Earnings Dynamics and Firm-Level Shocks

- *Preliminary and incomplete* - .

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Abstract

In this paper we use matched employer employee data to estimate the stochastic properties of the wage process for individuals and the way it may be impacted by productivity shocks to the firm. Our model accounts for endogenous participation and mobility decisions and thus deals with the potential truncation in the impact of productivity on wages that is induced by people quitting into unemployment or changing employer. The key finding is that permanent productivity shocks transmit to individual wages. However transitory (iid) shocks have no impact on wages. We find that the variance of wages increase over the lifecycle because of a permanent individual shock that sticks with the worker. However, by age 55 16% of the cross sectional variance is attributable to firm level shocks. There is no other source of match specific effects, other than through these firm level productivity shocks.

Keywords: Income process, Wage dynamics, Firm dynamics
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1 Introduction

There has been an increased interest in understanding pay policies of firms, and in particular the extent to which firm-level productivity shocks are transmitted to workers' wages and whether identical workers are paid different amounts depending on their workplace. Such departures from perfect competition and the law of one price have been motivated by the developments in search theory starting by the seminal models of Burdett and Mortensen (1998) and Mortensen and Pissarides (1994). More recent papers, such Postel-Vinay and Robin (2002), Cahuc, Postel-Vinay, and Robin (2006) and Lise, Meghir, and Robin (2016) develop frameworks where firms and workers share the economic surplus generated by the employment relationship in a world with frictions; importantly the sharing is induced by bilateral Bertrand competition between an incumbent and and a poaching firm. Lower productivity firms, paying workers lower wages only survive because of search frictions.

The causes of pay heterogeneity also underlie the reasons why workers may, under certain circumstances, share the shocks to firm productivity. There are multiple sources of risk distinct from workers' productivity shocks.[1], such as fluctuations in the fortunes and of the firm, induced by product market shocks. In a competitive labor market workers only bare the risk of shocks to their own productivity, which they carry with them wherever they work. However, in the presence of search frictions the transmission of shocks to wages is not straightforward. On the one hand productivity shocks may not affect wages immediately. On the other hand the worker may have to share some of the shocks to the productivity of the firm itself, since his immediate outside option is unemployment and thus may not have a credible threat to quit. This issue relates to whether workers share rents with the firm, and early study in this direction is Van-Reenen (1996).

While Lise, Meghir, and Robin (2016) do consider the effect of shocks to productivity, they

[1] Low, Meghir and Pistaferri (2010) illustrate the importance of such distinctions for the welfare effects of risk.

only have individual level data. This prevents them from addressing directly the question of whether firm productivity shocks matter for wages. The recent availability of matched employer-employee data gives rise to major new opportunities in this direction. In particular, these new data sources allow for an extended analysis of the role of the firm for the dynamics of earnings. Yet most papers using matched worker-firm data have focused on sorting and firm-worker heterogeneity rather than the dynamics of shocks, see Abowd, Kramarz, and Margolis (1999) and more recently Card, Heining, and Kline (2013), whose focus is the evolution of within and between firm inequality. Finally, Card, Rute-Cardoso, Heining *et al.* (2016) review the literature on the relationship of firm performance to wages and provide some theoretical insights.

In an earlier paper Guiso, Pistaferri, and Schivardi (2005) estimate the passthrough of firm level shocks to wages using Italian matched employer-employee data and interpret the results as estimates of the amount of insurance the firm provides. However, their approach is limited by the fact that they ignore job-to-job mobility and transitions between employment and unemployment. 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. More recently, Lamadon (2015) has developed a structural directed search model that offers a framework for understanding the role of firm level shocks.

This paper remains agnostic about the specific structural model that generates the data. We build on the literature on the stochastic process of earnings such as Abowd and Card (1989), MaCurdy (1982), Meghir and Pistaferri (2004), Guvenen (2007) and more recently Altonji, Smith, and Vidangos (2013). Our contribution is that we use matched employer-employee data and explicitly consider the sources of shocks. Thus, we propose a framework for introducing the firm in empirical models of the dynamic income process so as to understand how shocks at the firm level transmit to wages. The key innovation is that we account both for job-to-job transitions and for transitions between employment and unemployment to capture the role of job mobility and labor force participation in masking the impact of shocks. The model allows for a rich stochastic structure of the income process, both at the individual and the firm-worker match level.

In a related paper, Low, Meghir, and Pistaferri (2010) find that making job mobility and employment choices endogenous reduces the estimated variance of the permanent shock 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. A related paper is Altonji, Smith and Vidangos (2013), who specify a model of employment, hours, wages and earnings in order to distinguish different sources of risk. Selection into employment and between jobs is modeled in a similar way as in Low, Meghir, and Pistaferri (2010). Yet none of these studies consider the role of firm-level shocks for earnings dynamics, which is the main contribution of the present paper.

Our data is drawn from Swedish administrative records. We have matched these 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 includes annual earnings, detailed information of job histories, including the identity of the firm and other important information. However, it does not include hours of work. We thus focus our main analysis on men, who rarely if ever work part time. We split these into two education groups: those with some college and those with less.

We specify a model of wages, employment and job mobility, all of which are interrelated. 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. The stochastic structure of wages includes idiosyncratic effects, reflecting changes in individual productivities and match specific effects. The latter consist in part of shocks to firm productivity (transitory and permanent) as well as random match effects. As such it is a particularly rich framework that effectively nests earlier specifications of the stochastic process of income.

We find that firm productivity is quite volatile and that this volatility transmits to wages of high skill workers to a large extent, particularly when it relates to permanent shocks. It thus turns out that the firm is responsible for a very high fraction of cross sectional variance of wages attributable to unobserved components. The same is not true for unskilled workers: transitory shocks to productivity transmit to wages, but overall this does not explain a large fraction of the wage variance. We also find that employment is strongly related to wage shocks, consistent with self selection into work and work incentives. Finally, job mobility is highly dependent on wage offers, although other factors lead workers to take wage cuts when they move workplaces.

The paper proceeds as follows. Section 2 presents the model of the income process. Section 3 introduces the dataset and presents descriptive statistics. Section 4 presents the estimation and identification strategy. Section 5 shows the main results for the two-stage estimation procedure. Section 6 concludes.

2 The Model

2.1 Overview

The model we set up has various components. At the heart of the specification is a wage equation for each of the two education groups we consider (some college or less). Wages grow by age and have a stochastic structure that depends on general productivity shocks, that follow the worker wherever he is employed, match specific effects relating to the specific worker/firm combination and a direct dependence on shocks to firm level productivity. Since one of the points we wish to address is endogenous mobility we also include an equation on participation, that depends on the wage as well as an equation for firm to firm mobility that compares the wages in the two alternative jobs. However, individuals do not move randomly across sectors. We thus include a matching equation which assigns workers who move to sectors and types of firm, depending on the characteristics of their origin job. In this way we reproduce the industrial composition as in the data, in the dimensions that we specify. We now provide details on our specification.

2.2 The Model

Wages We consider a quarterly model of wages, participation and job mobility. Log wages of individual i aged a at calendar time t who started to work at firm j at the age of a_0 is given by

$$\ln w_{i,j(a_0),a,t} = x'_{i,a,t}\gamma + P_{i,a,t} + \varepsilon_{i,a,t} + v_{i,j(a_0),a,t}, \tag{1}$$

where x are observable worker characteristics, $\epsilon \sim N\left(0, \sigma_\epsilon^2\right)$ is an iid transitory productivity shock[2] and P_{iat} is permanent productivity at age a specified as

$$P_{i,a,t} = \rho P_{i,a-1,t-1} + \zeta_{i,a,t} = \rho^a P^{init}_{i,0,t-a} + \sum_{s=1}^{a} \rho^{a-s}\zeta_{i,s,t-a+s} \tag{2}$$

where P^{init} is the initial productivity draw upon entry into the labor market. The productivity shock is denoted be ζ and we make the distributional assumptions

$$P^{init} \sim N\left(0, \sigma_P^2\right), \quad \zeta \sim N\left(0, \sigma_\zeta^2\right). \tag{3}$$

The identity of the firm affects wages through the match-specific productivity $\nu_{i,j(a_0),a,t}$

[2]Note that we assume no measurement error because we will use high quality administrative data for estimation. 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 has economic implications, however, since measurement error is pure noise while transitory shocks reflect uncertainty that may give rise to economic responses. The authors suggest two ways of handling this issue, by obtaining bounds for the unidentified variances or by using an external estimate of the measurement error to recover the variance of the transitory shock.

of worker i at firm $j(a_0)$, which he joined when he was a_0 of age. This match specific effect consists of various components. When the worker starts in a new firm he draws a match specific component $v_{i,j(a_0),a,t} = v^{init}_{i,j(a),a,t}$. This is defined by

$$v^{init}_{i,j(a),a,t} = \tau_{j(a)} + \psi^{init}_{i,j(a),a,t}. \tag{4}$$

Thus the initial match value of a job $v^{init}_{i,j(a),a,t}$ is affected by firm characteristics $\tau_{j(a)}$ and an idiosyncratic match component for which we assume

$$\psi^{init}_{i,j(a),a,t} \sim N\left(0, \sigma^2_{\psi^{init}}\right).$$

Starting from this initial position the match effect evolves stochastically as a result of firm and match specific shocks. It is useful to distinguish between a component, which reflects permanent (or at least long-run persistent) changes in the value of the worker/firm match and transitory changes. For the periods when the worker does not change jobs we assume

$$v_{i,j(a_0),a,t} = v^p_{i,j(a_0),a,t} + v^t_{i,j(a_0),a,t} \tag{5}$$

where the permanent component evolves as

$$v^p_{i,j(a_0),a,t} = v^p_{i,j(a_0),a-1,t-1} + \kappa^p \xi^p_{j(a_0),t} + \psi^p_{i,j(a_0),a,t} \tag{6}$$

while the transitory component follows the law of motion

$$v^t_{i,j(a_0),a,t} = \kappa^t \xi^t_{j(a_0),t} + \psi^t_{i,j(a_0),a,t} \tag{7}$$

In the above $\xi^p_{j(a_0),t}$ is a permanent shock to the productivity of the firm and $\xi^t_{j(a_0),t}$ a transitory shock to its productivity. The properties of these shocks will be measured directly from the firm level data. The two ψ shocks are iid Normal. Specifically we assume that $\psi^j \sim N\left(0, \sigma^2_{\psi^j}\right), \quad j = p, t.$

The existence of a match-specific effect has been motivated theoretically within the search and matching framework and empirically by papers such as Topel and Ward (1992) and Abowd, Kramarz, and Margolis (1999). 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, but in their paper the match is not allowed to change within the firm-worker relationship and is not subject to shocks that could be related to firm-level productivity. These additions to the match-specific component are one of the contributions of our work compared to earlier studies.

Participation and Mobility One of the key issues is controlling for selection into work and for job mobility, both of which may truncate the distributions of shocks. For example, if there is a large pass through of firm level shocks the worker may actually quit their job rather than suffer the resulting pay cut, which may even be permanent. Similarly, workers with large pay cuts in firms that have had bad productivity shocks may be more likely to accept alternative job offers. Observationally, there may be two workers paid exactly the same one of whom moves, while the other does not, just because of the different reasons for their pay cut. In one case it may be because of an adverse firm level shock, while in the other a negative individual productivity shock that is carried everywhere.

We model participation decisions E as

$$E_{i,a,t} = 1\left\{z'_{i,a,t}\delta + \phi_1\left(P_{i,a,t} + \varepsilon_{i,a,t} + v_{i,j(a_0),a,t}\right) + u^E_{i,a,t} > 0\right\} \tag{8}$$

In the above we include taste shifter variables such as age, summarized in z. Importantly we also include the stochastic component of wages $P_{i,a,t}+\varepsilon_{i,a,t}+v_{i,j(a_0),a,t}$, which is the relevant component. However, it may be restrictive to impose that the transitory and the permanent component have the same effect, since the former only causes substitution effects, while the latter also causes wealth effects. The other parts are explained by z. The coefficient ϕ_1 in part reflects the incentive effect of working but also it reflects the importance of unobserved heterogeneity in participation choices.

Similarly, mobility J is defined as

$$J_{i,a,t} = 1\left\{z'_{i,a,t}\theta + b\left(v^{init}_{i,j(a),a,t} - v_{i,j(a_0),a,t}\right) + u^J_{i,a,t} > 0\right\}, \tag{9}$$

and is also explained by a set of variables z. Job mobility depends only on the difference in match values $(v^{init}_{i,j(a),a,t} - v_{i,j(a_0),a,t})$ 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 jobs. The importance of wage differences as opposed to worker observable characteristics in determining mobility is captured by b.

Finally, both the employment and the mobility equation depend on a stochastic shock - $u^E \sim N(0,1)$ and $u^J \sim N(0,1)$, respectively. This reflects exogenous job destruction and mobility (or lack thereof) due to unexplained random factors. 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 unexplained reasons.

Labor Market Frictions and Job Offers Workers receive job offers during unemployment at an age-dependent rate $\lambda_U = \lambda_{U,0} + \lambda_{U,1} \cdot age$. Job offers on the job are subsumed into age-dependent mobility preferences in equation (9). If a worker receives a new job offer, we also model the origin of the offer to match transition patterns across industries. We classify firms in bins based on their sector and firm size and we assume that the probability of new offers from any given sector and size group depend on the current job,

$$Pr\,(sector,\, size) = \omega_0 + \omega_1 1\left\{sect_{j(t)} = sect_{j(t_0)}\right\} + \omega_2 1\left\{size_{j(t)} = size_{j(t_0)}\right\}. \tag{10}$$

3 Data

3.1 The Data Set

We have put together a matched employer-employee data set that combines information from four different data sources, compiled by Statistics Sweden. The first is the Longitudinal Database on Education, Income and Employment (LOUISE) that contains information on demographic and socioeconomic variables for the entire working age population in Sweden from 1990 onwards. We use information about age, gender, municipality of residence, number and ages of children, marital status and education level as well as the collection of public transfers such as disability, public pension, sickness, unemployment and parental leave benefits. All variables in LOUISE are registered on a yearly basis.

The second data set is the Register-Based Labour Market Statistics (RAMS) that contains information about the universe of employment spells in Sweden from 1985 onwards. On the worker side, RAMS registers the gross yearly earnings and the first and last remunerated month for each employment, as well as firm and plant identifiers. On the firm side, RAMS registers information about institutional sector, industry and the type of legal entity for all firms with employees. The third data set is the Structural Business Statistics (SBS) that contains accounting data and balance sheet information for all non-financial corporations in Sweden from 1997 onwards, and a subset of corporations during 1990–1996. The fourth data set is the Unemployment Register that contains all spells of unemployment registered at the Public Employment Service.

Since the Structural Business Statistics covers all non-financial corporations in Sweden only from 1997 onwards, we focus the analysis on the period 1997–2008. We include all firms with the legal entity being limited partnership, limited company other than banking and insurance companies or economic association, but exclude personal companies because data for these firms does not cover the entire sample period. The final sample represents

Table 1: Summary statistics, firms

	Firm size: number of employees			
	<20	20–50	50–100	100+
A. Construction				
No. unique firms	11,699	973	1,738	1,143
Value added per worker	494,117	533,599	552,487	566,002
Growth, log va/worker	0.0377	0.0368	0.0338	0.0229
B. Manufacturing				
No. unique firms	11,654	2,696	9,971	1,166
Value added per worker	528,331	578,780	622,656	1,017,031
Growth, log va/worker	0.0282	0.0211	0.0136	0.0133
C. Retail Trade				
No. unique firms	20,016	2,244	555	402
Value added per worker	528,697	625,053	634,861	756,280
Growth, log va/worker	0.0303	0.0235	0.0260	0.0182
D. Services				
No. of unique firms	32,938	3,847	1,010	826
Value added per worker	575,102	682,203	861,547	775,826
Growth, log va/worker	0.0382	0.0375	0.0430	0.0302

Note: Revenue per worker is reported in real SEK for base year 2007.

83 percent of value added and 83 percent of employment in the Swedish private sector over 1997–2008.

Table 1 presents descriptive statistics of the firms in our data set. The data contains 98,630 unique firms and 678,792 firm-year observations from 1997 to 2008. The four sectors construction, manufacturing, retail and services account for 17%, 19%, 24% and 40% of firms in the sample respectively. Within sectors, larger firms on average have higher revenue per worker. The growth rate for revenue per worker does not follow the same pattern across sectors. For construction, larger firms grow more slowly on average, whereas growth rates are higher for larger firms in the other sectors.

We include all individuals who work at firms in our sample at some point during 1997–2008. We use the data from RAMS together with registrations of unemployment at the Public Employment Service to define employment on a quarterly basis. We use daily unemployment records to measure the exact length of employment spells. We keep the main employment per quarter, that is, the employment accounting for the largest share of quarterly earnings, and define a worker as employed if working at least 2 months for any employer during the quarter. In each quarter, we record if an individual is a job mover, a job stayer or an entrant from non-employment. Monthly earnings are recorded based on the yearly earnings and the number of remunerated months as registered in the RAMS data.

We exclude individuals until the last year they receive public study grants at the beginning of their working life. We also exclude individuals from the first year they receive disability benefits, occupational pension or public pension at the end of their working life. We further exclude individuals when they move to a workplace that is not in the firm sample, mainly to the public sector, to self-employment or to a financial corporation. Importantly, however, we keep all the records of non-employment that are in connection with employment spells at the firms in our sample.

We perform separate estimations for men and women in two education groups: workers with at most high school education and workers with at least some college education. Table 2 presents summary statistics for each group of workers. Individuals with less than high school or high school education are included from age 21 and individuals with some college are included from age 26. Table 2 shows that workers with lower 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. The employment rate increases with education, but the fraction of the employed who remain at their current job each quarter is fairly constant across groups. More educated workers are more likely to move from job to job, and less likely to enter a new job from non-employment. 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 2–3 percent enter employment after a period of non-employment.

The comparison between men and women shows that both female education groups are less likely to participate in the labor market compared to their male counterparts. Female workers are also slightly younger and more likely to have children living in the household.

Table 2: Summary statistics, workers

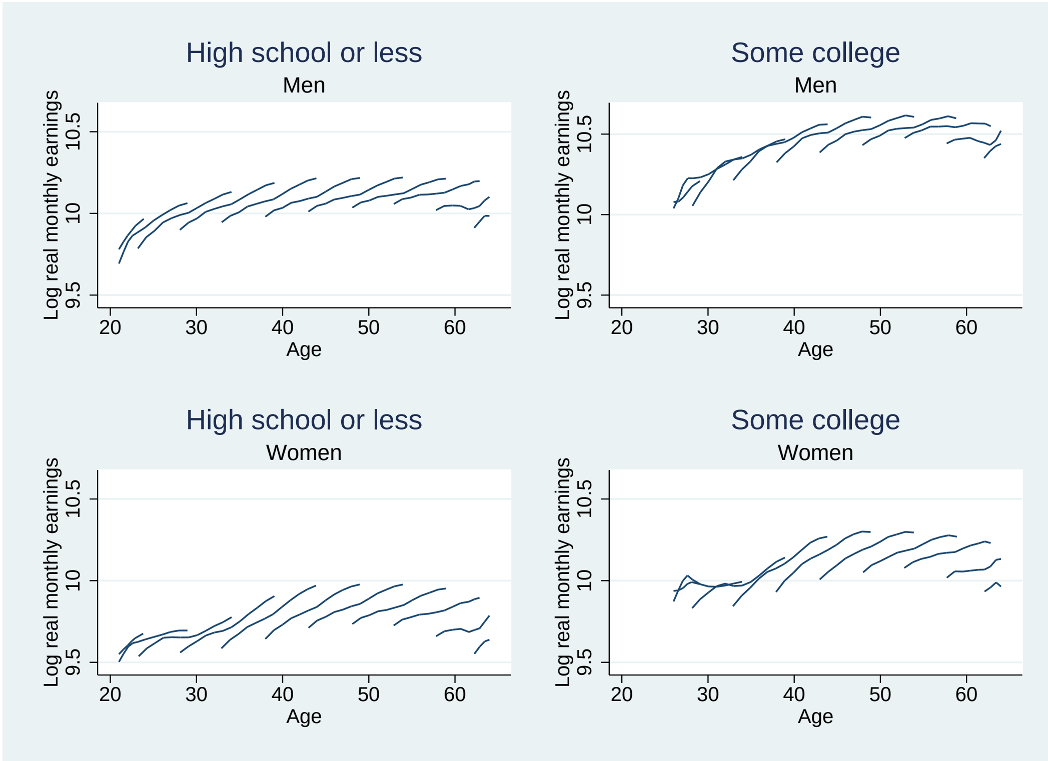
	Men		Women	
	≤High school	College	≤High school	College
No. unique workers	1,290,727	458,622	681,098	319,841
No. worker-quarter obs.	34,130,603	10,900,427	15,693,421	6,085,821
Monthly earnings,	24,562	36,095	18,750	26,350
(2008 SEK)	(7,899)	(17,097)	(6,864)	(12,123)
Age	38.16	39.00	38.08	37.89
Married	0.5181	0.6102	0.5811	0.6053
Having children	0.4196	0.4979	0.5228	0.5362
Employed, of which	0.8671	0.9063	0.8008	0.8565
Job stayer	0.9491	0.9496	0.9423	0.9422
Job mover	0.0248	0.0317	0.0227	0.0284
Re-entrant	0.0261	0.0186	0.0350	0.0294
Industry				
Construction	0.1518	0.0580	0.0282	0.0229
Manufacturing	0.4052	0.3602	0.2880	0.2209
Retail Trade	0.1878	0.1394	0.2766	0.1756
Services	0.2552	0.4424	0.4072	0.5806
Firm size				
≤20	0.3156	0.2611	0.2878	0.2894
20–50	0.1406	0.1214	0.1417	0.1213
50–100	0.1016	0.0884	0.1001	0.0834
100+	0.4421	0.5291	0.4704	0.5060

Women are employed in services and retail trade much more frequently, whereas men are more likely to work in manufacturing or construction.

Table 2 shows basic descriptive statistics which reveal differences in earnings across education groups, but also across gender for a given level of education. We take a more detailed look at life-cycle earnings profiles in Figure 1, using observations across different birth cohorts in the data. In particular, within each gender-education group we construct five-year cohort groups and separately plot their average log earnings over the age period in which we observe this particular cohort group. The vertical distance between different cohort groups' earnings for a given age can then be interpreted as cohort effects.

Overall, we observe the familiar life-cycle earnings profile increasing quite rapidly early in

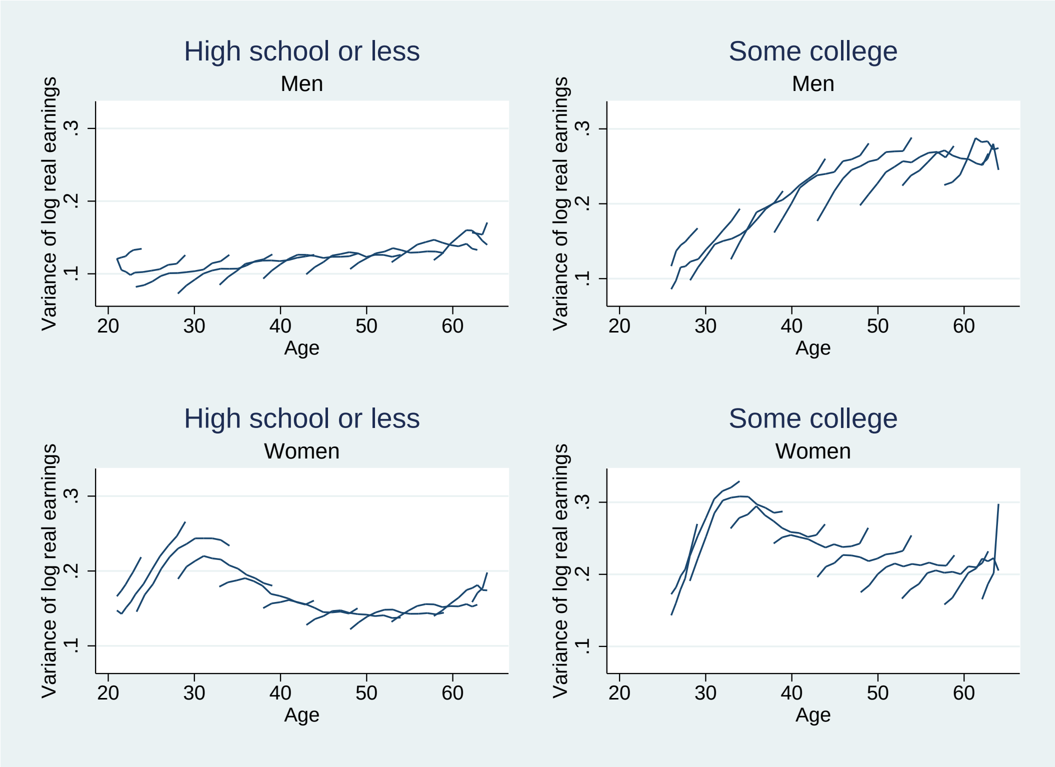
Figure 1: Log real monthly earnings by five-year cohort groups by age, 1997-2008



the career and then flattening or slightly decreasing towards the end of the life-cycle. Level-differences show the absolute gain from achieving a higher level of education. Differences across genders may reflect hours differences as well as different occupational choices labor market experience and possibly discrimination. For women, earnings appear to be flat or slightly decreasing in their main childbearing years, which occurs in their late 20s for women with at most high school degrees and in their mid-30s for women with at least some college education.

Figure 2 presents the evolution of the variance of residual log real earnings, when year and age effects have been removed. The patterns here display striking differences between education groups. While for the higher education group the variance increases by age, as has often been noted in US data, for lower education men the variance is either flat or increases at a very low rate. The former is consistent with a random walk (or possibly heterogeneous

Figure 2: The variance of log real monthly earnings by five-year cohort groups and age, 1997-2008



age profiles). However the latter is more consistent with stationary wages over the lifecycle. For men, the variance of earnings increases over the life-cycle for each successive cohort, but much more strongly for higher educated workers.

For women the variance of earnings follows a hump-shaped pattern. As we mentioned above, variation of hours and selection into employment because of children is an important issue for women and is likely to be driving the results we observe here.

Figure 3 presents the employment rate by age for each education group and gender. In our sample participation rates are above 70% for all age groups. The lower the achieved level of education, the lower participation at young ages. Interestingly, there is an increase in participation from the beginning of individuals' careers until their mid-50s for male high-school graduates, whereas participation for male workers with some college education quickly

Figure 3: Quarterly employment rates by gender, age and education group

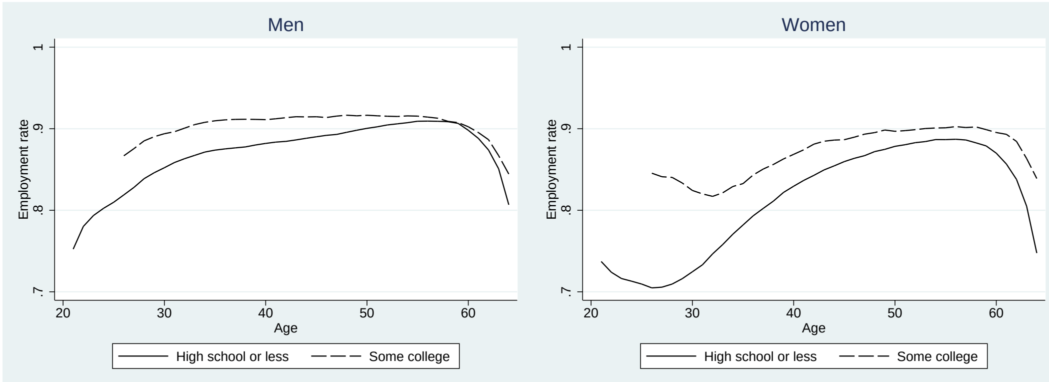
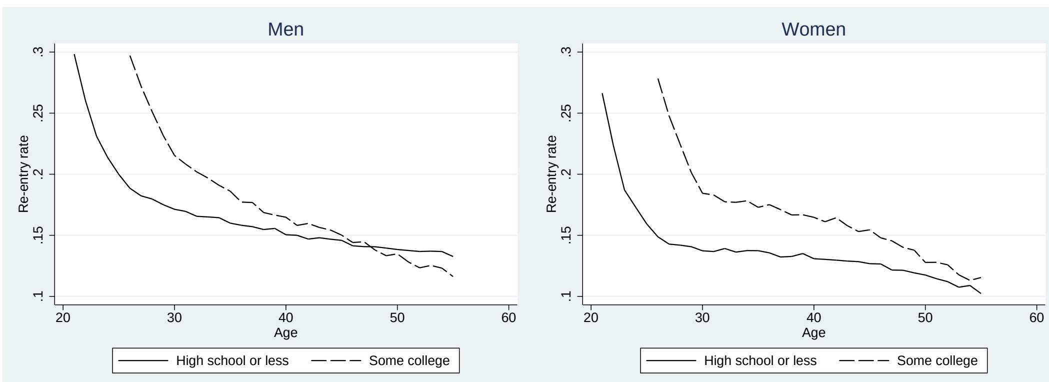


Figure 4: Quarterly re-entry rates from non-employment by gender, age and education group



levels off at 90%. For women, we see the familiar pattern of temporary absence from the labor market in their mid-20s for high school or less and in their mid-30s for some college education. The figure also shows a substantial drop in employment after the age of 55 in all education groups.

Figure 4 shows that young workers across all gender and education groups have high quarterly reentry rates when out-of-work. The entry rate from non-employment is rapidly falling with age and comparable across education groups, but the respective share of unemployed workers differs. As Figures 3 and 4 illustrate, transitions in and out of employment seem to be an important feature of the labor market. Figure 5 presents the quarterly job-to-job transition rates by age for each gender-education group. The frequency of job to job

Figure 5: Quarterly job-to-job transition rates by gender, age and education group

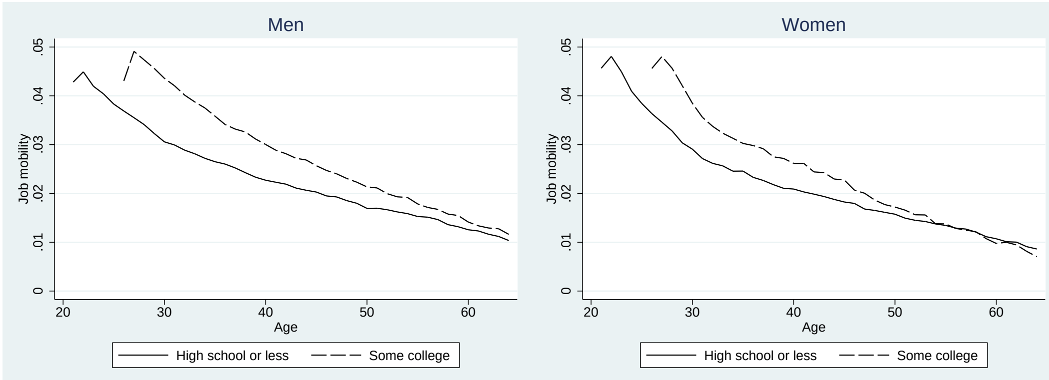


Table 3: Share of wage variance between firms

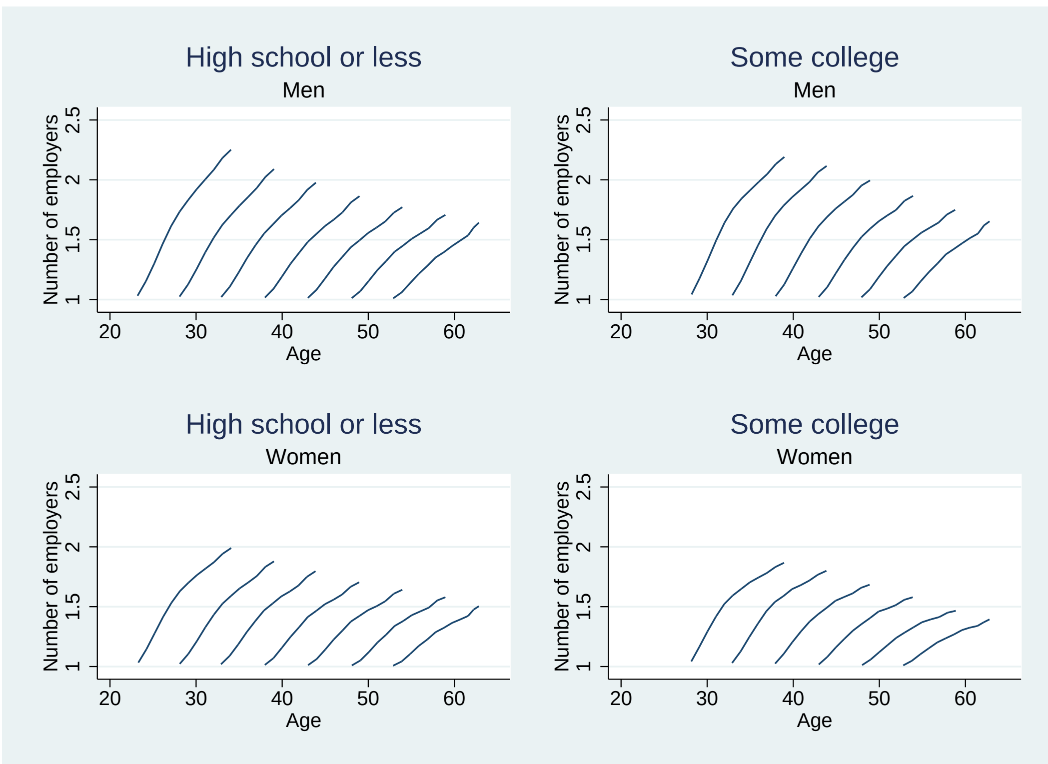
	At Least Some College		High School or Less	
Year	Log Earnings	Residual	Log Earnings	Residual
1997	37.09%	38.44%	38.74%	35.57%
2000	38.96%	39.95%	37.19%	35.01%
2004	42.32%	40.64%	38.28%	36.21%
2008	42.06%	40.70%	38.70%	36.60%

transitions is particularly high at younger ages. More workers with at least some college switch employers more frequently than less educated workers.

Finally, Figure 6 presents the average number of employers for each cohort that we observe over the sample period from 1997 to 2008 by their age in 1997. The figure confirms that the change of employer is an important feature of the labor market. Individuals of age 20–25 in 1997 had on average more than 2 employers until 2008.

Table 3 shows the share of wage variance between firms. It shows that most of the variance of wages is within firms. For low skill workers this remains stable over time. However, for high skill workers the share of between firm variance is increasing. The increase is in line with recent findings by Card, Heining, and Kline (2013) for Germany.

Figure 6: Number of jobs by age, education and gender in five-year cohort groups



Mobility and wages In Table 4 we describe mobility patterns between firms sorted by the average wage and describe the way wages change between jobs when mobility does not involve an unemployment spell in between jobs. Because of the nature of the wage this compares wage growth in the year before the job move to the year after the job move and conditional on no other transition happening in this three year period. Amongst job-to-job movers about 48% of low skill workers and 46% of high skill workers move to a firm of the same wage quartile level.

Table 4: Transitions, low skilled workers

		Low skill workers Departing firm quartile											
		Share of transitions				Log wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
Arriving firm quartile	1	0.145	0.071	0.038	0.014	0.063	0.026	–0.004	–0.021	0.337	0.410	0.482	0.475
	2	0.068	0.110	0.059	0.016	0.116	0.048	0.035	0.008	0.261	0.346	0.401	0.452
	3	0.041	0.077	0.144	0.042	0.168	0.083	0.051	0.034	0.199	0.277	0.324	0.391
	4	0.019	0.026	0.048	0.081	0.184	0.127	0.092	0.066	0.198	0.232	0.283	0.322
		High skill workers Departing firm quartile											
		Share of transitions				Log wage growth				Share wage cuts			
		1	2	3	4	1	2	3	4	1	2	3	4
Arriving firm quartile	1	0.114	0.050	0.033	0.016	0.099	0.056	0.044	–0.020	0.294	0.341	0.363	0.465
	2	0.060	0.107	0.067	0.022	0.134	0.093	0.083	0.055	0.211	0.246	0.294	0.360
	3	0.036	0.080	0.152	0.061	0.177	0.114	0.085	0.064	0.187	0.218	0.275	0.354
	4	0.023	0.033	0.062	0.084	0.186	0.153	0.141	0.100	0.217	0.215	0.232	0.311

On average wage movers improve their wages unless they move from the very top firms to the very bottom ones in terms of wage quartile. However, this average is masking a very large number of wage cuts: for both groups of workers between 20%-50% take a wage cut when moving from firm to firm. The size of the wage cut depends very much on the direction of the move.

4 Estimation Strategy

The estimation of the model is quite complex because of the dynamics and because of transitions between work and different jobs. Hence we will proceed in three steps. First, we estimate the stochastic process of firm-level productivity and treat the results as input into the model estimation. Second, we estimate wage residuals from a selection model that takes the quarterly frequency of mobility and annual frequency of earnings into account. Finally we estimate the full model using simulated method of moments based on the wage residuals, quarterly transition rates and firm-level shocks.

4.1 Firm Productivity Shocks

The source of stochastic variation that we are directly interested in are the productivity shocks to firms. We distinguish between permanent and transitory shocks because we can expect them to have very different impacts on wages, see also Guiso, Pistaferri and Schivardi (2005).

The key point is that by observing data on firms we are able to measure these shocks to productivity directly and then relate them to wages. As a first approach, we use log value added per worker as a firm-level measure of productivity.[3] The autocovariance structure of productivity is shown in Table 5. A random walk with an iid transitory component is a reasonable approximation because the second and third order autocovariances for productivity growth in the data are close to zero.

Based on this empirical pattern, we assume that the quarterly stochastic process of firm productivity can be decomposed into permanent and transitory components,

$$q_{jt} = q^p_{jt} + \xi^{tr}_{jt} \tag{11}$$

[3] We first run a regression of log VA per worker on year, municipality, industry and firm size fixed effects and conduct the estimation based on residual VA per worker.

Table 5: Autocovariance of Value Added per Worker: Data

	Value Added per Worker: Data				
	All firms	Construction	Manufacturing	Retail	Services
$\text{Var}\left(\Delta Q_t\right)$	0.2295	0.1950	0.1822	0.2182	0.2754
	(0.0017)	(0.0032)	(0.0033)	(0.0032)	(0.0031)
$\text{Cov}\left(\Delta Q_t, \Delta Q_{t-4}\right)$	-0.0666	-0.0709	-0.0520	-0.0607	-0.0768
	(0.0009)	(0.0020)	(0.0019)	(0.0017)	(0.0017)
$\text{Cov}\left(\Delta Q_t, \Delta Q_{t-8}\right)$	-0.0045	-0.0012	-0.0052	-0.0047	-0.0053
	(0.0005)	(0.0010)	(0.0009)	(0.0008)	(0.0010)
$\text{Cov}\left(\Delta Q_t, \Delta Q_{t-12}\right)$	-0.0022	-0.0034	-0.0028	-0.0014	-0.0018
	(0.0005)	(0.0011)	(0.0008)	(0.0008)	(0.0010)

where

$$q^p_{jt} = q^p_{jt-1} + \xi^p{}_{jt}$$
$$\xi^p_{jt} \sim N\left(0, \sigma^2_{\xi^p}\right)$$
$$\xi^{tr}_{jt} \sim N\left(0, \sigma^2_{\xi^{tr}}\right).$$

Note that in the data, we can only observe the annual aggregate shock

$$Q_t = q_t + q_{t-1} + q_{t-2} + q_{t-3}$$

where we drop notation for firm j for convenience.

We apply simulation-based estimation to estimate the quarterly firm-shock process. Given the parametric assumptions of the quarterly shock process, we guess the parameter vector $\left\{\sigma^2_{\xi^{tr}},\ \sigma^2_{\xi^p}\right\}$ and simulate firm productivity q_t for a set of hypothetical firms. Then we aggregate these simulated shocks to replicate the structure of the real data.[4] Finally,

[4] The quarterly shock process for log VA per worker is additive. As a result, the annual log VA per worker is the log of the sum of exponentiated quarterly realizations of VA per worker. Annual log VA per worker for year 1 can be written as

$$Q_1 = q^p_0 + log\left[\sum_{k=1}^{4} exp\left(\xi^{tr}_{1k} + \sum_{s=1}^{k} \xi^p_{1s}\right)\right].$$

we define a set of auxiliary moments that can be easily computed in the data as well as from the simulation and we minimize the distance between model and data in terms of these moments. 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.

Table 6 reports the estimation results for the variances of the shocks on a quarterly basis. The implied process for quarterly value added per worker shows sizable transitory shocks, which are similar across industries: this implies considerable mean reversion. On the other hand the permanent shocks are also substantial, implying quite volatile firm level productivity. This in itself is an important result and consistent with what Guiso, Pistaferri, and Schivardi (2005) find.[5] These estimates will be used to draw firm shocks in the simulation estimation below. There are some interesting differences between industries, with services being most volatile. 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 imply understating the transmission of the shocks to wages.

4.2 Wage Residuals

In the next step, we use individual-level earnings and labor market participation to estimate γ in equation (1). These coefficients are identified from the cross-section of workers without

Analogously, the value in the second year is

$$Q_2 = q_0^p + \sum_{k=1}^{4} \xi_{1k}^p + log \left[\sum_{k=1}^{4} exp \left(\xi_{2k}^{tr} + \sum_{s=1}^{k} \xi_{2s}^p \right) \right]$$

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

$$Q_2 - Q_1 = \sum_{k=1}^{4} \xi_{1k}^p + log \left[\sum_{k=1}^{4} exp \left(\xi_{2k}^{tr} + \sum_{s=1}^{k} \xi_{2s}^p \right) \right] - log \left[\sum_{k=1}^{4} exp \left(\xi_{1k}^{tr} + \sum_{s=1}^{k} \xi_{1s}^p \right) \right]$$

[5] If we shut down the transitory shock the annualized standard deviation of the permanent shock is 0.212. Similarly the annualized standard deviation of the transitory shock is 24.6%.

Table 6: Results: Quarterly Firm-Shock Process

	All firms	Construction	Manufacturing	Retail	Services
$\sigma_{\xi^{tr}}$	0.4755	0.4803	0.4333	0.4603	0.5034
	(0.0016)	(0.0034)	(0.0032)	(0.0029)	(0.0027)
$\sigma_{\xi^{p}}$	0.1552	0.1153	0.1399	0.1555	0.1745
	(0.0007)	(0.0019)	(0.0012)	(0.0012)	(0.0012)

taking job transitions into account. Based on this first stage, the wage residuals $P_{i,a,t} + \varepsilon_{i,a,t} + \upsilon_{i,j(a_0),a,t}$ can be used as the relevant input into the model estimation.

The estimation applies a modified Heckman two-step procedure that takes the discrepancy in data frequency between model and data into account. In theory, we assume that all decisions of individuals and firms happen at a quarterly basis. Yet, in the data we only observe wages as an annual average over all quarters. As a result, our observed outcome variable in levels is the average quarterly wage,

$$w_t = \frac{\sum_{qt=1}^{4} w_{qt}}{\sum_{qt=1}^{4} E_{qt}}.$$

To make the model consistent with the data, we aggregate quarterly selection correction terms in the annual wage model. If the error term follows a log normal distribution, the conditional expectation of observed average quarterly wages yields the empirical specification

$$\log E\left[w_t \,|\, x_t, z_t,\, E=1\right] = x_t'\beta + \log\left[\sum e^{\rho\lambda(z_{qt}'\delta)} / \sum E_{qt}\right] + \frac{1}{2}\sigma_v^2. \tag{12}$$

The last term in this equation explicitly shows the bias from aggregating individual wage information at annual frequency, even though wages are determined at a higher frequency.[6] The additional variance term $\frac{1}{2}\sigma_v^2$ will be absorbed by the constant in the regression. The second term is a nonlinear function of quarterly Mills ratios $\lambda\left(z_{qt}'\delta\right)$. This term implies that

[6]This aggregation bias term is reminiscent of the bias due to individual heterogeneity in Blundell, Reed and Stoker (2003) when analyzing aggregate wages.

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 the decision criteria for participation z_{qt} change at quarterly frequency, a nonlinear specification is needed that takes seasonal changes in participation into account when aggregating employment choices to the annual level. The estimation approach based on equation (12) 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.

In particular, our specification is given by

$$\begin{aligned}\ln w_{it} &= \gamma_0 + \sum_{\tau=1}^{4} \text{age}^{\tau} \cdot \gamma_{a\tau} + \text{educ} \cdot \gamma_{el} + \text{industry} \cdot \gamma_s + \text{married} \cdot \gamma_m \\ &\quad + \text{kids below age 4} \cdot \gamma_k + \text{benefits} \cdot \gamma_b + \gamma_r + \gamma_t + u_{it}^{w} \\ E_{it} &= 1\left\{ z_{it}'\delta + u_{it}^{E} > 0 \right\}.\end{aligned}$$

The above equation is estimated separately for our two braid education groups (less than college and some college or more). Within each category there are more detailed educational levels and we control for these. We also include a fourth-order polynomial in age and industry dummies. Since our selection equation also includes demographic characteristics, which we do not wish to use as exclusion restrictions we also include marital status and dummies for children in different age groups as well as region-fixed effects. Time dummies are used to control for aggregate trends. The same set of control variables are also included in the participation choice equation, but we use region-time fixed effects in the quarterly participation equation as excluded instruments to estimate the selection effect. These instruments are motivated by the fact that income taxes in Sweden are determined at a community level and the cost of living, in particular housing or rental prices, differs widely across regions and over time. As a consequence, the opportunity cost of work differs across regions and time. However, we assume that the labor market is integrated and that other than fixed regional effects and time effects the interactions can be excluded (see for example Blundell, Duncan, and Meghir (1998).

Finally, we acknowledge the role of measurement error in employment. For example, it is quite common for individuals in Sweden to receive some payments from their employers while on parental leave. If these payments are sufficiently high, then those individuals will be falsely considered employed and will appear as particularly bad working types in the data even though they should be considered out of work during that period. These cases would lead to overestimating the amount of low-productivity types in the labor market and will bias the estimation results.[7] In order to address this type of measurement error, we directly include controls for parental leave and sickness benefits into our wage and participation equations.

4.3 Full Model Estimation

Using the stochastic process of firm productivity and the wage residuals as inputs, we estimate the model parameters

$$\beta = \left\{\delta, \theta, \kappa^p \kappa^t, b, \phi_1, \rho, \sigma^2_\zeta, \sigma^2_\varepsilon, \sigma^2_{\psi^p}, \sigma^2_{\psi^t}, \sigma^2_{\psi^{init}}, \lambda_{U,0}, \lambda_{U,1}, \omega\right\}$$

by the simulated method of moments. This requires us to construct moments simulated from the model that are equivalent to those in the data. We treat wage residuals as observed and start the simulation when a worker enters a new job out of unemployment. Firm shocks are drawn from the productivity process in equation (11). We simulate workers' behavior for the number of periods that we observe them in the data and compute the auxiliary moments of participation, mobility and wages for the simulated economy. We use MCMC techniques

[7]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) for details.

following Chernozhukov and Hong (2003) to fit the model to data moments that capture the main aspects of labor market dynamics.

4.3.1 Initial Match Effect

The first empirical challenge is to measure the initial match value after labor market entry from unemployment in order to simulate wage dynamics forward. The annual wage residual is based on the sum of quarterly wages and is thus a nonlinear combination of quarterly shocks over the year,

$$u_{it} = \sum_{q=1}^{4} e^{(P_{qit} + \epsilon_{qit} + v_{qit})}.$$

As a result, the simulation estimation faces a complex combinatorial problem. Take someone who works in the same firm for the whole year. Not all combinations of shock draws over the year are consistent with the observed behavior because we know the worker did not go into unemployment and did not change jobs. In order to simulate the match effect at the end of the year, we need to condition on the total residual we observe, and on the entire employment history during that year. All residuals in every quarter must be consistent with the person working in the four quarters in that firm. Hence this procedure would require a complex algorithm that draws a sequence of residuals that add up to the total required *and* are consistent with the observed behavior.

Given these insights, we restrict the estimation sample to those workers who ever start a new job out of unemployment in the fourth quarter of a year. For this sample, we directly observe the wage residual of their fourth-quarter salary. We avoid issues of consistency within the year and back out the match effect at the current job given the observed quarterly wage residual. Conditional on a parameter guess β, we simulate the initial match effect and the transitory wage shock, and we infer the permanent productivity component as the remaining wage component. Based on these initial values, we can simulate a person's behavior forward.

4.3.2 Data Moments and Identification

This section describes the choice and computation of the data moments to estimate the model. In particular, we emphasize challenges because of different data frequencies. We provide intuition how these moments relate to structural parameters. Formal identification proofs are mostly absent in the literature using these simulation techniques (see Altonji, Smith and Vidangos (2013) or Bagger, Fontaine, Postel-Vinay and Robin (2011) for recent examples).

Employment and job mobility decisions are observed at a quarterly frequency, whereas wages and firm shocks are only observed yearly. We want to exploit the additional variation in choices and transition probabilities in order to estimate quarterly variances of permanent and transitory shocks to the worker. At the same time we acknowledge the coarser structure of the data with respect to wages in order to estimate the wage equation for example. In practice, we will assume quarterly processes for all shocks in the simulation, but in order to compute moments corresponding to the outcome in the real data, we need to aggregate firm shocks and wages within each year.[8]

The data moments first include quarterly participation and job mobility which relate directly to the structural parameters δ and θ respectively. Note that all transition and participation probabilities are computed for different five-year age groups $[26-30, 31-35, 36-40, 41-45, 46-50, 51-55]$ to capture differences in the cross-sectional variance of permanent shocks and the amount of search capital over the life cycle. Participation rates by age groups are an important indicator of how important wage residuals are (ϕ_1) relative to preferences $z'\delta$. Furthermore, the quarterly job creation rate relates to the arrival rate of offers by age and the distribution of initial offers. Quarterly job transition rates across sectors and firm size groups help identify job offer probabilities ω.

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

Quarterly job separations are endogenous and directly relate to transitory and permanent shock variances. We further measure the size of wage shocks from annual moments related to earnings. 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. Specifically, we use the variance and autocovariance of wage growth for stayers, which are related to both firm-level and individual-level shocks. The first-order autocovariance helps to separate out transitory and permanent shocks.

We distinguish idiosyncratic and firm-level shocks by measuring 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 intraclass correlation of wage growth is defined as

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

and is closely related to the structural parameters κ^p and κ^{tr}. We further distinguish match-specific and individual-specific shocks by comparing wage growth for stayers and movers. Wage information in transition years is not very reliable because we do not know the exact timing for job-to-job mobility. We therefore choose to not use wage information for these years and instead use mover information by looking at residual wage growth across periods before and after the switch occurred, $\tilde{e}_{t+1} - \tilde{e}_{t-1}$. We control for the number of periods of consecutive mobility ys and the number of job moves that occurred JJ,

$$\tilde{e}_{+1} - \tilde{e}_{-1} = const + c_1 \cdot JJ + c_2 \cdot ys + \epsilon_{jj}.$$

The residual from this regression, $\tilde{\epsilon}_{jj}$ can then be used to compute the variance of between-jobs wage growth, which in turn will be informative about the variance of match-specific effects for example. Finally, the covariance between wage residuals and mobility residuals helps to identify the variance of match-specific effects whereas the covariance between wage residuals and participation residuals is affected by transitory and permanent shock variances.

4.3.3 MCMC Estimation

We maximize the GMM objective function

$$L_n(\theta) = -\frac{n}{2}(g_n(\theta))' W_n(\theta)(g_n(\theta))$$

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

$$E[m_i(\theta_0)] = E\left[\Gamma^D - \Gamma^S(\theta_0)\right] = 0.$$

We use equally weighted minimum distance, $W = I$, for the reasons discussed in Altonji and Segal (1996).

The objective function will not necessarily be a smooth function of the underlying model parameters and there are likely to be multiple local optima. As a result, we use a Laplace type estimator (LTE) as proposed by Chernozhukov and Hong (2003) to estimate the remaining model parameters.

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 $L_n(\theta)$ into a quasi-posterior

$$p_n(\theta) = \frac{e^{L_n(\theta)}}{\int_\Theta e^{L_n(\theta)} d\theta}$$

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

$$\theta^{(j+1)} = \begin{cases} \xi & \text{with probability} \quad \rho\left(\theta^{(j)}, \xi\right) \\ \theta^{(j)} & \text{with probability} \quad 1 - \rho\left(\theta^{(j)}, \xi\right) \end{cases}$$

where

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

Our estimator follows as the quasi-posterior mean

$$\hat{\theta} = \int_{\Theta} \theta p_n(\theta)\, d\theta,$$

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

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

This estimation strategy is a good fit for our problem because MCMC only requires many function evaluations $L_n(\theta)$ at different parameter guesses but the method is derivative-free and can deal with multiple local minima quite well.[9]

5 Results

5.0.1 Model Fit

Table 7 shows the fit of the model compared to the data. Our model captures all key transition patterns closely and is able to predict wage variation for stayers and movers within and across firms very well. Importantly the labor market transitions are captured extremely well, including the transitions between industries and different firm types. We are

[9] See the discussion in Chernozhukov and Hong (2003) for more details.

Table 7: Moments: Data and Simulation

		Some College		High School or Less	
	by age	DATA	mean	DATA	mean1
Unemployment frequency	26-30	0.1220	0.1029	0.1644	0.1535
	31-35	0.0980	0.1030	0.1347	0.1351
	36-40	0.0900	0.0910	0.1234	0.1203
	41-45	0.0874	0.0840	0.1154	0.1148
	46-50	0.0862	0.0811	0.1061	0.1036
	51-55	0.0862	0.0845	0.0961	0.0936
Job creation frequency	26-30	0.2400	0.2206	0.1806	0.1705
	31-35	0.1945	0.1993	0.1659	0.1674
	36-40	0.1699	0.1848	0.1562	0.1593
	41-45	0.1548	0.1587	0.1480	0.1505
	46-50	0.1377	0.1403	0.1409	0.1422
	51-55	0.1231	0.1128	0.1367	0.1332
Job separation frequency	26-30	0.0194	0.0372	0.0283	0.0475
	31-35	0.0152	0.0284	0.0215	0.0316
	36-40	0.0134	0.0216	0.0192	0.0257
	41-45	0.0126	0.0179	0.0175	0.0235
	46-50	0.0120	0.0153	0.0158	0.0199
	51-55	0.0119	0.0149	0.0149	0.0166
Job mobility frequency	26-30	0.0458	0.0477	0.0336	0.0337
	31-35	0.0385	0.0373	0.0280	0.0276
	36-40	0.0319	0.0287	0.0241	0.0231
	41-45	0.0271	0.0234	0.0210	0.0199
	46-50	0.0227	0.0207	0.0182	0.0177
	51-55	0.0191	0.0199	0.0160	0.0158
Pr(EtoE to new industry)		0.3573	0.3557	0.3372	0.3366
Pr(EtoE to new firm size)		0.5066	0.5065	0.4779	0.4784
Pr(EtoE to new industry and new size)		0.2133	0.2131	0.2118	0.2118
$V(\Delta\tilde{e}_t \mid E_{t-1}=1, E_t=1, J_t=0)$		0.0345	0.0326	0.0250	0.0234
$C(\Delta\tilde{e}_t, \Delta\tilde{e}_{t-1} \mid J_t=0)$		-0.0047	-0.0075	-0.0035	-0.0019
$E(\tilde{e}_{t+1}-\tilde{e}_{t-1} \mid E_{t-1}=1, E_t=1, J_t=1)$		0.0394	0.0393	0.0258	0.0267
$V(\tilde{e}_{t+1}-\tilde{e}_{t-1} \mid E_{t-1}=1, E_t=1, J_t=1)$		0.0663	0.0620	0.0537	0.0533
spatial correlation coefficient (for stayers)		0.1821	0.1868	0.1783	0.1781
$Cov(U_t^E, U_t^w \mid E_t=E_{t-1}=1, J_t=0)$		0.0003	0.0005	-0.0002	0.0001
$Cov(U_t^E, U_t^w \mid E_t=E_{t-1}=1, J_t=1)$		0.0194	0.0183	0.0031	0.0047

also able to capture accurately the age profile of unemployment and job mobility.

At the bottom of the Table we report the covariance properties of residuals. The variance of wage growth for stayers is captured extremely well. We find that the autocovariance of wage growth for stayers is almost zero and while we do not capture it very well the magnitudes are unimportant from an economics perspective. When it comes to job movers, we only consider the wage growth between the year before the move and the year after the move. This reduces the effects of measurement error, induced by the fact that the earnings record concerns the entire year. The relevant statistics are presented at the bottom of the table ($E(\tilde{e}_{t+1} - \tilde{e}_{t-1} | E_{t-1} = 1, E_{t+1} = 1, J_t = 1)$ and $V(\tilde{e}_{t+1} - \tilde{e}_{t-1} | E_{t-1} = 1, E_{t+1} = 1, J_t = 1)$). They are reproduced very accurately by the model. The last two moments in the table relate to the covariance of an employment residual (from a linear probability model) with the wage residual for stayers and movers. This helps capture the selection effects on wages.

One of the most important moments for our purposes is the spatial autocorrelation of the shocks to wages. These relate to wage growth and hence do not reflect correlation in wages because of sorting among similar workers into a firm, but reflect how changes in wages are correlated, reflecting how wages of all workers may be changing because of firm level shocks. This correlations is quite high (0.18) and is reproduced by the model; in other words the model is able to reproduce the way wages of workers in the same workplace move together from period to period.

5.0.2 Parameter estimates

The model is estimated on men.[10] The estimates of the age profile of wages are presented in the appendix.

We compute the data moments based on workers who start working in the fourth quarter of a year during our sample period. We estimate 10 MCMC chains of 50,000 elements and

[10]We do not present results for women because these are much harder to interpret given that earnings variation reflects changes in hours as well as productivity.

Table 8: Participation and job mobility

		Male, At least some college		Male, High School or Less	
Parameter	Description	estimate	MCMC stdev	estimate	MCMC stdev
		Employment			
δ_0	Constant, participation	-0.4435	0.0927	3.7380	0.3133
δ_{age}	Age, participation	1.0399	0.0430	0.7696	0.1187
δ_{age2}	Age squared, participation	-0.0963	0.0066	-0.0131	0.0152
ϕ_1	wage residual	0.4931	0.1154	14.2421	0.9711
	Marginal Effect of 10% wage change	0.0088		0.328	
		Job-to-job Mobility			
θ_0	Constant, mobility	-0.2098	0.1956	-1.2212	0.1679
θ_{age}	Age, mobility	-0.6846	0.1055	-0.2673	0.0762
θ_{age2}	Age squared, mobility	0.0620	0.0177	0.0167	0.0115
b	Wage improvement	1.0514	0.1747	0.8824	0.0788
	Marginal Effect of 10% wage improvement	0.011		0.0066	

report average coefficients across the pooled chains based on the last 5,000 elements of each chain.[11] The moments simulated from the model mimic the moments we compute from the data and hence any sample selection is controlled for.

The results for participation in Table 8 show the expected increasing concave pattern in age (δ parameters). These patterns closely match what we see in the data. The impact of wages on participation is given by the coefficient ϕ in the Table. The effect is positive and significant, with a notably higher value for lower skill workers. As noted earlier this is a mix of a selection and an incentive effect and in this context we have no way of distinguishing the two.

In order to help interpret the size of the coefficient note that we normalize the variance of the error term in the participation equation to 1. Hence, instead of the absolute magnitude of the coefficients, we have to interpret the relative importance of ϕ_1 times the variances of productivity shocks on the one hand and worker observables like age on the other hand. The higher value for lower skill workers reflects both stronger self selection into the labor market and weaker attachment, in the sense that wage shocks induce lower skill workers to move in and out of work, something that is much less prevalent for high skill ones.

[11] The first 20,000 elements of the chain are computed based on a preset error variance. For the subsequent chain, we use an adaptive procedure to take the covariance structure of the previous chain into account and to target an acceptance rate of 23.4%.

Table 9: The stochastic process of individual productivity

		Male, At least some college		Male, High School or Less	
Parameter	Description	estimate	MCMC stdev	estimate	MCMC stdev
σ_ϵ	transitory shock, wages	0.1947	0.0192	0.1453	0.0071
ρ	AR(1) productivity coefficient	0.9954	0.0073	0.6364	0.0404
σ_ζ	permanent shock, wages	0.0332	0.0141	0.0001	0.0007

Mobility is decreasing in age matching what we see in the data. The coefficient b is estimated to be large and positive, which shows that mobility choices are highly influenced by the wage difference between incumbent and poaching firm; this is true for both education levels. This limits the ability of the incumbent firm to lower wages as a result of shocks. However, mobility is not driven by wages only. Mobility costs that vary by age also matter, as do exogenous shocks.

The stochastic process of wages, shown in Table 9, is remarkably different across skill groups, as we might expect when considering Figure 2. For the high skill group earnings are a random walk, pushing the variance up over the lifecycle, while for the lower skill workers the productivity process is effectively iid, with a relatively small variance of the random shock. The size of the autocorrelation coefficient is identified through the way that wages in subsequent periods are correlated to the initial draw at entry into the labor market.

Table 10 [resents information on the transition process between jobs and sectors. The arrival rate of job offers implies about one job sampled every 2.7 quarters for the high skilled and one every year for the lower skill workers. These rates do not change with age. However, there is an age profile in labor force participation. Identification is driven by the asymmetry between job exit and job re-entry by age.

The coefficients $\omega_k,\ k = 0, 1, 2$ show how offers to different firm types and industries vary. They imply that sampling jobs from other sectors is smaller than from the same sector.

Table 10: Estimation Results

	Parameter	At least some college Estimate	MCMC stdev	High School or Less Estimate	MCMC stdev
	Job arrival rate: $\lambda_{U,0} + \lambda_{U,age} \times age$				
	$\lambda_{U,0}$	0.3666	0.0157	0.2393	0.0091
	$\lambda_{U,age}$	0.0047	0.0004	0.0019	0.0002
	Origin of offer				
Parameter	Description	Estimate	MCMC stdev	Estimate	MCMC stdev
ω_0	different firm size and sector	0.2151	0.0080	0.2123	0.0048
$\omega_0 + \omega_1$	different firm size and same sector	0.2918	0.0112	0.2668	0.0070
$\omega_0 + \omega_2$	same firm size and different sector	0.1423	0.0112	0.1248	0.0069
$\omega_0 + \omega_1 + \omega_2$	same firm size and same sector	0.3508	-	0.3961	-

5.1 Match value and transmission of shocks.

In Table 11 we show the key parameters for our study, namely the transmission of shocks. For the workers with higher education the transitory shocks are not transmitted to workers at all. The coefficient is small and insignificant. In other words the firm absorbs any transitory changes to productivity without attempting to get the workers to share the shock. However, permanent shocks are transmitted. The effect is large with 38% of an innovation being transmitted to wages, an effect which is highly significant. Thus when the fortunes of firms change permanently they change the wages of high skill workers permanently, implying a high degree of rent sharing. which is consistent with what Guiso, Pistaferri and Schivardi (2005) found for Italy.

The story is quite different for lower skill workers. Their wages fluctuate based on transitory shocks (30% transmission) but not as a result of permanent shocks, where the effect is close to zero. This may indicate a stronger level of competition in the lower skill market, as well as wages closer to reservation values, which do not allow for any reductions, without workers quitting. It may also reflect more union protection.

The remaining coefficients in Table 11 relate to the idiosyncratic match value. The

Table 11: Shocks and their transmission

		Male, At least some college		Male, High School or Less	
Parameter	Description	estimate	MCMC stdev	estimate	MCMC stdev
κ^{tr}	transitory firm shock, match value	0.0329	0.0351	0.2971	0.0108
κ^{p}	permanent firm shock, match value	0.3831	0.0173	0.0496	0.0303
$\sigma_{\psi^{tr}}$	transitory idiosyncratic shock, match value	0.0067	0.0079	0.0007	0.0014
$\sigma_{\psi^{p}}$	permanent idiosyncratic shock, match value	0.0303	0.0304	0.0000	0.0000
$\sigma_{\psi^{init}}$	permanent initial shock, match value	0.0068	0.0106	0.1432	0.0075

Note: The standard deviation of the transitory firm-level shock is 0.4755, for the permanent firm-level shock the standard deviation is 0.1552.

results here indicate a small role for of for initial heterogeneity in idiosyncratic match effects for higher skill workers. The variance of the initial match value is effectively zero; the permanent shocks to this initial match value are comparable to the permanent productivity shocks (standard deviation 0.03 each) but transitory shocks are unimportant. When we turn to lower skill workers there seems to be substantial permanent heterogeneity in idiosyncratic match values (standard deviation 0.14) but this seems to remain unchanged with the variance of the shocks to this initial value being effectively zero. The important point that emerges from these results is that a large fraction of match effects on wage variability is explained by shocks to firm productivity.

It is important to note that these results are not driven by omitted match specific effects, but by the firm level shocks that are observed and by the correlation of wages between workers. Allowing for idiosyncratic match value is also important because it accounts for changes in wages across firms for the same worker, even without allowing for firm level productivity shocks. Thus match specificity originates from productivity shocks and essentially relates to non-competitive behavior in the labor market.

5.1.1 Simulations

In order to interpret our results, we report model simulations in Table 12. We simulate the life-cycle for 20,000 individuals, of which 85% receive an initial offer in the first period, while

15% enter into unemployment. We allocate these offers across individuals according to the cross-sectional distribution of workers in different sectors and firm-size bins as reported in Table 2. We then analyze earnings dispersion, participation and mobility over the life-cycle for the full model and when shutting down different types of shocks subsequently.

Table 12 considers the model with endogenous participation and mobility choices. As we expect from the data we see that the cross sectional variance of earnings increases over time. In the second set of three columns we switch off firm level shocks. By the age of 55 the cross sectional variance is 0.09, compared to the full variance of 0.22. In other words firm level shocks, which are transmitted to wages, explain more than half of the cross sectional dispersion of wages for workers with at least some college education. As we would expect from the parameter estimates standard match effects (last three columns) do not contribute to the cross sectional variance. Perhaps surprisingly, these shocks do not explain much of the overall participation or mobility rates by age; this is despite the fact both these decisions depend on the wage and the wage gains from moving, respectively. For workers with high school education, the share of wage variation explained by firm-level shocks at age 55 is around 25%. For these workers, variation in initial match values plays an important role for the overall wage variance.

6 Conclusion

In this paper we use matched employer employee data to estimate the stochastic properties of the wage process for individuals and the way it may be impacted by productivity shocks to the firm. Our model accounts for endogenous participation and mobility decisions and thus deals with the potential truncation in the impact of productivity on wages that is induced by people quitting into unemployment or changing employer.

The key finding is that permanent productivity shocks transmit to individual wages for

Table 12: Simulations

	At least some college			High School		
	Full Model			Full Model		
Age	Var(Earnings)	Participation	Mobility	Var(Earnings)	Participation	Mobility
26	0.0166	0.8019	0.0000	0.0246	0.7774	0.0000
35	0.0846	0.8899	0.0277	0.0249	0.9083	0.0175
45	0.1535	0.9341	0.0187	0.0273	0.9450	0.0146
55	0.2102	0.9278	0.0139	0.0275	0.9581	0.0112
	No Firm Shocks			No Firm Shocks		
Age	Var(Earnings)	Participation	Mobility	Var(Earnings)	Participation	Mobility
26	0.0137	0.8019	0.0000	0.0222	0.7774	0.0000
35	0.0470	0.8858	0.0283	0.0202	0.9668	0.0195
45	0.0722	0.9293	0.0193	0.0208	0.9839	0.0153
55	0.0906	0.9204	0.0154	0.0216	0.9893	0.0123
	No Firm Shocks, No Match Effects			No Firm Shocks, No Match Effects		
Age	Var(Earnings)	Participation	Mobility	Var(Earnings)	Participation	Mobility
26	0.0134	0.8018	0.0000	0.0061	0.7967	0.0000
35	0.0462	0.8860	0.0284	0.0054	0.9782	0.0220
45	0.0710	0.9293	0.0196	0.0053	0.9901	0.0174
55	0.0889	0.9202	0.0152	0.0053	0.9958	0.0145

high skill workers: the elasticity of wages with respect to permanent productivity shocks is 0.38. In other words firms pass a part of their permanent good or bad fortune to wages. However transitory (iid) shocks have no impact on the wages of the high skill workers. They do however affect the wages of the low skill workers. We find that the variance of wages increases over the lifecycle because of a permanent individual shock that sticks with the worker. However, by age 55 72% of the cross sectional variance of wages for high skill workers is is attributable to firm level shocks. For these workers, there is no other source of match specific effects, other than through these firm level productivity shocks. For lower skill workers, random match specific effects do play a role in driving the variance of wages.

A Wage Residuals

The results for the first-stage estimation are presented in Tables 13 and 14. For readability, we suppress region effects, time effects and region-time interactions in the participation equation and time and region effects in the wage regression. Instead we only report the coefficients for personal characteristics.

First, consider the results for participation choices in Table 13. The table reports probit estimates, and we focus on the sign patterns of the results. For men, having children up to three years of age significantly decreases the probability of participating in the labor market, but older children increase participation. Women with at most high school education are less likely to work if they have children and the relationship is stronger the younger the children are. Highly educated women often seem to combine having children and a career. They are likely to temporarily leave the workforce when the child is very young but they reenter soon afterwards and are more likely to participate than women without children. This behavior is consistent with high-productivity types achieving higher education and being more likely to work. Temporary absence is facilitated by the Swedish system of parental leave benefits that offers 80% of previous earnings 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 men with young children. Interestingly, married men are more likely to work, but the same is true to a lesser extent for women as well.

The coefficients on parental leave and sickness benefits confirm the measurement problems in employment status described above. For example, parental leave payments increase the probability of being employed for men. 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. For women the relationship is negative, but relatively small. Hence these results suggest that as for men, some women will be considered employed at low wages during their parental leave. The coefficient for sickness benefits is negative and significant for all gender-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.

Table 13: First-Stage Results: Participation Equation

	Male		Female	
	High School	Some College	High School	Some College
constant	0.1940***	0.9833***	0.3825***	1.0144***
	(0.008)	(0.019)	(0.013)	(0.026)
age	0.9059***	0.4661***	0.7258***	0.3402***
	(0.005)	(0.010)	(0.007)	(0.012)
age^2	-0.7315***	-0.5345***	-0.4293***	-0.3274***
	(0.004)	(0.011)	(0.006)	(0.014)
age^3	0.2609***	0.2313***	0.1456***	0.1445***
	(0.001)	(0.004)	(0.002)	(0.006)
age^4	-0.0314***	-0.0326***	-0.0187***	-0.0210***
	(0.000)	(0.001)	(0.000)	(0.001)
child 0-3 yrs	-0.0576***	-0.0062***	-0.2948***	-0.1838***
	(0.001)	(0.002)	(0.001)	(0.002)
child 4-6 yrs	0.0264***	0.0525***	-0.0995***	0.0022
	(0.001)	(0.002)	(0.001)	(0.002)
child 7-10 yrs	0.0262***	0.0495***	-0.0815***	-0.0017
	(0.001)	(0.002)	(0.001)	(0.002)
child 11-17 yrs	0.0341***	0.0983***	-0.1007***	0.0108***
	(0.001)	(0.002)	(0.001)	(0.002)
married	0.3060***	0.2279***	0.1476***	0.1532***
	(0.001)	(0.001)	(0.001)	(0.002)
parental leave	0.0205***	0.0318***	-0.0853***	-0.0583***
	(0.000)	(0.001)	(0.000)	(0.000)
sickness benefits	-0.0900***	-0.0987***	-0.0979***	-0.0872***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	38,824,193	11,653,681	17,881,403	6,463,989
Wald test [df=220]	19425.29	4102.50	5881.99	1623.23
Wald test [p-value]	0.0000	0.0000	0.0000	0.0000
Pseudo R-squared	0.0744	0.0406	0.1132	0.0688

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

Note: All specifications include region, year and region-year fixed effects. Standard errors in parentheses. Wald tests report test statistics and p-values for the exclusion restriction of region-time interactions in each specification.

Table 14: Wage equation

	Male		Female	
	High School	Some College	High School	Some College
constant	9.6343***	9.9937***	9.1751***	9.9701***
	(0.0075)	(0.0097)	(0.0103)	(0.0075)
age	0.6124***	0.7015***	0.7811***	0.4164***
	(0.003)	(0.008)	(0.005)	(0.009)
age^2	-0.3627***	-0.3701***	-0.4204***	-0.2532***
	(0.002)	(0.007)	(0.004)	(0.009)
age^3	0.1000***	0.1095***	0.1066***	0.0730***
	(0.001)	(0.003)	(0.001)	(0.003)
age^4	-0.0102***	-0.0133***	-0.0108***	-0.0086***
	(0.000)	(0.000)	(0.000)	(0.000)
child 0-3 yrs	-0.0373***	-0.0169***	-0.1694***	-0.1351***
	(0.000)	(0.001)	(0.001)	(0.002)
child 4-6 yrs	-0.0059***	0.0234***	-0.0888***	-0.0514***
	(0.000)	(0.001)	(0.001)	(0.001)
child 7-10 yrs	-0.0069***	0.0167***	-0.0785***	-0.0569***
	(0.000)	(0.001)	(0.001)	(0.001)
child 11-17 yrs	0.0006*	0.0230***	-0.0644***	-0.0525***
	(0.000)	(0.001)	(0.001)	(0.001)
married	0.0838***	0.1425***	-0.0213***	0.0388***
	(0.001)	(0.001)	(0.001)	(0.001)
parental leave	-0.0421***	-0.0402***	-0.0916***	-0.0830***
	(0.000)	(0.000)	(0.000)	(0.001)
sickness benefits	-0.0698***	-0.1006***	-0.0855***	-0.1005***
	(0.000)	(0.001)	(0.000)	(0.001)
Mills ratio	0.2161***	0.9770***	0.4693***	0.4431***
	(0.006)	(0.021)	(0.008)	(0.023)
Mills ratio * age	-0.1113***	-0.5110***	-0.0534***	0.3696***
	(0.004)	(0.017)	(0.005)	(0.015)
Mills ratio * age^2	0.0148***	0.0896***	0.0116***	-0.0654***
	(0.001)	(0.004)	(0.001)	(0.004)
Observations	9,010,548	2,796,200	3,921,223	1,514,611
R-squared	0.199	0.168	0.275	0.251

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

Note: All specifications include region and year fixed effects. Standard errors in parentheses. Wald tests report test statistics and p-values for the exclusion restriction of region-time interactions in each specification.

Next, consider the results for wages in Table 14. The results confirm the familar concave

Figure 7: Predicted Wages controlling for parental leave and sickness benefits (f0 = male, e0 = low-educated)

life-cycle profile of wages. These profiles are illustrated graphically in Figure 7. As we can see from the comparison with simple OLS earnings profiles in Figure 7, the model predicts that selection has an effect on the slope of the earnings profile. Positive selection into the labor market is stronger 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 increasing positive selection at the end of workers' careers again. One explanation could be early retirement based on disability, which is very common in Sweden and is more likely to be chosen by low-ability types. As a result, the wage decrease in the life-cycle of earnings is underestimated. Finally, the selection patterns for women are consistent with higher-educated women having children later in their lives, thereby leading to peak positive selection in their early to mid-thirties as illustrated in Figure 9 below.

To illustrate selection patterns across the lifecycle, 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 14 can be found in Figure 8. For male workers, 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. The same qualitative pattern holds for women with at most high-school education even though selection increases again quite strongly after the age of 45. Highly educated

Figure 8: Selection Coefficient by Age (f0 = male, e0 = low-educated)

graphs/selcoef_f0e0-eps-converted-to.pdf graphs/selcoef_f0e1-eps-converted-to.pdf

graphs/selcoef_f1e0-eps-converted-to.pdf graphs/selcoef_f1e1-eps-converted-to.pdf

Figure 9: Average Selection Effects by Age (f0 = male, e0 = low-educated)

graphs/selection_parsick_f0e0-eps-converted-to.pdf graphs/selection_parsick_f0e1-eps-converted-to.pdf

graphs/selection_parsick_f1e0-eps-converted-to.pdf graphs/selection_parsick_f1e1-eps-converted-to.pdf

females are the exception here, they display increasing selection in their 30s and 40s as lower productivity types are more likely to decide to stay out of work to bring up children for example. These patterns directly mirror the results for earnings profiles taking selection into account in Figure 7.

Overall, the wage regression implies a positive and significant selection effect for all samples. As Figure 9 suggests, wage differences because of selection are in the range of 0-20 log points, where these effects are higher for groups with higher education. Interestingly, selection among women tends to be larger than for their male counterparts conditional on education group.

References

Abowd, J. M. and Card, D. (1989). 'On the Covariance Structure of Earnings and Hours Changes.' vol. 57(2):pages 411–45.

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). 'High Wage Workers and High Wage Firms.' *Econometrica*, vol. 67(2):pages 251–333.

Altonji, J. G. and Segal, L. M. (1996). 'Small-Sample Bias in GMM Estimation of Covariance Structures.' *Journal of Business & Economic Statistics*, vol. 14(3):pages 353–66.

Altonji, J. G., Smith, A., and Vidangos, I. (2013). 'Modeling Earnings Dynamics.' *Econometrica*, vol. 81(4):pages 1395–1454.

Bagger, J., Fontaine, F., Postel-Vinay, F., and Robin, J.-M. (2011). 'Tenure, Experience, Human Capital and Wages: A Tractable Equilibrium Search Model of Wage Dynamics.' Sciences po publications, Sciences Po.

Blundell, R., Duncan, A., and Meghir, C. (1998). 'Estimating Labor Supply Responses Using Tax Reforms.' *Econometrica*, vol. 66(4):pages 827–862.

Blundell, R., Reed, H., and Stoker, T. M. (2003). 'Interpreting Aggregate Wage Growth: The Role of Labor Market Participation.' *American Economic Review*, vol. 93(4):pages 1114–1131.

Burdett, K. and Mortensen, D. T. (1998). 'Wage Differentials, Employer Size, and Unemployment.' *International Economic Review*, vol. 39:pages 257–273.

Cahuc, P., Postel-Vinay, F., and Robin, J.-M. (2006). 'Wage Bargaining with On-the-Job Search: Theory and Evidence.' *Econometrica*, vol. 74(2):pages 323–364.

Card, D., Rute-Cardoso, A., Heining, J., and Kline, P. (2016). 'Firms and Labor Market Inequality: Evidence and Some Theory.' *mimeo*.

Card, D. E., Heining, J., and Kline, P. M. (2013). 'Workplace Heterogeneity and the Rise of West German Wage Inequality.' *The Quarterly Journal of Economics*, vol. 128(3):pages 967–1015.

Chernozhukov, V. and Hong, H. (2003). 'An MCMC approach to classical estimation.' *Journal of Econometrics*, vol. 115(2):pages 293–346.

Guiso, L., Pistaferri, L., and Schivardi, F. (2005). 'Insurance within the Firm.' *Journal of Political Economy*, vol. 113(5):pages 1054–1087.

Guvenen, F. (2007). 'Learning Your Earning: Are Labor Income Shocks Really Very Persistent?' *American Economic Review*, vol. 97(3):pages 687–712.

Lamadon, T. (2015). 'Productivity shocks, Optimal Contracts and Income Dynamics.' *mimeo, University of Chicago*.

Lise, J., Meghir, C., and Robin, J.-M. (2016). 'Matching Sorting and Wages.' *Review of Economic Dynamics*, vol. 19, Special Issue in Honor of Dale Mortensen:page 63?87.

Low, H., Meghir, C., and Pistaferri, L. (2010). 'Wage Risk and Employment Risk over the Life Cycle.' *American Economic Review*, vol. 100(4):pages 1432–67.

MaCurdy, T. E. (1982). 'The Use of Time Series Processes to Model the Error Structure of Earnings in Longitudinal Data Analysis.' *Journal of Econometrics*, vol. 18:pages 82–114.

Meghir, C. and Pistaferri, L. (2004). 'Income Variance Dynamics and Heterogeneity.' *Econometrica*, vol. 72(1):pages 1–32.

Mortensen, D. and Pissarides, C. (1994). 'Job Creation and Job Destruction in the Theory of Unemployment.' *The Review of Economic Studies*, vol. 61:pages 397–415.

Postel-Vinay, F. and Robin, J.-M. (2002). 'Equilibrium Wage Dispersion with Worker and Employer Heterogeneity.' *Econometrica*, vol. 70(6):pages 2295–2350.

Topel, R. H. and Ward, M. P. (1992). 'Job Mobility and the Careers of Young Men.' *The Quarterly Journal of Economics*, vol. 107(2):pages 439–79.

Van-Reenen, J. (1996). 'The Creation and Capture of Rents: Wages and Innovation in a Panel of U.K. Companies.' *The Quarterly Journal of Economics*, vol. 111(1):pages 195–226. ISSN 00335533, 15314650.