}} + e^{y_{\tau_2}} + e^{y_{\tau_3}} + e^{y_{\tau_4}}\right) \end{aligned}$$

Figure B1: Wage Profiles and Selection



Using the stochastic process for log productivity, note that:

$$y_{\tau_q} = x'_\tau \nu + f + a^P_{(\tau-1)_4} + \sum_{s=1}^{q} \xi^P_{\tau_s} + \xi^T_{\tau_q}$$

for $q = \{1, 2, 3, 4\}$, and hence:

$$\begin{aligned} y_\tau &= \log\left(e^{y_{\tau_1}} + e^{y_{\tau_2}} + e^{y_{\tau_3}} + e^{y_{\tau_4}}\right) \\ &= x'_\tau \nu + f + a^P_{(\tau-1)_4} + \log\left(\sum_{q=1}^{4} \exp\left(\sum_{s=1}^{q} \xi^P_{\tau_s} + \xi^T_{\tau_q}\right)\right) \end{aligned}$$

Moreover, by the same token, in year $\tau + 1$:

$$\begin{aligned} y_{\tau+1} &= \log\left(e^{y_{(\tau+1)_1}} + e^{y_{(\tau+1)_2}} + e^{y_{(\tau+1)_3}} + e^{y_{(\tau+1)_4}}\right) \\ &= x'_{\tau+1} \nu + f + a^P_{(\tau-1)_4} + \log\left(\sum_{q=1}^{4} \exp\left(\sum_{s=1}^{4} \xi^P_{\tau_s} + \sum_{s=1}^{q} \xi^P_{(\tau+1)_s} + \xi^T_{(\tau+1)_q}\right)\right) \end{aligned}$$

and the analytical expression for annual growth in log VA per worker is:

$$\Delta y_{\tau+1} = \Delta x'_{\tau+1} \nu + \log\left(\sum_{q=1}^{4} \exp\left(\sum_{s=1}^{4} \xi^P_{\tau_s} + \sum_{s=1}^{q} \xi^P_{(\tau+1)_s} + \xi^T_{(\tau+1)_q}\right)\right) - \log\left(\sum_{q=1}^{4} \exp\left(\sum_{s=1}^{q} \xi^P_{\tau_s} + \xi^T_{\tau_q}\right)\right)$$

The important point is that the initial conditions (as well as the firm fixed effect) drop out of the expression and this remain only a function of observables and productivity shocks.

We apply simulation-based estimation to estimate the quarterly firm-shock process. Given the parametric assumptions of the quarterly shock process, we make guesses about the parameter vector $\left\{\sigma^2_{\xi^T},\ \sigma^2_{\xi^P}\right\}$ and simulate firm productivity for a set of hypothetical firms. We then aggregate these simulated shocks to replicate the structure of the actual data. To estimate the parameters of the productivity process we define a set of auxiliary moments that can be easily computed in the data as well as from the simulation. We choose the structural parameters that minimize the distance between these moments in the model and in the data. In particular, we identify the underlying parameters of the shock process from the variance and first-order autocovariance for the annual change in firm productivity.

In addition to the baseline model with a random walk for permanent productivity and an iid process for transitory shocks, we estimate alternatively an ARMA(1,1) model for quarterly firm productivity. Hence, we add an AR(1) persistence parameter ρ^P for permanent productivity and an MA(1) cofficient for transitory shocks, θ^T. To identify the four parameters of the ARMA model, we add the second- and third-order autocovariances for annual firm productivity growth to the set of targeted moments.

Table B3 compares the estimates for the two models. In the extended model, we find that the AR coefficient is very close to one, and we cannot reject a random walk. The MA coefficient is rather small at quarterly level such that the transitory shock variance only decreases slightly compared to the main estimates. Based on these results, we conduct the main analysis using the more parsimonious model estimated in Panel A.

Panel C provides alternative estimates for the quarterly baseline model using revenue per worker as the measure of firm productivity. This version indicates slightly lower transitory shock dispersion, consistent with a small amount of measurement error in value added. At the same time, the permanent shock variance is close to the baseline.

Panel D presents the estimates assuming the firm productivity process is at annual frequency. We use these estimates for the annual model we analyze in Section 6 and for the GPS life-cycle model. Consistent with the Monte Carlo simulation in section B.1, the annual model tends to yield a higher variance of permanent shocks. When using the quarterly estimates from Panel A and simulating their implied annual dispersion using the time aggregation of quarterly shocks as described above, we find an annualized standard deviation of 0.216 for the permanent shock, about two-thirds of the annual model estimate, and 0.2795 for the transitory shock, just slightly higher than the result in Panel D.

B.4 Simulation

Conditional on a guess for the parameter vector, we simulate life-cycle behavior and wages for overlapping cohorts of workers and a fixed number of firms in the model.[67] Specifically, we draw from the distribution of idiosyncratic shocks to determine the stochastic evolution of individual productivity (which is estimated simultaneously with the entire model) and from the distribution of permanent and transitory firm-level shocks, which we pre-estimate, to determine the evolution of firm types and transmission of firm shocks to current employees.

When entering the labor market after completing their education, some workers receive an offer immediately and others do not. The model includes a probability of this event as a parameter (λ_{entry}), which is estimated by matching it to the actual proportions working in the data. Throughout their career, workers draw job offers according to the offer arrival process in unemployment or on-the-job depending on their current firm type (see equation (11)). For those workers who get an offer, the offer origin (firm type) is drawn based on the offer arrival process for the current or most recent firm type, and randomly if a worker never

[67] A simulated economy consists of 4 overlapping cohorts with 6,000 individuals per cohort followed over their entire life cycle and who are matched with 80 firms. We repeat this simulation procedure for 5 independent samples of workers and firms to further increase precision.

Table B3: **Quarterly Firm Productivity Process: Estimates**

Panel A: Main Estimates			
σ_{ξ^T}		σ_{ξ^P}	
0.5329		0.158	
(0.0012)		(0.0006)	

Panel B: ARMA(1,1) Estimates			
σ_{ξ^T}	θ^T	σ_{ξ^P}	ρ^P
0.4692	0.2419	0.1583	0.9998
(0.016)	(0.067)	(0.002)	(0.00011)

Panel C: Revenue per Worker			
σ_{ξ^T}		σ_{ξ^P}	
0.4907		0.1645	
(0.0013)		(0.0005)	

Panel D: Annual Firm Process			
σ_{ξ^T}		σ_{ξ^P}	
0.2510		0.3179	
(0.0009)		(0.0012)	

had a job before.

For previously employed workers, firm shocks (and idiosyncratic match shocks) are realized and affect the current value of the firm-related component of the wage. Co-workers at the same firm experience the same firm-level shocks; this will allow us to use the observed spatial correlation of wage growth within a firm to identify the transmission coefficients. Workers compare available offers (if any) to their current job, determine their best option, and decide whether to switch jobs (if applicable) and whether to participate. We then allocate entrants or movers with equal probability to one of the firms in the firm-type group from which their offer originated. We keep track of employment status, firm type, individual productivity, and current match value, because all these factors affect future offers, participation and mobility decisions.

Once we simulate these career paths we compute moments from the simulated data to match them to those from the actual matched employer-employee dataset. In doing this we aggregate data from a quarterly to an annual frequency whenever needed to match the observed data. The wages in the data are the residuals we constructed earlier.[68]

The moments simulated from the model mimic the moments we compute from the data

[68]This aggregation step requires aggregating in levels and then taking logs to maintain the properties of the wage shock process.

and hence any sample selection is controlled for. In order to exactly replicate the data structure in the simulation, we use the empirical age distribution by education group as weights to compute the simulated moments from the model.

B.5 MCMC Estimation

We maximize the GMM objective function

$$L_n(\beta) = -\frac{n}{2}\left(g_n(\beta)\right)' W_n(\beta)\left(g_n(\beta)\right)$$

where $g_n(\beta) = \frac{1}{n}\sum_{i=1}^{n} m_i(\beta)$ and $m_i(\beta)$ is a vector of differences between simulated moments $\Gamma^S(\beta)$ and data moments Γ^D such that

$$E\left[m_i(\beta_0)\right] = E\left[\Gamma^D - \Gamma^S(\beta_0)\right] = 0.$$

The concerns raised by Altonji and Segal (1996) are particularly pertinent for our context, where we are estimating variances. As a result we use an equally weighted distance criterion, which we minimize to obtain our parameter estimates.[69] Since the simulated moments may not be smooth, we use a Laplace-type estimator (LTE) following Chernozhukov and Hong (2003) to obtain this minimum. The main computational advantage of the LTE approach is that it uses functions of the criterion function that can be computed by Markov Chain Monte Carlo methods (MCMC). In particular, we use the Metropolis-Hastings algorithm with uniform priors. We transform the objective function $L_n(\beta)$ into a quasi-posterior:

$$p_n(\beta) = \frac{e^{L_n(\beta)}}{\int_{\beta \in B} e^{L_n(\beta)} d\beta}$$

and evaluate this function at the current parameter guess $\beta^{(j)}$ and at an alternative draw χ from a multivariate normal distribution. The parameter guess is then updated according to:

$$\beta^{(j+1)} = \begin{cases} \chi & \text{with probability} \quad \pi\left(\beta^{(j)}, \chi\right) \\ \beta^{(j)} & \text{with probability} \quad 1 - \pi\left(\beta^{(j)}, \chi\right) \end{cases}$$

[69] Moments that are calculated across the entire age distribution are weighted by a factor of 6 to give them equal importance as the job transition moments we compute separately by 6 age groups. Weights for job transition moments across firm types are discounted by a factor of 0.25, while weights for moments related to wage growth of stayers and mobility in response to firm shocks are increased by a factor of 4 and 8, respectively.

where

$$\pi(x,y) = \min\left(\frac{p_n(y)}{p_n(x)}, 1\right) = \min\left(e^{L_n(y)-L_n(x)}, 1\right).$$

Our estimator follows as the quasi-posterior mean

$$\hat{\beta} = \int_{\beta \in B} \beta p_n(\beta)\, d\beta,$$

which in practice can be computed as the average over all N_S elements of the converged Markov chain

$$\hat{\beta}_{MCMC} = \frac{1}{N_S}\sum_{j=1}^{N_S} \beta^{(j)}.$$

In practice, we estimate 100 chains of 40,000 elements per education group and, since we do not use the MCMC chain to compute standard errors (see below), we determine $\hat{\beta}_{MCMC}$ as the best parameter vector among all chains.[70]

Standard Errors To estimate standard errors we use the sandwich formula. Normally, the variance of the MCMC chain would provide an estimate of the variance of the parameters if the weights used in the method of moments criterion function were the optimal ones. But we use a diagonally weighted approach. The estimated covariance matrix has the form

$$\hat{V}(\hat{\beta}) = (G'(\hat{\beta})\Omega G(\hat{\beta}))^{-1} G'(\hat{\beta})\Omega \hat{E}\left[(g(\hat{\beta}) - \hat{g})(g(\hat{\beta}) - \hat{g})'\right] \Omega G(\hat{\beta})(G'(\hat{\beta})\Omega G(\hat{\beta}))^{-1}$$

where Ω is the weight matrix used in the estimation, $G\left(\hat{\beta}\right)$ is the gradient matrix evaluated at the estimated parameter vector $\hat{\beta}$. Finally, $\hat{E}$ denotes an estimated expected value.

We obtain estimates for G through simulation. We first calculate each element j of the numerical gradient vector at the parameter estimate $\hat{\beta}$ as

$$\hat{G}_j = \frac{g\left(\hat{\beta} + h_j\right) - g\left(\hat{\beta} - h_j\right)}{0.02\hat{\beta}_j}$$

where g is the vector of moments that we evaluate at $\hat{\beta} + h_j$ and $\hat{\beta} - h_j$ respectively, in our case the vector of participation rates, mobility rates, wage growth moments, spatial correlation of wage growth etc. Lastly, h_j is a vector of zeros with one positive element at the j-th position equal to 1% of the parameter value $\hat{\theta}_j$, the j-th element of the vector of parameter estimates.

[70] The first 10,000 elements of the chain are computed based on a preset error variance. For the subsequent chain, we use adaptive MCMC to target the asymptotically optimal acceptance rate of 23.4% (Roberts, Gelman, and Gilks (1997)).

We also need to compute $\hat{E}\left[(g(\hat{\beta})-\hat{g})(g(\hat{\beta})-\hat{g})'\right]$, which turns out to be the most complex component: this is because of the combination of serial and spatial correlation combined with the large number of observations and the huge combination of workers that can find themselves in a particular firm. While it is relatively straightforward to deal with either spatial correlation or serial correlation, doing both is intractable. We thus decided to simplify. For all moments other than the spatial correlation we allow only for within individual serial correlation, which is likely to be a very important source of dependence; in our calculation of the standard errors we ignore the within firm spatial correlation of residuals; allowing for both sources would have been straightforward with the bootstrap, but the estimation procedure is far too slow for this to be feasible. For the spatial correlation coefficient we assume all variation is between firms. While the simplification may underestimate our standard errors, the size of our data set is so large that this shortcut is unlikely to make much of a difference. The standard errors we compute are very small in general. We show below the details of the derivation of our covariance matrix, which draws from Hansen (1982).

Deriving Standard Errors Define an outcome k relevant for period t and individual i as y_{kit}. This could be the log wage or the log wage squared or the log wage in t multiplied by the log wage in period $t-1$. The expected value of this moment given the model is denoted by $E(y_{kit}) = g_k(\theta)$. This is a function of the p parameters of the model θ. The empirical counterpart for g_k is

$$\hat{g}_k = \frac{1}{\Sigma_i^{N_k} T_{ki}} \Sigma_i^{N_k} \Sigma_t^{T_{ki}} y_{kit}$$

where T_{ki} the number of observations over time used for moment k for the case of individual i, N_k is the number of individuals used in computing moment k.

The model counterpart is

$$\widehat{g_k(\theta)} = \frac{1}{\Sigma_i^{N_k} T_{ki}} \Sigma_i^{N_k} \Sigma_t^{T_{ki}} g_{kit}(\theta)$$

where $g_{kit}(\theta)$ is a function defined by the model and predicting an individual level outcome such as participation or mobility. The $\hat{}$ denotes the fact that this is a simulated object. Given the data for each individual we can use many simulations to improve the approximation and mitigate simulation error. We henceforth drop the $\hat{}$ for simplicity of notation and assume that there are enough simulations to make simulation errror negligible.

We associate a weight with each moment. Denote the $k \times k$ weight matrix by Ω with diagonal element ω_k. The average of these predictions is the finite sample model counterpart of the moment we are fitting as defined above.

We only take diagonal weight matrices here. The criterion to be minimized is

$$D = \frac{1}{2} min_\theta [\Sigma_{k=1}^K \omega_k (g_k(\theta) - \hat{g}_k)^2]$$

Define the $k \times 1$ vector of moments as $g(\theta)$ and the $k \times p$ matrix of first derivatives by $G(\theta)$. The k-th row is denoted by $g'_k(\theta)$ and is a $1 \times p$ vector.

The first order conditions for minimizing D are

$$\frac{\partial D}{\partial \theta} \equiv \Sigma_{k=1}^K \omega_k (g_k(\theta) - \hat{g}_k) \frac{\partial g_k(\theta)}{\partial \theta} = 0$$

Approximating the first order conditions around the true value θ^0 we get

$$\frac{\partial D}{\partial \theta^0} + \frac{\partial^2 D}{\partial \theta^0 \partial \theta^{0'}} (\hat{\theta} - \theta^0) = 0$$

which gives

$$\hat{\theta} - \theta^0 \simeq - (\frac{\partial^2 D}{\partial \theta^0 \partial \theta^{0'}})^{-1} \times \frac{\partial D}{\partial \theta^0}$$

Hence the variance of the method of moments estimator is

$$Var(\hat{\theta}) = (\frac{\partial^2 D}{\partial \theta^0 \partial \theta^{0'}})^{-1} E(\frac{\partial D}{\partial \theta^0} \times \frac{\partial D}{\partial \theta^{0'}})(\frac{\partial^2 D}{\partial \theta^0 \partial \theta^{0'}})^{-1}$$

Taking each component in turn and evaluating it at the estimated $\hat{\theta}$ and taking plims we have that

$$plim[\frac{\partial^2 D}{\partial \theta^0 \partial \theta^{0'}}] = \Sigma_k \omega_k [plim(g_k - \hat{g}_k) \frac{\partial^2 g_k}{\partial \hat{\theta} \partial \hat{\theta}'} + plim \frac{\partial g}{\partial \hat{\theta}} \times \frac{\partial g}{\partial \hat{\theta}'}] = \Sigma_k \omega_k [plim \frac{\partial g}{\partial \hat{\theta}} \times \frac{\partial g}{\partial \hat{\theta}'}] = G' \Omega G$$

where G is the $k \times p$ matrix of first derivatives of the moments. The k-th row contains the derivatives of of the k-th moment with respect to all parameters.

We can write the first order conditions as

$$\frac{\partial D}{\partial \hat{\theta}} = G' \Omega (g(\hat{\theta}) - \hat{g})$$

with $g(\hat{\theta})$ being the vector of moments from the model evaluated at the estimated parameters $\hat{\theta}$ and $\hat{g}$ being their data counterparts. Hence the covariance matrix for the estimated parameters is given by

$$\hat{V}(\hat{\theta}) = (G'(\theta) \Omega G(\theta))^{-1} G'(\theta) \Omega E \left[(g(\hat{\theta}) - \hat{g})(g(\hat{\theta}) - \hat{g})' \right] \Omega G(\theta) (G'(\theta) \Omega G(\theta))^{-1}$$

To estimate $E\left[(g(\hat{\theta})-\hat{g})(g(\hat{\theta})-\hat{g})'\right]$ for arbitrary heteroskedasticity and serial correlation we need to express each element of $(g(\hat{\theta})-\hat{g})$ as

$$g_k(\hat{\theta})-\hat{g}_k=\frac{1}{\Sigma_{i=1}^{N}T_{ki}}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_{ki}}(g_{kit}(\hat{\theta})-y_{kit})\equiv\frac{1}{\Sigma_{i=1}^{N}T_{ki}}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_{ki}}v_{kit}$$

For variables such as frequency of unemployment at age a we have that

$$v_{kia}=y_{kia}-g_{kia}(\hat{\theta})$$

where y_{kia} is the value of the outcome (say unemployed or not) for person i in period t when their age is a and all other variables that enter the moment are evaluated at the value for person i in period when they are age a. If a is an interval say 26-30 then the person will appear five times, possibly with other conditioning variables (if present) taking on different values each time. While a will not change the other predictive variables may change. For variables such as $V(\Delta\tilde{e}_t|E_{t-1}=1,E_t=1,J_t=0)$ we will get

$$v_{kit}=(\tilde{e}_{it}-\tilde{e}_{it-1})^2-(\text{predicted amount for this object by model for person } i \text{ in period } t)$$

This will be operative for the periods where the conditions are true and this will define T_{kit}. Note that $plim_{N\to\infty}E\left[(g(\hat{\theta})-\hat{g})(g(\hat{\theta})-\hat{g})'\right]=0$ because once we impose independence across individuals the numerator will be of order N while the denominator of order N^2.

So the (k,s) element of $E\left[(g(\hat{\theta})-\hat{g})(g(\hat{\theta})-\hat{g})'\right]$ can be written as

$$E\left[(g(\hat{\theta})-\hat{g})(g(\hat{\theta})-\hat{g})'\right]_{k,s}=plim_{N\to\infty}\left[\frac{1}{\Sigma_{i=1}^{N}T_{ki}\Sigma_{i=1}^{N}T_{si}}\Sigma_{i=1}^{N}\Sigma_{t=1}^{T_{ki}}\Sigma_{q=1}^{T_{si}}v_{kit}v_{siq}\right]$$

A more complex issue is the variance related to the spatial correlation

$$\rho_{\Delta\tilde{e}}=\frac{\sum_{\text{firms } j}\sum_{\text{worker } k\in j}\sum_{l\in j,k\neq l}(\Delta\tilde{e}_{kt}-\Delta\bar{e})(\Delta\tilde{e}_{lt}-\Delta\bar{e})}{Var(\Delta\tilde{e}_{it})\sum_j n_j(n_j-1)}$$

Here, we assume that all the independent variation comes from between firms. Then denoting

$$\rho_{\Delta\tilde{e}}-g_\rho(\hat{\theta})=\Sigma_{j=1}^{M}v_j$$

where M is the number of firms. Then the variance for this residual will be

$$Var(\rho_{\Delta\tilde{e}}-g_\rho(\hat{\theta}))\doteqdot\Sigma_{j=1}^{M}v_j^2.$$

C Main Estimation Results

C.1 Goodness of Fit

This section provides goodness-of-fit statistics for the model estimates from section 5. We simulate the model and report the patterns of data vs. model.

We start with Table C1 (employment and labor market transitions by age group). Next, we look at transitions and wage growth of movers across different firm types (Tables C2 and C3). For the latter exercise, we group firms into four bins based on their average residual wages paid. We consider wage growth for movers between one year before the move and one year after the move analogous to our measure in the data. Since the model analyzes residual wages, we provide the empirical patterns for job mobility and residual wage growth for comparison below in Table C2 (which reproduces Table 3 in the main text).

Next, we report the corresponding results from the model simulation in Table C3. The results show the expected pattern of most mobility among similar firms, higher wage growth when moving to a higher ranked firm, and substantial shares of residual wage cuts after job mobility. Yet, the gradient of these patterns across firm types is steeper in the data than in the simulation. The last matrix in Tables C2 and C3 compares actual and simulated shares of wage cuts experienced by workers moving across different types of firms. This is a validation exercise since we do not target these moments explicitly.

C.2 Comparison with Bonhomme, Lamadon, and Manresa (2019) and Carlsson, Messina, and Skans (2016)

Some papers in the literature use Swedish data to estimate the importance of firms in explaining wage variation (Bonhomme, Lamadon, and Manresa (2019)) and the extent of pass-through of firm productivity shocks onto wages (Carlsson, Messina, and Skans (2016)). In this Appendix we compare our findings with theirs.

We start with Bonhomme, Lamadon, and Manresa (2019). Since the model they estimate and the one we estimate are different, we focus on the case when firms are completely shut down. This would correspond to the column labeled "No Firm" in Table C4 below, and to the contribution of the composite term $\frac{\mathrm{Var}(\psi)+2Cov(\alpha,\psi)}{\mathrm{Var}(y)}$ in their Table 5.[71] In their paper this contribution is 18%.

[71] Bonhomme, Lamadon, and Manresa (2019) present results for a "static case" (no movers) in Table 2, and a dynamic case, which includes movers, in Table 5. We compare results from the latter because we allow for mobility.

Table C1: **Model Fit for Moments on Labor Market Transitions**

	Age Group	Low Education		High Education	
		Data	Model	Data	Model
Quarterly Labor Market Transitions					
Unemployment frequency	26–30	0.164	0.162	0.121	0.123
	31–35	0.134	0.128	0.098	0.099
	36–40	0.123	0.121	0.090	0.082
	41–45	0.115	0.113	0.087	0.079
	46–50	0.106	0.105	0.086	0.081
	51–55	0.096	0.089	0.086	0.098
Job creation frequency	26–30	0.180	0.179	0.239	0.225
	31–35	0.165	0.166	0.194	0.198
	36–40	0.156	0.160	0.169	0.180
	41–45	0.147	0.151	0.155	0.157
	46–50	0.141	0.137	0.138	0.138
	51–55	0.137	0.129	0.123	0.113
Job separation frequency	26–30	0.027	0.026	0.019	0.029
	31–35	0.021	0.024	0.015	0.021
	36–40	0.019	0.021	0.013	0.016
	41–45	0.017	0.019	0.013	0.013
	46–50	0.016	0.015	0.012	0.012
	51–55	0.015	0.012	0.012	0.013
Job mobility frequency	26–30	0.033	0.038	0.046	0.051
	31–35	0.028	0.033	0.039	0.041
	36–40	0.024	0.029	0.032	0.034
	41–45	0.021	0.026	0.027	0.029
	46–50	0.018	0.022	0.023	0.026
	51–55	0.016	0.019	0.019	0.023
Residual Wage Variance over the Life Cycle					
Variance of residual wages	26	0.090	0.088	0.105	0.101
	30	0.085	0.083	0.114	0.130
	35	0.085	0.085	0.137	0.144
	40	0.088	0.085	0.157	0.155
	45	0.087	0.087	0.171	0.164
	50	0.086	0.087	0.178	0.171
	55	0.087	0.087	0.186	0.189

Note: All transitions are quarterly.

Table C2: **Data: Job Mobility and Wage Growth**

		Low-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.006	.014	.010	.003	.159	.276	.392	.466	.346	.166	.132	.125
Departing	2	.020	.134	.123	.027	–.005	.031	.087	.146	.554	.455	.351	.272
firm type	3	.016	.124	.311	.088	–.067	–.043	–.001	.053	.631	.610	.529	.406
	4	.003	.023	.055	.043	–.164	–.123	–.073	–.015	.703	.700	.636	.535
		High-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.007	.010	.010	.003	.167	.279	.371	.417	.347	.231	.163	.173
Departing	2	.012	.079	.126	.028	.001	.044	.084	.169	.519	.436	.361	.251
firm type	3	.013	.113	.390	.088	–.075	–.027	.011	.091	.599	.568	.498	.361
	4	.003	.018	.063	.039	–.221	–.136	–.082	.017	.694	.671	.634	.470

Note: Firms are sorted on the basis of average residual wages paid.

Table C3: **Model Simulation: Job Mobility and Wage Growth**

		Low-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.007	.031	.019	.002	.166	.314	.361	.457	.322	.159	.117	.062
Departing	2	.015	.143	.158	.024	–.002	.041	.080	.145	.497	.425	.336	.222
firm type	3	.008	.127	.298	.075	–.078	–.043	.008	.043	.672	.615	.490	.399
	4	.000	.010	.058	.024	–.165	–.132	–.069	–.038	.868	.764	.657	.605
		High-educated workers											
		Arriving firm type											
		Share of transitions				Residual wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
	1	.009	.026	.011	.001	.168	.280	.338	.411	.252	.138	.093	.000
Departing	2	.013	.142	.155	.018	.004	.074	.110	.176	.483	.375	.310	.225
firm type	3	.006	.124	.360	.075	–.097	–.038	.005	.052	.668	.572	.494	.411
	4	.000	.005	.041	.015	–.222	–.132	–.076	–.039	.893	.704	.627	.557

Note: Firms are sorted on the basis of average residual wages paid.

Note that in Table C4 we report results separately by age and education, while Bonhomme, Lamadon, and Manresa (2019) aggregate across these groups. From their Table 1, 77% of the sample corresponds to our low education group, and 23% to our high education group. Since we use a similar sample, we assume average age is 40, as in our Table 2. Using a simple extrapolation from our Table C4, we calculate that the share of total log variance explained by the firm at age 40 is: (0.086-0.0705)/0.086=18% for the low educated and (0.154-0.1095)/0.154=29% for the high educated. Hence, aggregating across education with the correct proportions, the variance of log wages explained by the firm in our case is $0.77 \times 0.18 + 0.23 \times 0.29 = 20.5\%$. This number is very much in the ballpark of what Bonhomme, Lamadon, and Manresa (2019) report for their dynamic model (18%).

Comparing our estimates to Carlsson, Messina, and Skans (2016) is more complicated because of the many differences between their papers and ours. First, their focus is on manufacturing, which is only about 20% of our sample; second, they do not consider mobility; third, the firm shocks do not distinguish between permanent and transitory ones; fourth, they aggregate across education groups; fifth, their measure of firm productivity is TFP rather than value added; and finally, they do not estimate the role of individual idiosyncratic shocks, as opposed to the ones originating from the firm. Here we show that if we account for some of these differences (at least at a very broad level), our implied estimates are in the same ballpark as those in Carlsson, Messina, and Skans (2016).

If one ignores the distinction between transitory and permanent shocks and between education groups (as done in their paper), the overall pass-through is given by the following expression:

$$\begin{aligned} \eta &= \frac{\sigma_T^2}{\sigma_T^2+\sigma_P^2}\left(\omega_{LE}\eta_{T,LE}+(1-\omega_{LE})\eta_{T,HE}\right)+\frac{\sigma_P^2}{\sigma_T^2+\sigma_P^2}\left(\omega_{LE}\eta_{P,LE}+(1-\omega_{LE})\eta_{P,HE}\right) \\ &= 0.92\times(0.71\times0.181+0.29\times0.139)+0.08\times(0.71\times0.111+0.29\times0.222) \\ &= 0.167 \end{aligned}$$

This is a weighted average of the transmission coefficients with respect to transitory and permanent firm shocks, which in turn are weighted averages of the pass-through coefficients for the different education groups. Here $\eta_{T,LE}, \eta_{T,HE}, \eta_{P,LE}, \eta_{P,HE}$ are the pass-through against transitory and persistent shocks for low and high educated people, respectively, and the other terms in the expression are appropriate weights (which account for the fact that the share of variability in value added due to transitory shock is larger than that due to permanent shocks, see Table 4, and the share of low-skilled is higher than the share of high educated, see Table 2). If we use these estimates plus the pass-through estimates from Table

10, we get an estimate of the implied overall pass-through of η=0.167, which is comparable to the 0.149 estimate of Carlsson, Messina, and Skans (2016) and in the upper part of the range reported by Card et al. (2018).

C.3 Counterfactual Experiments

In this section we report the results of conducting counterfactual experiments designed to demonstrate the role of firms in impacting wage risk. We measure the latter with the variance of log wages over the life cycle. Table C4 reports the variance in the full model at selected ages (26, 30, 35, 45, 55), column (1), and then that obtained ruling out, one at a time, the four channels through which firms impact careers: initial differences in wage premia (column 2), transmission of firm shocks onto wages (column 3), search capital (column 4), and idiosyncratic shocks to the worker-firm pair effects (column 5). Columns 6 shows the combined effects of the first two channels; and column 7 the combined effect of all four channels at once.

Table C4: **Simulations: The Role of Firms over the Life-Cycle**

Panel A: Low Education							
Age	Full model	No firm premium	No firm shocks	No offer diff.	No idios. match	No firm prem. or shocks	No firm
	(1)	(2)	(3)	(4)	(5)	(6)=(2)+(3)	(7)=(6)+(4)+(5)
26	0.088	0.068	0.096	0.077	0.088	0.066	0.066
30	0.083	0.075	0.099	0.080	0.083	0.070	0.069
35	0.085	0.078	0.097	0.083	0.084	0.071	0.070
45	0.087	0.081	0.093	0.086	0.086	0.072	0.071
55	0.087	0.081	0.088	0.085	0.086	0.071	0.069

Panel B: High Education							
Age	Full model	No firm premium	No firm shocks	No offer diff.	No idios. match	No firm prem. or shocks	No firm
	(1)	(2)	(3)	(4)	(5)	(6)=(2)+(3)	(7)=(6)+(4)+(5)
26	0.101	0.096	0.099	0.100	0.100	0.095	0.094
30	0.130	0.122	0.118	0.124	0.127	0.110	0.107
35	0.144	0.135	0.123	0.138	0.138	0.116	0.110
45	0.164	0.156	0.126	0.157	0.155	0.119	0.109
55	0.189	0.185	0.134	0.179	0.175	0.127	0.114

Table C5: **Simulations: Participation and Mobility as Insurance**

Panel A: Earnings variance among workers with low education

Scenario	Baseline		Full participation		No OTJ Offers		Full part., No OTJ Offers	
	base	w/o firm	base	w/o firm	base	w/o firm	base	w/o firm
Age		prem/shocks		prem/shocks		prem/shocks		prem/shocks
26	0.088	0.066	0.086	0.064	0.098	0.066	0.096	0.064
30	0.083	0.070	0.082	0.070	0.105	0.070	0.109	0.070
35	0.085	0.071	0.084	0.071	0.108	0.071	0.117	0.071
45	0.087	0.072	0.089	0.073	0.110	0.072	0.128	0.073
55	0.087	0.071	0.091	0.071	0.110	0.071	0.133	0.072

Panel B: Earnings variance among workers with high education

Scenario	Baseline		Full participation		No OTJ Offers		Full part., No OTJ Offers	
	base	w/o firm	base	w/o firm	base	w/o firm	base	w/o firm
Age		prem/shocks		prem/shocks		prem/shocks		prem/shocks
26	0.101	0.095	0.101	0.095	0.101	0.095	0.102	0.095
30	0.130	0.110	0.132	0.112	0.132	0.110	0.140	0.113
35	0.144	0.116	0.150	0.118	0.150	0.116	0.172	0.121
45	0.164	0.119	0.180	0.123	0.177	0.120	0.235	0.131
55	0.189	0.127	0.224	0.136	0.206	0.129	0.323	0.151

Panel A shows simulation results for life-cycle earnings variance among low-skill workers, Panel B for high-skill workers. Each panel compares four mobility and participation scenarios: "Baseline" allows for both endogenous choices; "Full Participation" rules out non-participation; "No OTJ Offers" rules out job-to-job mobility by excluding on-the-job offers; "Full Part, No OTJ Offers" excludes mobility and non-participation. For each scenario that limits individual choices, we consider two alternatives, with and without transmission of firm-level shocks, respectively.

Table C6: **Simulations: Search Frictions and the Role of the Firm**

Panel A: Earnings variance among workers with low education

Scenario	Baseline		Stable offers		More better offers		Common offer dist	
	base	w/o firm	base	w/o firm	base	w/o firm	base	w/o firm
Age		prem/shocks		prem/shocks		prem/shocks		prem/shocks
26	0.101	0.095	0.101	0.095	0.101	0.095	0.100	0.095
30	0.130	0.110	0.130	0.111	0.128	0.110	0.124	0.110
35	0.144	0.116	0.144	0.116	0.139	0.116	0.138	0.115
45	0.164	0.119	0.165	0.119	0.156	0.118	0.157	0.116
55	0.189	0.127	0.191	0.129	0.175	0.126	0.179	0.124

Panel B: Earnings variance among workers with high education

Scenario	Baseline		Stable offers		More better offers		Common offer dist	
	base	w/o firm	base	w/o firm	base	w/o firm	base	w/o firm
Age		prem/shocks		prem/shocks		prem/shocks		prem/shocks
26	0.088	0.066	0.088	0.066	0.087	0.066	0.077	0.066
30	0.083	0.070	0.083	0.070	0.082	0.070	0.080	0.070
35	0.085	0.071	0.086	0.071	0.084	0.071	0.083	0.071
45	0.087	0.072	0.087	0.072	0.086	0.072	0.086	0.072
55	0.087	0.071	0.086	0.071	0.085	0.071	0.085	0.070

Panel A shows simulation results for life-cycle earnings variance among low-skill workers, Panel B for high-skill workers. Each panel compares three scenarios: "Stable offers" removes the age penalty and keeps offer rates constant over the career, "more better offers" increases offers from higher-ranked firms while reducing offers from lower-ranked firms, and "common offer dist" removes differences in the frequency of offers across firms. For each scenario, we consider two alternatives, with and without transmission of firm-level shocks, respectively.

D Estimation Results for Extensions

This section provides full estimation results and model fit for all extensions from section 6 in the main text. Tables D1 and D7 report estimation results for high educated workers, while Tables D2 and D8 provide estimates for low educated workers, respectively. For space constraints, we omit the firm-shock transmission estimates that are provided in Table 12. In addition, Tables D3–D6 and D9–D12 report the full lists of targeted moments and model fit.

Worker Heterogeneity To allow for the most flexible worker heterogeneity within education groups, we estimate the baseline model separately for the four worker types defined for each education group based on their cognitive and non-cognitive scores. Tables D1 and D2 present the estimates across worker types within education groups, as defined in Section 2. Corresponding moments are reported in Tables D3 and D4 for high education and Tables D5 and D6 for low education, respectively.

The estimates in Tables D1 and D2 show that many results are similar across types, including the distribution of permanent shocks to worker productivity, participation and mobility preferences, and the offer process. However, there are also several interesting differences that hold for both high and low education groups, and complement the differences in firm shock transmission reported in Table 12: First, dispersion in firm premia is smaller for workers with low cognitive skills. Second, permanent match shocks are least important for workers with low scores on both cognitive and non-cognitive skills. In contrast, dispersion in initial productivity is highest for this low-low group and smallest for the high-high category.

Turning to model fit, the life-cycle profile of earnings variances takes a key role in identifying differences across groups. The high-high group has the steepest profile, consistent with larger firm shock transmission, whereas the profile for low-low is the flattest. The high spatial correlation of wage growth among stayers then speaks to the contribution of (permanent) firm shocks in explaining this increasing dispersion over workers' careers.

Annual frequency The first column in Table D7 (Table D8) reports the estimates for the annual model for high (low) educated workers, while the first two columns in Tables D9 and D10 (Tables D11 and D12) report the targeted moments and the model fit for this annual model specification.

The important point to understand differences in the targeted moments between the annual model and the quarterly baseline is how we construct the annual sample. Specifically, we build the annual data set based on the annual snapshot of individuals in the fourth quarter. This implies that participation, entry rates, separation rates, and job transition

Table D1: **Estimates: Heterogeneity among Highly Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
Parameter	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Wage premia and match effects								
τ_4	0.088	(0.002)	0.098	(0.004)	0.108	(0.003)	0.083	(0.002)
τ_3	0.010	(0.004)	0.015	(0.009)	0.009	(0.005)	0.025	(0.003)
τ_2	—0.052	(0.009)	-0.048	(0.010)	-0.056	(0.005)	-0.040	(0.004)
τ_1	-0.366	(-)	-0.366	(-)	-0.136	(-)	-0.176	(-)
$\sigma_{\psi^{init}}$	0.019	(0.000)	0.014	(0.000)	0.026	(0.000)	0.026	(0.000)
σ_{ψ^T}	0.022	(0.000)	0.043	(0.000)	0.042	(0.000)	0.024	(0.000)
σ_{ψ^P}	0.023	(0.000)	0.014	(0.000)	0.017	(0.000)	0.006	(0.000)
Workers' idiosyncratic productivity								
σ_f	0.256	(0.008)	0.297	(0.015)	0.298	(0.007)	0.317	(0.005)
ρ	0.960	(0.001)	0.952	(0.002)	0.950	(0.001)	0.953	(0.000)
σ_ϵ	0.075	(0.001)	0.078	(0.001)	0.059	(0.001)	0.057	(0.001)
μ_{ζ_2}	0.000	(0.000)	0.001	(0.000)	0.001	(0.000)	0.002	(0.001)
σ_{ζ_2}	0.010	(0.000)	0.006	(0.000)	0.012	(0.000)	0.013	(0.000)
μ_{ζ_2}	-0.003		-0.005		-0.005		-0.005	
σ_{ζ_2}	0.294	(0.011)	0.297	(0.022)	0.302	(0.010)	0.289	(0.005)
λ_m	0.912	(0.000)	0.912	(0.000)	0.908	(0.000)	0.905	(0.000)
Employment								
δ_0	0.383	(0.042)	0.392	(0.029)	0.479	(0.033)	0.353	(0.020)
δ_{age}	0.854	(0.012)	0.842	(0.011)	0.810	(0.012)	0.786	(0.009)
δ_{age^2}	0.854	0.002	0.842	0.002	-0.092	(0.002)	-0.082	(0.001)
ϕ	0.654	(0.070)	0.680	(0.091)	0.754	(0.043)	0.550	(0.018)
Job-to-Job Mobility								
θ_0	-0.946	(0.022)	-0.958	(0.067)	-1.026	(0.041)	-0.913	(0.032)
θ_{age}	-0.208	(0.014)	-0.278	(0.018)	-0.246	(0.006)	-0.254	(0.012)
θ_{age^2}	0.006	(0.001)	0.023	(0.001)	0.020	(0.001)	0.018	(0.000)
b	3.655	(0.264)	3.512	(0.087)	4.266	(0.145)	3.966	(0.081)
Job arrival rate								
λ_{entry}	0.843	(0.001)	0.831	(0.000)	0.892	(0.000)	0.852	(0.000)
$\lambda_{U,0}$	0.424	(0.000)	0.341	(0.000)	0.403	(0.000)	0.345	(0.000)
$\lambda_{U,1}$	0.005	(0.000)	0.004	(0.000)	0.005	(0.000)	0.004	(0.000)
Origin of offer								
ω_1	0.007	(0.000)	0.004	(0.000)	0.001	(0.000)	0.002	(0.000)
ω_2	0.235	(0.001)	0.275	(0.001)	0.233	(0.001)	0.152	(0.000)
ω_3	0.964	(0.001)	0.984	(0.001)	0.960	(0.000)	0.983	(0.001)
ω_{dist}	1.901	(0.115)	2.177	(0.083)	2.110	(0.061)	1.967	(0.059)

Table D2: **Estimates: Heterogeneity among Low Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
Parameter	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Wage premia and match effects								
τ_4	0.182	(0.007)	0.140	(0.006)	0.159	(0.007)	0.141	(0.005)
τ_3	0.060	(0.006)	0.050	(0.002)	0.051	(0.003)	0.049	(0.003)
τ_2	—0.038	(0.004)	-0.021	(0.003)	-0.016	(0.006)	0.004	(0.001)
τ_1	-1.590	(-)	-1.590	(-)	-1.325	(-)	-0.941	(-)
$\sigma_{\psi^{init}}$	0.004	(0.000)	0.009	(0.000)	0.003	(0.000)	0.001	(0.000)
σ_{ψ^T}	0.038	(0.000)	0.042	(0.000)	0.035	(0.000)	0.032	(0.000)
σ_{ψ^P}	0.005	(0.000)	0.002	(0.000)	0.002	(0.000)	0.001	(0.000)
Workers' idiosyncratic productivity								
σ_f	0.179	(0.017)	0.229	(0.006)	0.211	(0.005)	0.249	(0.009)
ρ	0.962	(0.001)	0.941	(0.001)	0.945	(0.001)	0.940	(0.000)
σ_ϵ	0.032	(0.000)	0.035	(0.000)	0.030	(0.000)	0.019	(0.000)
μ_{ζ_2}	-0.001	(0.001)	-0.001	(0.000)	-0.001	(0.001)	-0.001	(0.000)
σ_{ζ_2}	0.013	(0.000)	0.008	(0.000)	0.011	(0.000)	0.007	(0.000)
μ_{ζ_2}	0.018		0.015		0.016		0.015	
σ_{ζ_2}	0.282	(0.007)	0.297	(0.011)	0.291	(0.013)	0.287	(0.005)
λ_m	0.925	(0.000)	0.915	(0.000)	0.917	(0.000)	0.911	(0.000)
Employment								
δ_0	2.318	(0.019)	2.317	(0.013)	2.404	(0.015)	1.949	(0.010)
δ_{age}	-0.107	(0.003)	-0.182	(0.002)	-0.233	(0.004)	-0.129	(0.002)
δ_{age^2}	-0.107	0.000	-0.182	0.000	0.039	(0.001)	0.033	(0.000)
ϕ	0.311	(0.031)	0.273	(0.017)	0.284	(0.012)	0.238	(0.012)
Job-to-Job Mobility								
θ_0	-1.927	(0.020)	-1.938	(0.029)	-1.879	(0.018)	-1.907	(0.015)
θ_{age}	0.062	(0.002)	0.071	(0.003)	0.069	(0.002)	0.059	(0.001)
θ_{age^2}	-0.021	(0.001)	-0.024	(0.001)	-0.023	(0.001)	-0.020	(0.000)
b	3.901	(0.100)	4.701	(0.140)	3.979	(0.070)	4.758	(0.098)
Job arrival rate								
λ_{entry}	0.691	(0.000)	0.754	(0.000)	0.753	(0.000)	0.634	(0.000)
$\lambda_{U,0}$	0.275	(0.000)	0.265	(0.000)	0.280	(0.000)	0.245	(0.000)
$\lambda_{U,1}$	0.003	(0.000)	0.002	(0.000)	0.002	(0.000)	0.002	(0.000)
Origin of offer								
ω_1	0.975	(0.004)	1.000	(0.003)	0.938	(0.013)	0.999	(0.004)
ω_2	0.543	(0.003)	0.482	(0.006)	0.503	(0.034)	0.523	(0.003)
ω_3	0.938	(0.001)	0.860	(0.000)	0.982	(0.001)	0.810	(0.001)
ω_{dist}	3.632	(0.153)	5.197	(0.196)	34.375	(16.473)	6.372	(0.442)

Table D3: **Model Fit I: Heterogeneity among Highly Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
	Data	Model	Data	Model	Data	Model	Data	Model
Residual wage variance								
$\text{Var}(\tilde{e}\|age = 26)$	0.0840	0.0773	0.0915	0.0948	0.0963	0.0935	0.1066	0.1034
$\text{Var}(\tilde{e}\|age = 30)$	0.0996	0.1142	0.0964	0.1036	0.1044	0.1135	0.1031	0.1102
$\text{Var}(\tilde{e}\|age = 35)$	0.1240	0.1333	0.1088	0.1101	0.1292	0.1250	0.1170	0.1159
$\text{Var}(\tilde{e}\|age = 40)$	0.1493	0.1485	0.1222	0.1185	0.1484	0.1386	0.1195	0.1228
$\text{Var}(\tilde{e}\|age = 45)$	0.1587	0.1612	0.1308	0.1266	0.1592	0.1508	0.1342	0.1307
$\text{Var}(\tilde{e}\|age = 50)$	0.1776	0.1721	0.1459	0.1329	0.1658	0.1622	0.1475	0.1367
$\text{Var}(\tilde{e}\|age = 55)$	0.1914	0.1963	0.1688	0.1485	0.1843	0.1840	0.1573	0.1526
Residual wage growth moments for job stayers								
$\text{Var}(\Delta\tilde{e}_t\|J_t = 0)$	0.0379	0.0308	0.0325	0.0301	0.0359	0.0318	0.0342	0.0282
$\text{Cov}(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1}\|J_t = 0)$	-0.0061	0.0007	-0.0049	-0.0005	-0.0052	0.0009	-0.0042	0.0011
$Skew(\Delta\tilde{e}_t\|J_t = 0)$	0.0374	0.0380	0.0301	0.0303	0.0457	0.0442	-0.0633	-0.0607
$Kurt(\Delta\tilde{e}_t\|J_t = 0)$	5.5318	5.5209	5.6441	5.6392	5.5649	5.5789	5.9244	5.9049
Residual wage growth moments for job movers								
$\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1)$	0.0312	0.0391	0.0148	0.0244	0.0306	0.0391	0.0202	0.0269
$\text{Var}(\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1)$	0.0784	0.0732	0.0698	0.0682	0.0802	0.0731	0.0729	0.0673
Covariance between wage growth and employment residuals								
$\text{Cov}(\tilde{u}_t, \tilde{e}_t\|, J_t = 0)$	-0.0006	-0.0003	0.0001	-0.0004	-0.0004	-0.0002	0.0003	-0.0002
$\text{Cov}(\tilde{u}_t, \tilde{e}_t\|, J_t = 1)$	0.0045	0.0141	0.0054	0.0124	0.0051	0.0159	0.0054	0.0130
Common shocks at the firm level among stayers								
$\rho_{\Delta\tilde{e}}$	0.2060	0.2016	0.1832	0.1832	0.2148	0.2116	0.1940	0.1913
$\text{Cov}(\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}])$	-0.0029	-0.0007	-0.0019	-0.0011	-0.0026	-0.0005	-0.0020	-0.0006
Worker mobility in response to firm-level shocks								
$\Delta Pr(J2J_{\tau_q})/\Delta a_{j,\tau}$	-0.0147	-0.0144	-0.0170	-0.0137	-0.0163	-0.0156	-0.0145	-0.0124
$\Delta Pr(E2U_{\tau_q})/\Delta a_{j,\tau}$	-0.0019	-0.0014	-0.0028	-0.0014	-0.0024	-0.0020	-0.0037	-0.0013
Average Wage Growth for Movers by Firm Types								
From Type 1 to Type 1	0.1600	0.1796	0.1589	0.1589	0.2080	0.2074	0.1690	0.1778
From Type 1 to Type 2	0.3722	0.3248	0.3042	0.2738	0.2826	0.2632	0.2736	0.2570
From Type 2 to Type 1	0.0386	0.0317	-0.0450	-0.0387	0.0123	0.0260	-0.0171	-0.0103
From Type 2 to Type 2	0.0558	0.1018	0.0396	0.0802	0.0446	0.0735	0.0410	0.0731
From Type 2 to Type 3	0.0965	0.1265	0.0753	0.1067	0.0848	0.1074	0.0814	0.0991
From Type 3 to Type 2	-0.0105	-0.0319	-0.0352	-0.0457	-0.0250	-0.0386	-0.0354	-0.0380
From Type 3 to Type 3	0.0195	0.0164	0.0026	0.0010	0.0202	0.0144	0.0023	0.0011
From Type 3 to Type 4	0.1032	0.0615	0.0877	0.0576	0.1004	0.0704	0.0804	0.0469
From Type 4 to Type 3	-0.0701	-0.0699	-0.0988	-0.0873	-0.0722	-0.0536	-0.1042	-0.0809
From Type 4 to Type 4	0.0334	-0.0198	-0.0076	-0.0300	0.0097	-0.0126	-0.0107	-0.0312

Table D4: **Model Fit II: Heterogeneity among Highly Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
	Data	Model	Data	Model	Data	Model	Data	Model
Quarterly Non-Participation Rates by Age								
Age 26-30	0.0755	0.0821	0.0911	0.0933	0.0886	0.0876	0.1291	0.1236
Age 31-35	0.0532	0.0598	0.0637	0.0639	0.0693	0.0680	0.1037	0.0980
Age 36-40	0.0462	0.0485	0.0525	0.0503	0.0619	0.0580	0.0896	0.0819
Age 41-45	0.0450	0.0479	0.0489	0.0456	0.0607	0.0583	0.0843	0.0795
Age 46-50	0.0533	0.0507	0.0531	0.0453	0.0651	0.0641	0.0909	0.0814
Age 51-55	0.0653	0.0637	0.0601	0.0508	0.0727	0.0814	0.0968	0.0963
Quarterly Entry Rates from Unemployment by Age								
Age 26-30	0.2924	0.2805	0.2665	0.2461	0.2730	0.2586	0.2392	0.2252
Age 31-35	0.2406	0.2444	0.2189	0.2200	0.2230	0.2271	0.2030	0.1990
Age 36-40	0.2188	0.2287	0.2101	0.2069	0.1948	0.2089	0.1810	0.1810
Age 41-45	0.1936	0.1944	0.1907	0.1860	0.1733	0.1781	0.1652	0.1579
Age 46-50	0.1624	0.1733	0.1659	0.1697	0.1515	0.1556	0.1388	0.1395
Age 51-55	0.1266	0.1414	0.1439	0.1492	0.1368	0.1274	0.1207	0.1160
Quarterly Separation Rates into Unemployment by Age								
Age 26-30	0.0138	0.0217	0.0156	0.0213	0.0164	0.0228	0.0228	0.0290
Age 31-35	0.0105	0.0150	0.0118	0.0143	0.0131	0.0160	0.0180	0.0207
Age 36-40	0.0096	0.0115	0.0104	0.0107	0.0113	0.0128	0.0149	0.0159
Age 41-45	0.0087	0.0098	0.0090	0.0087	0.0106	0.0110	0.0134	0.0135
Age 46-50	0.0096	0.0095	0.0095	0.0081	0.0109	0.0110	0.0138	0.0126
Age 51-55	0.0101	0.0103	0.0101	0.0083	0.0113	0.0121	0.0140	0.0132
Quarterly Job-to-Job Transition Rates by Age								
Age 26-30	0.0482	0.0603	0.0449	0.0537	0.0469	0.0528	0.0439	0.0495
Age 31-35	0.0411	0.0458	0.0382	0.0432	0.0402	0.0403	0.0362	0.0392
Age 36-40	0.0344	0.0364	0.0311	0.0363	0.0329	0.0337	0.0304	0.0332
Age 41-45	0.0287	0.0300	0.0264	0.0316	0.0281	0.0292	0.0264	0.0285
Age 46-50	0.0244	0.0246	0.0237	0.0279	0.0232	0.0259	0.0227	0.0251
Age 51-55	0.0179	0.0210	0.0177	0.0264	0.0179	0.0245	0.0177	0.0230
Quarterly Job-to-Job Transition Rates by Firm Types								
Type 1 to Type 1	0.0022	0.0022	0.0025	0.0013	0.0048	0.0039	0.0072	0.0025
Type 1 to Type 2	0.0041	0.0121	0.0063	0.0088	0.0082	0.0186	0.0135	0.0124
Type 2 to Type 1	0.0062	0.0070	0.0083	0.0060	0.0125	0.0170	0.0141	0.0112
Type 2 to Type 2	0.0536	0.0942	0.0667	0.1156	0.0776	0.1363	0.0934	0.1291
Type 2 to Type 3	0.1017	0.1296	0.1221	0.1471	0.1277	0.1472	0.1460	0.1608
Type 3 to Type 2	0.1025	0.1128	0.1110	0.1236	0.1147	0.1186	0.1207	0.1344
Type 3 to Type 3	0.4131	0.4164	0.4277	0.4354	0.3621	0.3689	0.3677	0.3926
Type 3 to Type 4	0.1045	0.1037	0.0877	0.0783	0.0915	0.0840	0.0766	0.0728
Type 4 to Type 3	0.0849	0.0615	0.0658	0.0448	0.0708	0.0488	0.0504	0.0387
Type 4 to Type 4	0.0589	0.0292	0.0366	0.0170	0.0486	0.0226	0.0295	0.0116

Table D5: **Model Fit I: Heterogeneity among Low Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
	Data	Model	Data	Model	Data	Model	Data	Model
Residual wage variance								
Var($\tilde{e}\|age = 26$)	0.0889	0.0902	0.0797	0.0762	0.0801	0.0824	0.0845	0.0869
Var($\tilde{e}\|age = 30$)	0.0864	0.0904	0.0739	0.0764	0.0796	0.0794	0.0760	0.0719
Var($\tilde{e}\|age = 35$)	0.0963	0.0993	0.0736	0.0775	0.0838	0.0831	0.0725	0.0706
Var($\tilde{e}\|age = 40$)	0.0997	0.1014	0.0753	0.0776	0.0862	0.0835	0.0719	0.0703
Var($\tilde{e}\|age = 45$)	0.1009	0.1028	0.0772	0.0793	0.0834	0.0858	0.0685	0.0706
Var($\tilde{e}\|age = 50$)	0.1032	0.1052	0.0794	0.0799	0.0852	0.0873	0.0684	0.0697
Var($\tilde{e}\|age = 55$)	0.1061	0.1018	0.0831	0.0785	0.0844	0.0855	0.0650	0.0696
Residual wage growth moments for job stayers								
Var($\Delta\tilde{e}_t\|J_t = 0$)	0.0282	0.0245	0.0257	0.0268	0.0280	0.0260	0.0260	0.0241
Cov($\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1}\|J_t = 0$)	-0.0047	-0.0013	-0.0039	-0.0013	-0.0044	-0.0010	-0.0035	-0.0006
$Skew(\Delta\tilde{e}_t\|J_t = 0)$	0.1835	0.1836	0.1692	0.1708	0.1785	0.1809	0.1238	0.1262
$Kurt(\Delta\tilde{e}_t\|J_t = 0)$	6.0314	6.0210	6.0840	6.0746	6.0306	6.0223	6.2877	6.2837
Residual wage growth moments for job movers								
$\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1)$	0.0230	0.0281	0.0114	0.0225	0.0153	0.0233	0.0111	0.0202
Var($\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1$)	0.0638	0.0596	0.0579	0.0596	0.0620	0.0624	0.0591	0.0567
Covariance between wage growth and employment residuals								
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 0$)	-0.0005	-0.0002	-0.0004	-0.0001	-0.0006	-0.0001	-0.0001	-0.0002
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 1$)	0.0040	0.0077	-0.0043	0.0059	-0.0027	0.0063	-0.0075	0.0052
Common shocks at the firm level among stayers								
$\rho_{\Delta\tilde{e}}$	0.2675	0.2650	0.2079	0.2110	0.2350	0.2355	0.1941	0.1935
Cov($\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}]$)	-0.0028	-0.0029	-0.0016	-0.0025	-0.0023	-0.0025	-0.0015	-0.0022
Worker mobility in response to firm-level shocks								
$\Delta Pr(J2J_{\tau_q})/\Delta a_{j,\tau}$	-0.0118	-0.0079	-0.0117	-0.0095	-0.0126	-0.0103	-0.0121	-0.0087
$\Delta Pr(E2U_{\tau_q})/\Delta a_{j,\tau}$	-0.0030	-0.0009	-0.0036	-0.0008	-0.0035	-0.0009	-0.0057	-0.0008
Average Wage Growth for Movers by Firm Types								
From Type 1 to Type 1	0.1977	0.1991	0.1519	0.1603	0.2164	0.2273	0.1513	0.1542
From Type 1 to Type 2	0.3000	0.2903	0.2770	0.2540	0.3173	0.2965	0.2566	0.2533
From Type 2 to Type 1	-0.0172	-0.0060	-0.0032	0.0161	-0.0076	0.0195	-0.0230	0.0107
From Type 2 to Type 2	0.0322	0.0451	0.0302	0.0427	0.0250	0.0473	0.0263	0.0372
From Type 2 to Type 3	0.1027	0.0864	0.0843	0.0760	0.0924	0.0772	0.0802	0.0609
From Type 3 to Type 2	-0.0251	-0.0305	-0.0461	-0.0313	-0.0435	-0.0334	-0.0554	-0.0325
From Type 3 to Type 3	0.0091	0.0128	-0.0057	-0.0015	0.0002	-0.0065	-0.0086	-0.0068
From Type 3 to Type 4	0.0720	0.0626	0.0471	0.0379	0.0582	0.0432	0.0315	0.0309
From Type 4 to Type 3	-0.0579	-0.0600	-0.0795	-0.0776	-0.0680	-0.0684	-0.0920	-0.0738
From Type 4 to Type 4	-0.0076	-0.0396	-0.0221	-0.0391	-0.0012	-0.0382	-0.0358	-0.0404

Table D6: **Model Fit II: Heterogeneity among Low Educated Workers**

	Type High-High		Type High-Low		Type Low-High		Type Low-Low	
	Data	Model	Data	Model	Data	Model	Data	Model
Quarterly Non-Participation Rates by Age								
Age 26-30	0.1035	0.1131	0.1296	0.1232	0.1124	0.1153	0.1917	0.1948
Age 31-35	0.0779	0.0714	0.1041	0.0986	0.0871	0.0908	0.1600	0.1505
Age 36-40	0.0702	0.0687	0.0938	0.0975	0.0825	0.0888	0.1445	0.1428
Age 41-45	0.0684	0.0659	0.0902	0.0957	0.0800	0.0856	0.1335	0.1312
Age 46-50	0.0714	0.0670	0.0895	0.0947	0.0813	0.0826	0.1226	0.1215
Age 51-55	0.0712	0.0642	0.0858	0.0871	0.0759	0.0723	0.1113	0.1042
Quarterly Entry Rates from Unemployment by Age								
Age 26-30	0.2058	0.1996	0.1964	0.1936	0.2128	0.2081	0.1725	0.1795
Age 31-35	0.1909	0.1790	0.1809	0.1804	0.2024	0.1943	0.1609	0.1661
Age 36-40	0.1759	0.1739	0.1723	0.1736	0.1843	0.1874	0.1545	0.1582
Age 41-45	0.1632	0.1634	0.1625	0.1630	0.1740	0.1756	0.1482	0.1494
Age 46-50	0.1440	0.1450	0.1451	0.1482	0.1561	0.1620	0.1395	0.1350
Age 51-55	0.1348	0.1331	0.1337	0.1379	0.1472	0.1527	0.1287	0.1263
Quarterly Separation Rates into Unemployment by Age								
Age 26-30	0.0184	0.0147	0.0229	0.0200	0.0214	0.0195	0.0325	0.0316
Age 31-35	0.0143	0.0138	0.0180	0.0199	0.0167	0.0195	0.0267	0.0293
Age 36-40	0.0123	0.0126	0.0164	0.0185	0.0154	0.0179	0.0239	0.0256
Age 41-45	0.0112	0.0116	0.0150	0.0173	0.0139	0.0165	0.0213	0.0222
Age 46-50	0.0112	0.0103	0.0144	0.0153	0.0139	0.0142	0.0197	0.0180
Age 51-55	0.0113	0.0091	0.0135	0.0130	0.0128	0.0116	0.0177	0.0140
Quarterly Job-to-Job Transition Rates by Age								
Age 26-30	0.0356	0.0406	0.0317	0.0392	0.0356	0.0410	0.0318	0.0363
Age 31-35	0.0305	0.0336	0.0273	0.0329	0.0299	0.0352	0.0271	0.0310
Age 36-40	0.0260	0.0296	0.0236	0.0291	0.0256	0.0315	0.0236	0.0283
Age 41-45	0.0227	0.0259	0.0206	0.0256	0.0222	0.0278	0.0204	0.0252
Age 46-50	0.0199	0.0221	0.0188	0.0219	0.0187	0.0236	0.0186	0.0221
Age 51-55	0.0160	0.0191	0.0157	0.0190	0.0154	0.0202	0.0149	0.0193
Quarterly Job-to-Job Transition Rates by Firm Types								
Type 1 to Type 1	0.0026	0.0043	0.0036	0.0047	0.0034	0.0045	0.0062	0.0058
Type 1 to Type 2	0.0082	0.0216	0.0104	0.0252	0.0090	0.0259	0.0161	0.0305
Type 2 to Type 1	0.0143	0.0129	0.0179	0.0152	0.0156	0.0156	0.0255	0.0191
Type 2 to Type 2	0.0928	0.1135	0.1173	0.1410	0.1105	0.1423	0.1653	0.1680
Type 2 to Type 3	0.1064	0.1375	0.1261	0.1633	0.1176	0.1622	0.1389	0.1774
Type 3 to Type 2	0.1149	0.1061	0.1308	0.1285	0.1291	0.1282	0.1353	0.1425
Type 3 to Type 3	0.2930	0.3049	0.3145	0.3216	0.3102	0.3142	0.3011	0.2963
Type 3 to Type 4	0.1163	0.1134	0.0917	0.0761	0.0970	0.0739	0.0697	0.0520
Type 4 to Type 3	0.0781	0.0849	0.0587	0.0548	0.0647	0.0566	0.0402	0.0431
Type 4 to Type 4	0.0782	0.0541	0.0453	0.0251	0.0528	0.0348	0.0252	0.0175

rates are now measured at annual frequency, comparing the current year's Q4 employment status to the last quarter of the previous year. As a consequence, these rates are substantially higher than in the baseline model. In contrast, wage moments are overall very similar to the baseline.

These differences in the targeted moments first explain differences in the estimated annual participation and mobility preferences, as well as annual offer arrival rates. Second, and as expected, the worker and match productivity processes at annual frequency typically imply smaller transitory and larger permanent variances. Related, we also find a higher frequency of large shocks at annual level for the mixture of permanent worker productivity shocks.

Wage Sample Next, we present the results for wages for high (low) educated workers in column 2 of Table D7 (Table D8). Corresponding moments are reported in the third and fourth column of Tables D9 and D10 (Tables D11 and D12).

In constructing the moments for this extension, we keep the full sample to capture participation and job transitions. Yet, we replace all earnings moments using information from the wage survey. Specifically, we utilize the actual hours worked in the most recent month as reported for all workers covered by the survey and construct indicators for 10-hour bins. We then augment the first-stage wage regression model from equation (**??**) with these indicators and residualize earnings accounting for hours worked. The resulting residual wage measure is the key input in constructing all wage-related moments targeted in the subsequent estimation.

As noted in the main text, the wage survey is administered at the level of firms and oversamples large firms. In order to keep the wage sample as comparable to the baseline as possible, we use inverse probability weighting. Specifically, we use the full sample to predict the probability of being covered by the wage survey. We construct three sets of weights at the individual level for being in the survey (i) in a given year, (ii) in two subsequent years, (iii) in years t and $t-2$. The last two weights are important to make the sample used to construct moments for wage growth of stayers and movers comparable with the baseline. Each set of weights is calculated using a linear probability model for the sample of employed workers, using the three indicators (i)–(iii) as the dependent variables, respectively, and predicting these outcomes using a vector of characteristics of the current employer. Specifically, we use firm fixed effects, second-order polynomials in log revenue and value added, industry-year fixed effects, and fixed effects for employment size bins.[72] We predict the probability of being in the sample, winsorize the predictions at 0.005 and 1 to avoid outliers in the weights

[72] We define these bins using 10-employee increments up to 100 employees, then 50-employee increments up to 1000, then 500-employee steps up to 10000 and 5000-employee bins above that.

distribution, and define the weights as the inverse probabilities.

Focusing on the new wage moments in Tables D9 and D11, the residual variance of wages over the life cycle, as well as cross-sectional variance of wage growth are systematically lower than for earnings in the baseline. The model can match these moments very well, especially by reducing the variance of initial permanent productivity and of transitory idiosyncratic shocks.

Asymmetric Shock Transmission Finally, the extension allowing for different pass-through rates of positive and negative firm-level shocks to wages is largely similar to the baseline. The key difference can be seen in the last two columns of Tables D9 and D11: We now target separate spatial correlation coefficients for stayers in firms with overall positive versus negative firm shocks in a given year. These moments show substantially higher correlation among stayers for positive than for negative shocks in the data. Based on the estimates, the model explains these differences through selection rather than differences in transmission rates. Intuitively, stayers without good outside offers and/or with positive shocks to their match effect will be more likely to stay in the case of a negative firm shock. This selection explains the lower spatial correlation coefficient.

Table D7: **Estimates for Highly Educated Workers: Annual Model, Wages, Asymmetric Shocks**

	Annual Frequency		Wage Sample		Asymmetric Shocks	
Parameter	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Wage premia and match effects						
τ_4	0.129	(0.004)	0.088	(0.000)	0.098	(0.001)
τ_3	0.040	(0.002)	0.069	(0.002)	0.022	(0.001)
τ_2	–0.042	(0.003)	0.152	(0.015)	0.055	(0.003)
τ_1	–0.504	(-)	–0.153	(-)	–0.172	(-)
$\sigma_{\psi^{init}}$	0.002	(0.000)	0.011	(0.000)	0.028	(0.000)
σ_{ψ^T}	0.013	(0.000)	0.030	(0.000)	0.021	(0.000)
σ_{ψ^P}	0.004	(0.000)	0.002	(0.000)	0.016	(0.000)
Workers' idiosyncratic productivity						
σ_f	0.250	(0.002)	0.220	(0.005)	0.304	(0.003)
ρ	0.933	(0.000)	0.966	(0.001)	0.963	(0.000)
σ_ϵ	0.086	(0.000)	0.108	(0.001)	0.063	(0.000)
μ_{ζ_2}	0.005	(0.001)	–0.001	(0.000)	–0.001	(0.000)
σ_{ζ_2}	0.030	(0.000)	0.018	(0.000)	0.007	(0.000)
μ_{ζ_2}	–0.039	–	0.005	–	0.039	–
σ_{ζ_2}	0.329	(0.002)	0.193	(0.002)	0.291	(0.005)
λ_m	0.883	(0.000)	0.852	(0.000)	0.905	(0.000)
Employment						
δ_0	0.130	(0.006)	0.335	(0.021)	0.312	(0.007)
δ_{age}	0.910	(0.005)	–0.802	(0.011)	–0.813	(0.003)
δ_{age^2}	–0.910	0.001	0.083	(0.002)	0.086	(0.001)
ϕ	1.093	(0.034)	0.554	(0.020)	0.617	(0.013)
Job-to-Job Mobility						
θ_0	–0.365	(0.008)	–0.780	(0.074)	–0.956	(0.013)
θ_{age}	–0.199	(0.004)	0.284	(0.011)	0.250	(0.004)
θ_{age^2}	0.008	(0.000)	–0.016	(0.000)	–0.016	(0.000)
b	4.162	(0.049)	2.940	(0.069)	3.841	(0.051)
Job arrival rate						
λ_{entry}	0.707	(0.000)	0.708	(0.000)	0.895	(0.000)
$\lambda_{U,0}$	0.617	(0.000)	0.356	(0.000)	0.345	(0.000)
$\lambda_{U,1}$	0.005	(0.000)	0.005	(0.000)	0.004	(0.000)
Origin of offer						
ω_1	0.278	(0.001)	0.023	(0.000)	0.004	(0.000)
ω_2	0.885	(0.000)	0.552	(0.006)	0.228	(0.000)
ω_3	1.000	(0.000)	0.939	(0.001)	0.956	(0.000)
ω_{dist}	1.801	(0.038)	208.208	(171.901)	2.275	(0.024)

Table D8: **Estimates for Low Educated Workers: Annual Model, Wages, Asymmetric Shocks**

Parameter	Annual Frequency Estimate	s.e.	Wage Sample Estimate	s.e.	Asymmetric Shocks Estimate	s.e.
Wage premia and match effects						
τ_4	0.089	(0.001)	0.180	(0.002)	0.172	(0.003)
τ_3	0.035	(0.001)	0.063	(0.003)	0.065	(0.003)
τ_2	–0.017	(0.001)	0.010	(0.002)	0.025	(0.002)
τ_1	–0.868	(-)	–1.209	(-)	–1.090	(-)
$\sigma_{\psi^{init}}$	0.002	(0.000)	0.002	(0.000)	0.002	(0.000)
σ_{ψ^T}	0.059	(0.000)	0.102	(0.000)	0.038	(0.000)
σ_{ψ^P}	0.004	(0.000)	0.004	(0.000)	0.001	(0.000)
Workers' idiosyncratic productivity						
σ_f	0.228	(0.001)	0.116	(0.005)	0.247	(0.005)
ρ	0.888	(0.000)	0.960	(0.000)	0.947	(0.000)
σ_ϵ	0.047	(0.000)	0.026	(0.000)	0.031	(0.000)
μ_{ζ_2}	0.008	(0.000)	–0.002	(0.000)	–0.001	(0.000)
σ_{ζ_2}	0.010	(0.000)	0.010	(0.000)	0.011	(0.000)
μ_{ζ_2}	–0.057	–	0.021	–	0.057	–
σ_{ζ_2}	0.303	(0.001)	0.188	(0.001)	0.294	(0.003)
λ_m	0.878	(0.000)	0.910	(0.000)	0.911	(0.000)
Employment						
δ_0	2.007	(0.005)	1.863	(0.006)	2.068	(0.006)
δ_{age}	0.125	(0.001)	–0.071	(0.001)	–0.161	(0.001)
δ_{age^2}	–0.016	0.000	0.027	(0.000)	0.035	(0.000)
ϕ	1.061	(0.016)	0.537	(0.009)	0.250	(0.003)
Job-to-Job Mobility						
θ_0	–1.418	(0.005)	–2.162	(0.007)	–1.919	(0.007)
θ_{age}	–0.044	(0.001)	0.180	(0.006)	0.067	(0.001)
θ_{age^2}	0.024	(0.000)	–0.032	(0.000)	–0.016	(0.000)
b	10.052	(0.031)	3.040	(0.199)	4.082	(0.057)
Job arrival rate						
λ_{entry}	0.617	(0.000)	0.760	(0.000)	0.741	(0.000)
$\lambda_{U,0}$	0.426	(0.000)	0.251	(0.000)	0.254	(0.000)
$\lambda_{U,1}$	0.002	(0.000)	0.002	(0.000)	0.002	(0.000)
Origin of offer						
ω_1	0.717	(0.003)	0.582	(0.011)	0.866	(0.008)
ω_2	0.984	(0.000)	0.663	(0.001)	0.508	(0.004)
ω_3	0.997	(0.000)	0.992	(0.000)	0.914	(0.000)
ω_{dist}	7.825	(0.488)	209.341	(81.788)	4.179	(0.046)

Table D9: **Other Extensions: Model Fit I for Highly Educated Workers**

	Annual Model		Wage Sample		Asymmetric Shocks	
	Data	Model	Data	Model	Data	Model
Residual wage variance						
Var($\tilde{e}\|age = 26$)	0.0927	0.0860	0.0745	0.0661	0.1053	0.0997
Var($\tilde{e}\|age = 30$)	0.1035	0.1134	0.0864	0.0967	0.1140	0.1275
Var($\tilde{e}\|age = 35$)	0.1266	0.1341	0.0973	0.1093	0.1369	0.1418
Var($\tilde{e}\|age = 40$)	0.1481	0.1470	0.1171	0.1174	0.1574	0.1518
Var($\tilde{e}\|age = 45$)	0.1621	0.1590	0.1455	0.1231	0.1706	0.1613
Var($\tilde{e}\|age = 50$)	0.1696	0.1649	0.1327	0.1278	0.1775	0.1692
Var($\tilde{e}\|age = 55$)	0.1785	0.1758	0.1459	0.1365	0.1861	0.1900
Residual wage growth moments for job stayers						
Var($\Delta\tilde{e}_t\|J_t = 0$)	0.0364	0.0364	0.0247	0.0255	0.0364	0.0298
Cov($\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1}\|J_t = 0$)	-0.0063	-0.0090	-0.0040	-0.0011	-0.0050	0.0013
$Skew(\Delta\tilde{e}_t\|J_t = 0)$	0.2637	0.2668	0.0573	0.0572	0.0287	0.0319
$Kurt(\Delta\tilde{e}_t\|J_t = 0)$	5.8546	5.8240	4.0902	4.0783	5.8351	5.8196
Residual wage growth moments for job movers						
$\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1)$	0.0230	0.0416	0.0105	0.0164	0.0262	0.0330
Var($\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1$)	0.0666	0.0661	0.0493	0.0566	0.0770	0.0712
Covariance between wage growth and employment residuals						
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 0$)	0.0009	-0.0007	0.0003	-0.0003	0.0002	-0.0003
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 1$)	0.0009	-0.0003	0.0043	0.0118	0.0130	0.0172
Common shocks at the firm level among stayers						
$\rho_{\Delta\tilde{e}}$	0.1832	0.1828	0.1488	0.1500		
Cov($\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}]$)	-0.0019	-0.0007	-0.0005	-0.0002		
$\rho^+_{\Delta\tilde{e}}$					0.2077	0.2013
Cov($\mathbb{E}_j[\Delta\tilde{e}_t]^+, \mathbb{E}_j[\Delta\tilde{e}_{t-1}]^+$)					-0.0016	-0.0008
$\rho^-_{\Delta\tilde{e}}$					0.1696	0.1744
Cov($\mathbb{E}_j[\Delta\tilde{e}_t]^-, \mathbb{E}_j[\Delta\tilde{e}_{t-1}]^-$)					-0.0017	-0.0007
Worker mobility in response to firm-level shocks						
$\Delta Pr(J2J_{\tau_q})/\Delta a_{j,\tau}$	-0.0293	-0.0233	-0.0160	-0.0102	-0.0160	-0.0129
$\Delta Pr(E2U_{\tau_q})/\Delta a_{j,\tau}$	-0.0099	-0.0041	-0.0033	-0.0011	-0.0033	-0.0014
Average Wage Growth for Movers by Firm Types						
From Type 1 to Type 1	0.1545	0.1572	0.1892	0.1489	0.1672	0.1676
From Type 1 to Type 2	0.2971	0.2490	-0.0036	0.1099	0.2794	0.2332
From Type 2 to Type 1	-0.0144	0.0201	-0.0994	-0.0293	0.0014	0.0181
From Type 2 to Type 2	0.0443	0.0555	0.0114	0.0219	0.0441	0.0712
From Type 2 to Type 3	0.0825	0.1006	0.0547	0.1176	0.0841	0.1026
From Type 3 to Type 2	-0.0332	-0.0319	0.0075	-0.0180	-0.0269	-0.0284
From Type 3 to Type 3	0.0075	-0.0001	0.0115	0.0033	0.0112	0.0088
From Type 3 to Type 4	0.0864	0.0321	0.0382	0.0213	0.0909	0.0569
From Type 4 to Type 3	-0.0886	-0.0774	-0.1135	-0.0963	-0.0822	-0.0636
From Type 4 to Type 4	0.0054	-0.0600	-0.1557	-0.0896	0.0168	-0.0241

Table D10: **Other Extensions: Model Fit II for Highly Educated Workers**

	Annual Model		Wage Sample		Asymmetric Shocks	
	Data	Model	Data	Model	Data	Model
Quarterly Non-Participation Rates by Age						
Age 26-30	0.1053	0.1762	0.1213	0.1339	0.1213	0.1171
Age 31-35	0.0898	0.0829	0.0976	0.0918	0.0976	0.0955
Age 36-40	0.0848	0.0681	0.0897	0.0755	0.0897	0.0796
Age 41-45	0.0837	0.0683	0.0871	0.0724	0.0871	0.0754
Age 46-50	0.0837	0.0768	0.0858	0.0739	0.0858	0.0770
Age 51-55	0.0859	0.0960	0.0860	0.0873	0.0860	0.0924
Quarterly Entry Rates from Unemployment by Age						
Age 26-30	0.5068	0.5427	0.2387	0.2288	0.2387	0.2239
Age 31-35	0.4417	0.3994	0.1941	0.1994	0.1941	0.1983
Age 36-40	0.3970	0.3881	0.1694	0.1814	0.1694	0.1804
Age 41-45	0.3701	0.3684	0.1547	0.1574	0.1547	0.1576
Age 46-50	0.3389	0.3320	0.1376	0.1364	0.1376	0.1387
Age 51-55	0.3088	0.3109	0.1229	0.1127	0.1229	0.1134
Quarterly Separation Rates into Unemployment by Age						
Age 26-30	0.0375	0.0444	0.0188	0.0272	0.0188	0.0285
Age 31-35	0.0319	0.0323	0.0151	0.0192	0.0151	0.0200
Age 36-40	0.0294	0.0279	0.0133	0.0146	0.0133	0.0154
Age 41-45	0.0290	0.0271	0.0126	0.0121	0.0126	0.0127
Age 46-50	0.0290	0.0294	0.0120	0.0111	0.0120	0.0118
Age 51-55	0.0304	0.0356	0.0119	0.0115	0.0119	0.0124
Quarterly Job-to-Job Transition Rates by Age						
Age 26-30	0.1806	0.1847	0.0460	0.0610	0.0460	0.0498
Age 31-35	0.1536	0.1569	0.0389	0.0487	0.0389	0.0378
Age 36-40	0.1270	0.1289	0.0322	0.0404	0.0322	0.0311
Age 41-45	0.1079	0.1104	0.0273	0.0336	0.0273	0.0264
Age 46-50	0.0917	0.0949	0.0229	0.0284	0.0229	0.0226
Age 51-55	0.0770	0.0805	0.0193	0.0244	0.0193	0.0203
Quarterly Job-to-Job Transition Rates by Firm Types						
Type 1 to Type 1	0.0080	0.0186	0.0069	0.0109	0.0073	0.0046
Type 1 to Type 2	0.0115	0.0413	0.0023	0.0324	0.0098	0.0188
Type 2 to Type 1	0.0124	0.0275	0.0085	0.0227	0.0117	0.0150
Type 2 to Type 2	0.0797	0.1677	0.0568	0.1211	0.0794	0.1138
Type 2 to Type 3	0.1250	0.1640	0.1275	0.1189	0.1261	0.1497
Type 3 to Type 2	0.1142	0.1157	0.1074	0.0983	0.1128	0.1208
Type 3 to Type 3	0.3833	0.3152	0.5535	0.4525	0.3897	0.4003
Type 3 to Type 4	0.0874	0.0622	0.0511	0.0583	0.0881	0.0797
Type 4 to Type 3	0.0636	0.0305	0.0425	0.0450	0.0628	0.0455
Type 4 to Type 4	0.0383	0.0094	0.0103	0.0229	0.0385	0.0181

Table D11: **Other Extensions: Model Fit I for Low Educated Workers**

	Annual Model		Wage Sample		Asymmetric Shocks	
	Data	Model	Data	Model	Data	Model
Residual wage variance						
Var($\tilde{e}\|age = 26$)	0.0790	0.0794	0.0571	0.0613	0.0897	0.0920
Var($\tilde{e}\|age = 30$)	0.0756	0.0743	0.0540	0.0562	0.0849	0.0855
Var($\tilde{e}\|age = 35$)	0.0776	0.0770	0.0560	0.0592	0.0854	0.0891
Var($\tilde{e}\|age = 40$)	0.0801	0.0785	0.0618	0.0604	0.0877	0.0897
Var($\tilde{e}\|age = 45$)	0.0799	0.0808	0.0608	0.0613	0.0870	0.0904
Var($\tilde{e}\|age = 50$)	0.0792	0.0825	0.0610	0.0617	0.0856	0.0903
Var($\tilde{e}\|age = 55$)	0.0815	0.0831	0.0631	0.0618	0.0873	0.0895
Residual wage growth moments for job stayers						
Var($\Delta\tilde{e}_t\|J_t = 0$)	0.0266	0.0296	0.0162	0.0178	0.0267	0.0261
Cov($\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1}\|J_t = 0$)	-0.0047	-0.0085	-0.0027	-0.0028	-0.0039	-0.0003
$Skew(\Delta\tilde{e}_t\|J_t = 0)$	0.4408	0.4404	0.1795	0.1811	0.1863	0.1840
$Kurt(\Delta\tilde{e}_t\|J_t = 0)$	6.3324	6.3297	4.3222	4.3276	6.2154	6.2123
Residual wage growth moments for job movers						
$\mathbb{E}(\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1)$	0.0153	0.0319	0.0021	0.0140	0.0177	0.0211
Var($\tilde{e}_{t+1} - \tilde{e}_{t-1}\|, J_t = 1$)	0.0505	0.0517	0.0351	0.0405	0.0597	0.0626
Covariance between wage growth and employment residuals						
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 0$)	0.0009	-0.0005	0.0001	-0.0001	-0.0001	-0.0002
Cov($\tilde{u}_t, \tilde{e}_t\|, J_t = 1$)	0.0008	-0.0001	-0.0030	0.0087	0.0001	0.0069
Common shocks at the firm level among stayers						
$\rho_{\Delta\tilde{e}}$	0.1798	0.1772	0.1812	0.1831		
Cov($\mathbb{E}_j[\Delta\tilde{e}_t], \mathbb{E}_j[\Delta\tilde{e}_{t-1}]$)	-0.0013	-0.0023	-0.0004	-0.0012		
$\rho^+_{\Delta\tilde{e}}$					0.2037	0.1901
Cov($\mathbb{E}_j[\Delta\tilde{e}_t]^+, \mathbb{E}_j[\Delta\tilde{e}_{t-1}]^+$)					-0.0012	-0.0023
$\rho^-_{\Delta\tilde{e}}$					0.1572	0.1724
Cov($\mathbb{E}_j[\Delta\tilde{e}_t]^-, \mathbb{E}_j[\Delta\tilde{e}_{t-1}]^-$)					-0.0011	-0.0017
Worker mobility in response to firm-level shocks						
$\Delta Pr(J2J_{\tau_q})/\Delta a_{j,\tau}$	-0.0295	-0.0228	-0.0124	-0.0065	-0.0124	-0.0098
$\Delta Pr(E2U_{\tau_q})/\Delta a_{j,\tau}$	-0.0110	-0.0010	-0.0045	-0.0017	-0.0045	-0.0008
Average Wage Growth for Movers by Firm Types						
From Type 1 to Type 1	0.1633	0.1606	0.2539	0.2382	0.1586	0.1810
From Type 1 to Type 2	0.2926	0.2663	0.2244	0.2249	0.2763	0.2367
From Type 2 to Type 1	-0.0146	0.0335	0.0455	0.0125	-0.0047	0.0057
From Type 2 to Type 2	0.0271	0.0487	0.0242	0.0238	0.0314	0.0398
From Type 2 to Type 3	0.0871	0.0515	0.0465	0.0569	0.0872	0.0710
From Type 3 to Type 2	-0.0509	-0.0176	-0.0114	-0.0337	-0.0429	-0.0322
From Type 3 to Type 3	-0.0031	-0.0155	-0.0088	-0.0062	-0.0010	-0.0023
From Type 3 to Type 4	0.0529	0.0128	0.0457	0.0463	0.0534	0.0416
From Type 4 to Type 3	-0.0791	-0.0554	-0.0921	-0.0632	-0.0726	-0.0612
From Type 4 to Type 4	-0.0189	-0.0424	0.0461	-0.0294	-0.0150	-0.0443

Table D12: **Other Extensions: Model Fit II for Low Educated Workers**

	Annual Model		Wage Sample		Asymmetric Shocks	
	Data	Model	Data	Model	Data	Model
Quarterly Non-Participation Rates by Age						
Age 26-30	0.1539	0.2402	0.1636	0.1650	0.1636	0.1602
Age 31-35	0.1276	0.1132	0.1343	0.1365	0.1343	0.1346
Age 36-40	0.1181	0.1052	0.1230	0.1272	0.1230	0.1289
Age 41-45	0.1113	0.1020	0.1151	0.1156	0.1151	0.1202
Age 46-50	0.1032	0.0993	0.1059	0.1071	0.1059	0.1116
Age 51-55	0.0944	0.1000	0.0958	0.0918	0.0958	0.0964
Quarterly Entry Rates from Unemployment by Age						
Age 26-30	0.3961	0.4666	0.1805	0.1800	0.1805	0.1851
Age 31-35	0.3685	0.3416	0.1654	0.1686	0.1654	0.1720
Age 36-40	0.3488	0.3318	0.1559	0.1600	0.1559	0.1647
Age 41-45	0.3314	0.3309	0.1475	0.1509	0.1475	0.1555
Age 46-50	0.3171	0.3220	0.1406	0.1344	0.1406	0.1408
Age 51-55	0.3054	0.3214	0.1366	0.1263	0.1366	0.1313
Quarterly Separation Rates into Unemployment by Age						
Age 26-30	0.0547	0.0398	0.0269	0.0295	0.0269	0.0284
Age 31-35	0.0435	0.0388	0.0213	0.0264	0.0213	0.0267
Age 36-40	0.0398	0.0385	0.0191	0.0226	0.0191	0.0238
Age 41-45	0.0374	0.0374	0.0174	0.0194	0.0174	0.0210
Age 46-50	0.0352	0.0353	0.0158	0.0156	0.0158	0.0171
Age 51-55	0.0346	0.0355	0.0148	0.0121	0.0148	0.0136
Quarterly Job-to-Job Transition Rates by Age						
Age 26-30	0.1324	0.1348	0.0333	0.0358	0.0333	0.0388
Age 31-35	0.1134	0.1172	0.0284	0.0330	0.0284	0.0335
Age 36-40	0.0978	0.1018	0.0244	0.0309	0.0244	0.0312
Age 41-45	0.0859	0.0886	0.0213	0.0282	0.0213	0.0287
Age 46-50	0.0753	0.0752	0.0184	0.0249	0.0184	0.0260
Age 51-55	0.0665	0.0678	0.0161	0.0215	0.0161	0.0235
Quarterly Job-to-Job Transition Rates by Firm Types						
Type 1 to Type 1	0.0062	0.0113	0.0002	0.0057	0.0057	0.0069
Type 1 to Type 2	0.0148	0.0410	0.0098	0.0307	0.0136	0.0304
Type 2 to Type 1	0.0193	0.0292	0.0137	0.0226	0.0196	0.0198
Type 2 to Type 2	0.1336	0.2144	0.1375	0.1636	0.1343	0.1463
Type 2 to Type 3	0.1243	0.1822	0.0878	0.1372	0.1230	0.1570
Type 3 to Type 2	0.1270	0.1519	0.1052	0.1212	0.1238	0.1241
Type 3 to Type 3	0.3032	0.2278	0.4369	0.3351	0.3114	0.3253
Type 3 to Type 4	0.0876	0.0402	0.1010	0.0637	0.0885	0.0682
Type 4 to Type 3	0.0555	0.0286	0.0449	0.0518	0.0547	0.0552
Type 4 to Type 4	0.0429	0.0105	0.0271	0.0409	0.0432	0.0317

E GPS Benchmark and Life-Cycle Analysis

In this section, we first present estimates for firm shock transmission to wages analogous to Guiso, Pistaferri, and Schivardi (2005). We then discuss how to augment the GPS framework to analyze the role of firms for the cross-sectional dispersion of earnings over the life-cycle.

E.1 IV Estimates of Pass-Through

GPS use an IV strategy to decompose the transmission of transitory and permanent firm shocks to wages. For this strategy, they require residual growth in firm productivity, denoted $\Delta\epsilon$, and residual wage growth, denoted $\Delta\omega$. Note that we have already estimated these two components in our main analysis, see Sections 4.2 and 4.3, and we can use them directly to apply the GPS IV approach for stayers.

Following GPS, we first use $(\Delta\epsilon_{jt+1})^k$ with $k \in \{1, 2, 3\}$ as instruments to identify the transitory shock transmission rate, β. Second, we use $\left(\sum_{\tau=-2}^{2} \Delta\epsilon_{jt+\tau}\right)^k$ with $k \in \{1, 2, 3\}$ to identify the transmission rate for permanent shocks, α.[73]

The estimates are reported in Table 13 in the main text, with pass-through rates for transitory shocks between 3.3% and 4.7% and transmission rates for permanent shocks of around 6.1–7.1%.

E.2 Life-Cycle Analysis

Next, we turn to the life-cycle analysis, using the estimates for the firm shock transmission, α and β as inputs.

Specifically, we use simulated methods of moments to estimate the transitory and permanent idiosyncratic shocks to wages, σ_ϵ and σ_ζ, as well as the moving average parameter θ_ϵ and the AR(1) parameter ρ_ζ. We target the autocovariance structure of workers' earnings up to the third-order autocovariance to identify these parameter, taking as given the estimated firm shock process and the shock transmission coefficients. Finally, we use the variance of log earnings at labor market entry (at age 26) conditional on all prior estimates to back out the initial dispersion of permanent worker productivity, $\sigma_{P^{init}}$.

Table E1 reports model fit and estimates. In addition to the data moments in the first and fifth column, respectively, we report the model fit and estimates for our annual baseline model for comparison. Note that our model assumes iid transitory shocks, and we provide

[73] Under the assumption of iid transitory firm shocks, we can simplify and use $\left(\sum_{\tau=-1}^{1} \Delta\epsilon_{jt+\tau}\right)^k$ but this does not make a quantitative difference for the results.

Table E1: **GPS Comparison: Worker Productivity Process**

	Low Education				High Education			
	Data	Model	GPS	GPS + $\hat{\kappa}$	Data	Model	GPS	GPS + $\hat{\kappa}$
$\text{Var}(\Delta\tilde{e}_t \mid J_t = 0)$	0.0266	0.0296	0.0266	0.0266	0.0364	0.0364	0.0364	0.0364
$\text{Cov}(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1})$	-0.0047	-0.0085	-0.0047	-0.0047	-0.0063	-0.0090	-0.0063	-0.0063
$\text{Cov}(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-2})$	-0.0006	-0.0003	-0.0006	-0.0026	-0.0008	-0.0003	-0.0008	-0.0009
$\text{Cov}(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-3})$	-0.0003	-0.0005	-0.0003	0.0000	-0.0003	-0.0005	-0.0003	-0.0002
$\text{Var}(\tilde{e} \mid age26)$	0.0790	0.0794	0.0787	0.0786	0.0927	0.0860	0.0957	0.0956
$\text{Var}(\tilde{e} \mid age55)$	0.0815	0.0831	0.2376	0.3803	0.1785	0.1758	0.3767	0.3773
σ_ϵ		0.0474	0.0708	0.0688		0.0863	0.0823	0.0784
θ_ϵ			0.0580	0.0000			0.0602	0.0000
σ_ζ		0.1042	0.1286	0.1025		0.1150	0.1515	0.1290
ρ_ζ		0.8880	0.9637	1.0000		0.9328	0.9681	0.9761
σ_{Pinit}		0.2284	0.2066	0.2072		0.2497	0.2631	0.2643

Var: Variance, Cov: Covariance, $\tilde{e}$: the estimated wage residual, ϵ: the transitory shock to worker productivity with variance σ_ϵ^2 and MA(1) coefficient θ_ϵ, ζ: the permanent shock to worker productivity with variance σ_ζ^2 and AR(1) coefficient ρ_ϵ. For our model, we report the composite variance of the mixture distribution of ζ_1 and ζ_2.

the composite variance of the mixture distribution for permanent productivity shocks for comparison.

The main results for the GPS life-cycle model are provided in column 3 and 7 for high and low educated workers, respectively. Note that the GPS version does not target the variance of earnings at age 55 in estimation, whereas our model does not target second- and third-order autocovariances of wage growth among stayers.

Starting with the model fit, our annual model is able to fit closely the moments for both level and growth of wages. In contrast, the fit for the untargeted variance of earnings at age 55 is poor for the GPS model.

The reason for this difference in model fit is clear from the estimates in the bottom part of the table. Because of the lower transmission of firm-level shocks, GPS infers a much larger variance of permanent shocks to worker productivity. Moreover, to fit the autocovariance structure, GPS estimates a substantially higher AR(1) coefficient for permanent productivity.

As expected, when we impose the transmission coefficients κ from our annual model onto the GPS life-cycle model in columns 4 and 8, the implied variances of idiosyncratic worker shocks decline. But crucially, the permanent productivity process remains much more persistent than in our annual model, as evidenced by a comparison of the AR(1) coefficient ρ. This result then implies that the GPS models cannot match the life-cycle profile of wage dispersion well and vastly overshoot the (untargeted) variance of earnings at age 55. As a result, GPS continues to underestimate the role of the firm over the life cycle.