Earnings Dynamics and Firm Level Shocks

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Preliminary and incomplete

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 worker's wages. 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). While the theoretical justification for departures from the law of one price are compelling the empirical evidence is not quite there. First, most equilibrium search models that have been estimated on empirical data assume no productivity shocks. These include recently Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay and Robin (2006). An exception is the model of Lise, Meghir and Robin (2010) which allows for the effect of productivity shocks in a context of a model with productive complementarities. However, their model is estimated on individual level data and hence cannot measure directly the productivity shocks, but infers them from the structure of the model. The recent availability of matched employer-employee data gives rise to major new opportunities in this direction. Second, models that have been estimated on matched employer-employee data, without a specific economic structure, such as Abowd, Kramarz and Margolis (1999), have focussed on sorting and firm/worker heterogeneity rather than the dynamics of shocks. A recent paper by Guiso, Pistaferri and Schivardi (2005) (GPS) has indeed measured the impact

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of firm level shocks on wages using matched employer employee data. 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 productivity shocks on wages because a worker may quit instead of suffering too large a pay cut.

In this paper we use a newly set up matched employer/employee data set from Sweden to test whether firm level productivity shocks are passed on to wages. Other than the data the key innovation is that we account both for job to job transitions and for transitions between work and unemployment. In our model we allow for a rich stochastic structure, both at the individual and the match level. We thus build on GPS by allowing for permanent and transitory productivity thus detecting which type of shock, if any, are transmitted to wages. The approach is clearly not structural in the sense that we do not estimate a model that defines the way pay setting is defined. This is left for another paper (see Lamadon, Lise, Meghir and Robin LLMR) for the simple reason that we need detailed empirical investigation and understanding of the dynamics in the data before we impose a specific structurure. While a equilibrium model defines clearly the way that shocks are transmitted it comes with a number of strong assumptions both on the form of contracting and on the structure of production if one is to have a tractable model (see LLMR). Thus our paper is the opening investigation into an agenda that will lead to richer structural models taking the firm side more seriously and allowing for a rich dynamic stochastic structure.

2 The Model

Assume wages for a particular individual i of age a and working in a firm j at time t are determined by

$$lnw_{i,a,t} = d_t^g + x_{i,a,t}'\gamma^g + P_{i,a,t}^g + \varepsilon_{i,a,t}^g + \upsilon_{i,j,a,t}^g \tag{1}$$

where x are observable characteristics explaining wages and the stochastic structure of wages includes a permanent component P, a transitory component ε and a time varying match-specific effect υ. The superscripts g indicate that the individual belongs to a specific group defined by education and gender and imply that the stochastic terms may be drawn from distributions that depend on the group.

The match-specific effect is specified as follows

$$\upsilon^g_{i,j,a,t} = \begin{cases} \rho\upsilon^g_{i,j,a-1,t-1} + \xi^g_{i,j,a,t} & J_{i,a,t} = 0 \\ \xi^g_{i,j',a,t} & J_{i,a,t} = 1 \end{cases} \tag{2}$$

where $J_{i,a,t}$ is an indicator variable that takes the value 1 if the individual change employer. The match-specific effect follows an AR(1) process for individuals who remain at their firm. Each time a worker joins a new firm they get a new draw from the distribution of initial matches $\upsilon^{init}_{i,j}$ that we assume is completely idionsyncratic to the worker/firm pair. The match specific effects of successive accepted jobs will be correlated because of the job acceptance strategy of the individual. This will be controlled for using the job change probability.

The match specific effect is subject to shocks, which in our description allows wages to fluctuate within the firm. In a competitive framework these shocks will be purely idiosyncratic and will not relate to shocks at firm level productivity. One of the key issues we are interested in is whether the shocks $\xi^g_{i,j,a,t}$ are related to total factor productivity shocks at the firm level. In other words we can consider as an alternative to purely idiosyncratic shocks the following process

$$\begin{aligned} \xi^g_{i,j,a,t} &= \kappa^g q_{j,t} + \psi^g_{i,j,a,t} \\ \psi^g_{i,j,a,t} &\sim iidN\left(0, \sigma^2_\psi\right) \end{aligned}$$

where $q_{j,t}$ are firm level shocks to total factor productivity that we assume observable. This issue involves a number of difficulties relating to identification of the TFP shocks, so we return to it later.

The permanent individual specific shock is assumed to follow

$$\begin{aligned} P^g_{i,a,t} &= P^g_{i,a-1,t-1} + \zeta^g_{i,a,t} = P^{init}_i + \sum_{s=1}^{a} \zeta^g_{i,s,t-a+s} \\ P^{init} &\sim iidN\left(0, \sigma^2_P\right) \end{aligned}$$

The transitory individual specific shock is assumed to be iid for now and subsumes the measurement error. We can generalize the model to include a "random growth" term g_i,i.e.

$$lnw_{i,a,t} = d^g_t + g_i Age_{i,a,t} + x'_{i,a,t}\gamma^g + P^g_{i,a,t} + \varepsilon^g_{i,a,t} + \upsilon^g_{i,j,a,t}$$

The model as specified allows a large variety of patterns for the shocks and is consistent with the findings in the literature, which support both the presence of heterogeneous growth profiles and unit roots, at least in the US. Thus, while specifiying a structure that is identifiable we have not constrained the model, allowing both stochastic growth and heterogeneous profiles.

One of the key issues is controlling for selection into work and for job mobility, both of which may truncate the distributions of the shocks. We now specify two selection equations similar to Low, Meghir and Pistaferri (2009) and Altonji, Vidangos and Smith (2009).

Define $E_{i,a,t} = 1$ if the individual works and zero otherwise. Then we assume that employment is governed by

$$E_{i,a,t} = 1\left\{Z'_{i,a,t}\delta + \phi_1\left(P_{i,a,t} + \upsilon_{i,j,a,t}\right) + u^E_{i,a,t} > 0\right\}$$

and job mobility by

$$J_{i,a,t} = 1\left\{Z'_{i,a,t}\theta + b_1\upsilon_{i,j,a,t} + b_2\xi_{i,j',a,t} + u^J_{i,a,t} > 0\right\}$$

In the above equations employment and job mobility depends on exogenous characteristics $Z_{i,a,t}$ which includes $X_{i,a,t}$ as well as exclusion restrictions such as number of children and marital status that will be excluded from the wage equation. Importantly we have allowed the participation and job mobility equations to depend on the stochastic elements of the wage equation and on the permanent heterogeneity.

The model at this point includes firm information just to identify job mobility. We now consider the way that firm level shocks can affect individual wages. The aim here is to provide a link between the firm performance and wages based on the match specific effect. Ultimately, this should be achieved based on a structural model, but such a model, where there are potential complementarities between the firm and the worker are not available at this point and are likely to be highly complicated, particularly when we wish to account for shocks. The key difficulty is that we need to model how wage negotiations take place as workers arrive and depart from the company and as the firm and the worker receive productivity shocks.

We assume that the firm produces output based on the production function$Y_{jt}/K^{1-\theta}$

$$Y_{jt} = TFP_{jt}\left[\sum_{g=1}^{G} H_{gjt}^{\rho}\right]^{\frac{\theta}{\rho}} K^{(1-\theta)}$$

where, H_{gjt} represents human capital of group g employed in firm j in period t and K represents physical capital. The issue with this production function is that the amount of human capital is not directly observed and has to be inferred from wages. As Lise, Meghir and Robin (2009) have shown amongst others the pay rates are a complex function of underlying heterogeneity. Moreover, different assumptions imply a different relationship between underlying unobservables and human capital. We have thus decided to follow three different approaches to extract firm level shocks and relate them to wages.

Our first measure is based simply on (log) output. In this case we will define shocks to relate to output. Output can change as a result of physical investment K, changes in the number of employees, changes in the composition of employees and changes in total factor productivity. None of these factors should affect wages in a competitive labour market. Thus our first approach relates the individual match specific effect to output shocks.

Next, in an attempt to decompose the originin of the shocks we control for changes in physical capital by considering how shocks to $Y_{jt}/K^{1-\theta}$ affect wages. These shocks are due to all changes in the firm, other than investment in physical capital.

Finally, we attempt to get to shocks to TFP by constructing levels of human capital by averaging wages within the firm and controlling for the aggregate price of human capital $exp(d_t^g)$ in equation 1.[1]Thus we define human capital in each group as

$$H_{jt}^{g} = \sum_{i\epsilon j} exp(lnw_{ijt} - d_t).$$

Having defined human capital in this way we can estimate the substitution elasticity between different forms of capital and thus construct TFP as

$$TFP_{jt} = Y_{jt}/\left\{\left[\sum_{g=1}^{G} H_{gjt}^{\rho}\right]^{\frac{\theta}{\rho}} K^{1-\theta}\right\}$$

[1]It should be noted that this procedure is, strictly speaking, valid under the null of no search frictions; otherwise wages do not reveal necessarily the amount of human capital employed because of the complex nature of pay setting in the presence of search frictions.

Denote the source of production shocks by S_{jt}. This will be taken to be log output, log output adjusted for capital and log output adjusted for capital and human capital. We consider time series structures for this of the form

$$\Delta S_{jt} = f_j + \psi_{jt} + \tau_{jt}$$

where

$$\tau_{jt} = \pi \tau_{jt-1} + \varpi_{jt}.$$

Thus we decompose the growth in TFP in a permanent firm growth rate, a permanent shock and transitory shock. The latter may be better specified as an MA process, but this is an empirical question we will addressing.

3 Estimation

The estimation of the model is quite complex because of the dynamics and because of transitions between work and different jobs. We will first estimate the dynamics of wages, ignoring the firm as well as the dynamics of the productivity shocks ignoring wages. In the next step we will will bring the two together. All estimation steps will be based on the method of simulated moments.

To estimate the dynamics of wages we will construct variances and autocovariances from the observed data, which we will match the the equivalent moments derived from simulated data. To capture the effects of mobility, we will construct moments depending on the whether the individual changed jobs, or moved to work from unemployment, or remained in the same employment etc. Such moments will also be conditioned on the exogenous variables driving mobility and participation. Similar ideas will be used to estimate the dynamics of firm productivity. To capture the impact of the productivity shocks on wages we will subsequently add cross moments between the firm and the worker.

As discussed in Section 2, we estimate earnings dynamics separately for different education-gender groups. We use three different education groups: less than high school; high school; and some college. This implies six different education-gender groups in the estimation.

4 Data

4.1 The Data Set

The data set we have compiled combines information from three different data sources at Statistics Sweden. From The Longitudinal Database for Education, Income and Employment (LOUISE) we use register-based information on demographic and socioeconomic variables for the entire working age population in Sweden during 1990–2007. In particular, we use information about age, gender, municipality of residence, number and ages of children, marital status and education level as well as collection of benefits from the public pension system, the disability, sickness and unemployment insurances, the parental leave system and the student aid system. All variables in LOUISE are registered on a yearly basis.

For detailed information on the labor market activities of individuals we use data from The Register-Based Labour Market Statistics (RAMS) during 1990-2007. RAMS contains information on the universe of employment spells of the working age population in Sweden along with some information about the employers. For each employment there are records of the worker, firm and plant identifiers, the start and end months of the employment and the gross yearly earnings from the employment. We define monthly earnings as gross earnings per month worked, and exclude employment spells with monthly earnings below the discounted 1990 basic amount[2] - about 300 euros in 2007. We use the data from RAMS to define employment on a quarterly basis. 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. Combined with the LOUISE data, we thereby get the complete employment histories per quarter for all working age individuals in Sweden during 1990-2007. In each quarter, we record if an individual is a job mover, a job stayer or an entrant from non-employment.

On the firm side, RAMS contains information about institutional sector, industry and the type of legal entity of all firms with employees. We combine this with accounting data and balance sheet information from The Structural Business Statistics (SBS). SBS covers all non-financial corporations in Sweden from 1997 onwards, and a subset of corporations during 1990-1996. Since we want to analyze a comparable sample of firms and inviduals over the entire

[2]The basic amount is set by the government each year and is used in calculations of taxable transfers.

period, we base our selection of firms in RAMS on the types of firms that are represented in SBS from 1997 onwards. In particular, we select firms in the non-financial corporate sector, within a large set of industries[3]and of certain types of legal entity[4]. We exclude firms with less than 5 employees in any quarter in a year. For the firms that fulfill our selection criteria, we select all workers in each quarter from the worker panel described above along with their entire employment histories.

4.2 Description of the Data

Table 1 presents summary statistics for the firms in our data set. The data contains more than 130,000 unique firms and more than 800,000 firm-year observations from 1990 to 2007, an average of 45,000 firms per year. As explained above, we have accounting data for all firms from 1997 onwards, but only for a subset of firms from 1990 to 1996. In total, we have accounting data for 75 percent of the firm-year observations during the time period. The included firms cover a large part of the private sector with the most important industries being wholesale and retail trade, manufacturing and real estate, leasing and business activities.

Table 1: Summary statistics, firms

Number of unique firms	132,139
Number of firm-year observations	819,624
Share of firm-year observations with accounting data	0.75
Industry	
Wholesale and retail trade	0.30
Manufacturing	0.24
Real estate, leasing and business activities	0.18
Construction	0.13
Transport, storage and communication	0.08
Hotels and restaurants	0.06

[3]Mining and quarrying; Manufacturing; Electricity, gas and water supply; Construction; Wholesale and retail trade; Hotels and restaurants; Transport, storage and communication; and Real estate, leasing and business activities.

[4]Limited partnerships; Limited companies other than banking and insurance companies; and Economic associations.

Table 2: Summary statistics, workers

	Less than high school	High school	Some college
A. Men			
Number of unique workers	594,825	1,388,086	531,328
Number of worker-year obs	5,072,126	11,912,158	4,324,708
Real monthly earnings*	20,336	22,338	32,993
Age	45.4	38.8	40.4
Married	0.49	0.40	0.51
Having children living at home	0.30	0.37	0.44
Number of children	0.56	0.67	0.82
Employed, of which	0.78	0.81	0.86
Job stayer	0.94	0.93	0.93
Job mover	0.03	0.04	0.05
Entrant from nonemployment	0.03	0.03	0.02
B. Women			
Number of unique workers	344,535	818,903	325,263
Number of worker-year obs	2,442,611	5,390,792	1,934,190
Real monthly earnings*	14,637	16,118	22,497
Age	45.3	37.6	38.5
Married	0.54	0.41	0.47
Having children living at home	0.37	0.47	0.49
Number of children	0.66	0.83	0.87
Employed, of which	0.69	0.74	0.79
Job stayer	0.93	0.91	0.91
Job mover	0.03	0.04	0.05
Entrant from nonemployment	0.03	0.04	0.04

* In 2007 SEK (1 USD ≈ 7.5 SEK)

As discussed above, we perform separate estimations for men and women in three education groups: less than high school; high school; and some college. 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. The workers must have worked at a firm in our sample at least one quarter during the time period. If so, we include the worker's full employment history.

Table 2 shows that the workers with less than high school education are on average older than the workers in the two higher education groups. This is due to changes in years of schooling across cohorts. Workers with less than high school education are also more likely to be married and less likely to have children living at home. The employment rate increases with education, but the fraction of the employed who remains at their job each quarter is fairly constant across groups. The 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 indicates that job to job mobility and transition between employment and nonemployment are fairly common. Each quarter, about 4 percent of the workforce change jobs and about 3 percent enter employment after a period of nonemployment.

Figure 1: Log real earnings for five-year cohorts, 1990–2007

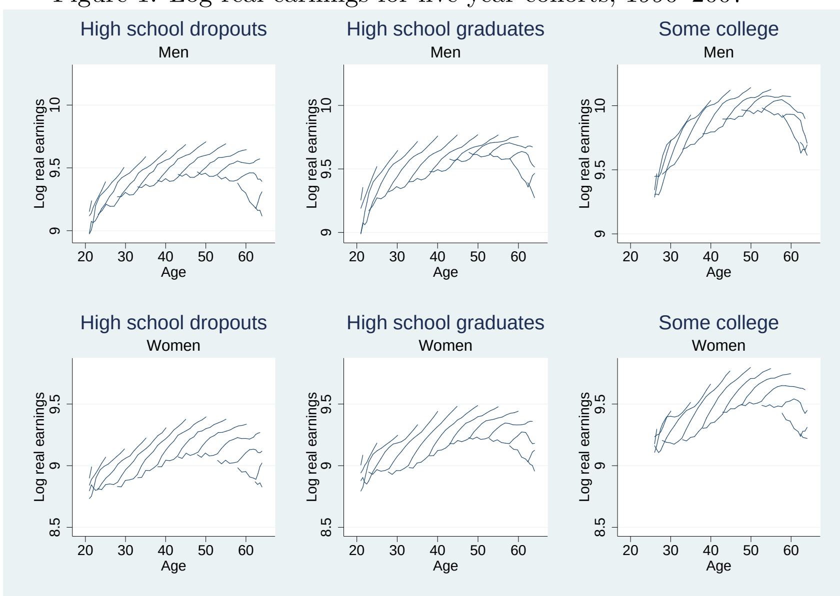
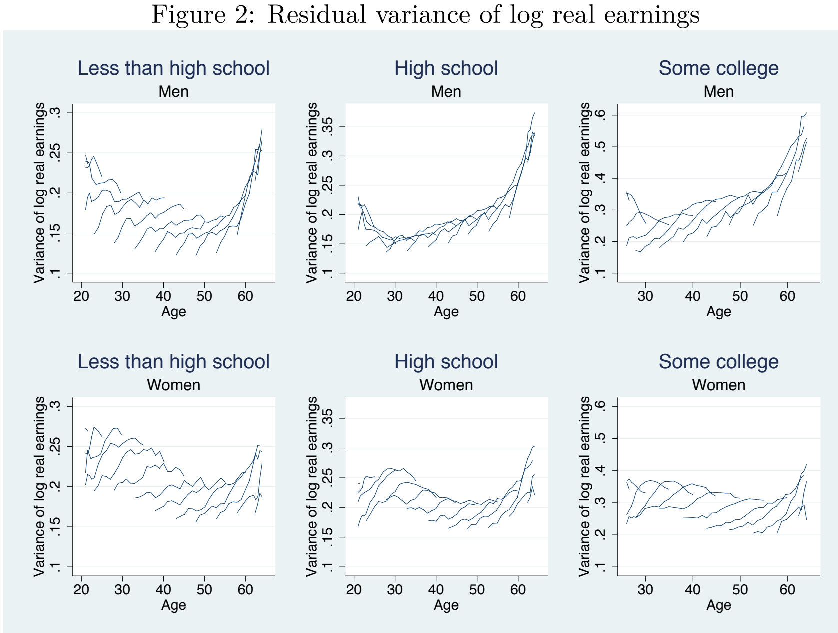


Table 2 shows that the level of earnings for the two lowest education groups are fairly similar, while earnings for the highest education group is substantially larger than for the other two. Figure 1 presents the development of the logarithm of real monthly earnings, calculated as an average for each individual and year. The earnings profiles are plotted by five-year cohorts over the period 1990–2007. For all education groups, we see the familiar concave earnings profile by age. The slope of the earnings profile increases with education, and the level of earnings is substantially higher for workers with some college education. Looking at the specific cohort paths, we see that successive cohorts earn on average more than previous cohorts at the same age.

Figure 2 presents the development of the variance of residual log real earnings, when year and age effects have been removed. Except for men with high school education, the variance of earnings increases for each successive cohort. The variance is largest for young and old workers, which might be associated with entry and exit from the labor market. The largest increase in the variance of earnings by age takes place for men with college education. This might indicate a larger degree of risk taking for this group, which also seem to pay off in terms of average earnings, as indicated in Figure 1.

Figure 2: Residual variance of log real earnings



Let us take a closer look at the importance transitions in and out of employment and of job to job transitions . Figure 3 presents the employment rate by age for each education group. Employment is particularly low for individuals with less than high school education and more so at younger ages. The figure also shows a substantial drop in employment above age 60 in all education groups. Transitions in and out of employment seems to be an important feature of the labor market, in particular for low educated workers.

Figure 3: Employment rate by age and education

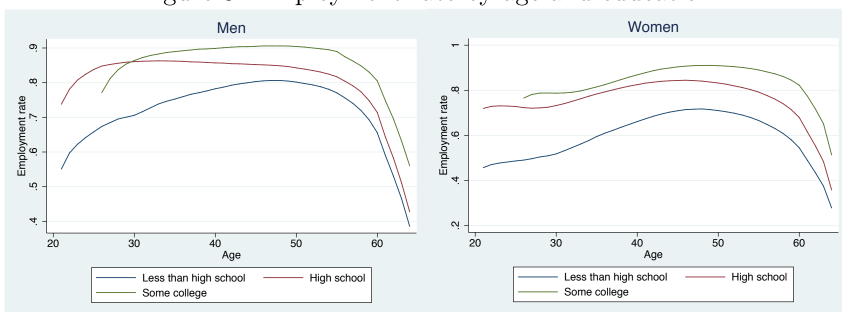


Figure 4: Job mobility by age and education

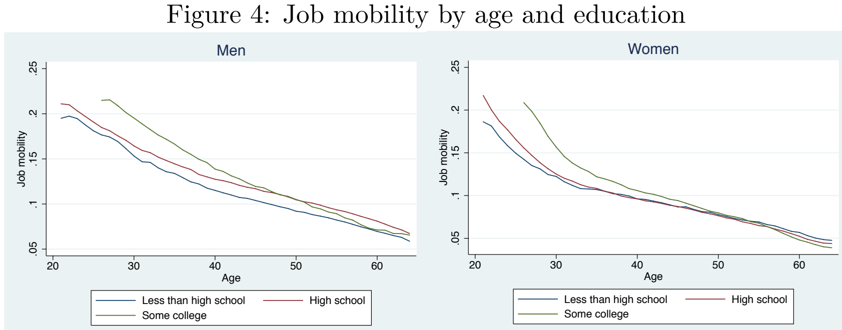


Figure 5: Entry rate from nonemployment by age and education

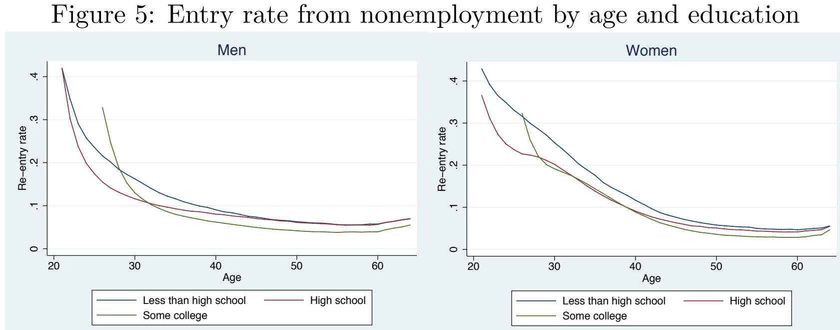
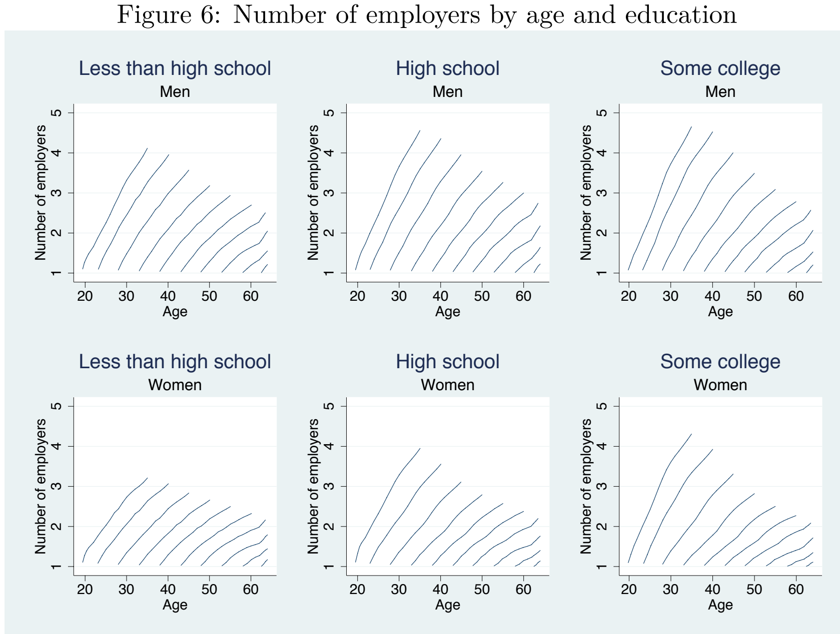


Figure 4 presents the fraction of workers by age who change employer at least once during a year. The importance of job to job transitions is particularly large at younger ages and more so for higher educated workers. Figure 5 presents the share of workers who enter employment from nonemployment at least once during a year. Also the entry rate from nonemployment is particularly large for younger workers. A sigificant fraction of the workforce enter from nonemployment, and the level is fairly constant across education groups. Figure 6, lastly, presents the number of employers by cohort and age from 1990 to 2007. The figure confirms that the change of employer is an important feature of the labor market. Individuals of age 20 in 1990 had on average 3–4 employers until 2007.

Figure 6: Number of employers by age and education



5 Results

[To be completed]

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