Job Changes and Individual-Job Specific Wage Dynamics*

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Abstract

This paper develops an error components model that is used to examine the impact of job changes on the dynamics and variance of individual log earnings. I use data on work histories drawn from the Panel Study of Income Dynamics (PSID), that makes possible to do the distinction between voluntary and involuntary job-to-job changes. The potential endogeneity of job mobility in relation to earnings is circumvented by means of an instrument variable estimation method that also allows to control for unobserved individual-job specific heterogeneity.

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1 Introduction

A large literature on labour economics has focused on the determinants of wages. On the one hand, studies based on the human capital theory (Becker, 1975) examine the impact of general experience on wages, ignoring job mobility. On the other hand, studies based on job search and matching theories (Burdett, 1978; Jovanovic, 1979) or purely learning by doing (Rosen, 1972), look at the effect of job specific human capital on wages. This literature has focused on estimating the returns to experience and tenure[1], trying to control for the endogeneity of tenure using different methods[2].

Another related literature on earnings dynamics has modelled and estimated the heterogeneity and time series properties of individual wage processes (Lillard and Willis, 1978; MaCurdy, 1982; Abowd and Card, 1989; Meghir and Pistaferri, 2004), but many have ignored job mobility and the distinction between dynamics within and between jobs. However, job mobility may affect the mean but also the shape of the distribution of earnings and, moreover, this effect may last for several periods after the job change.

The relationship between job mobility and earnings dynamics is economically relevant as, for instance, transitions into poverty may increase dramatically following a job loss, but also because job mobility may have an equalizing role over the life-cycle inequality, depending on whether workers are more o less able to improve their economic situation by changing jobs.

In Hospido (2010), I consider a model for the heterogeneity and dynamics of the conditional mean and the conditional variance of individual wages. In the empirical analysis - conducted on data drawn from the Panel Study of Income Dynamics (PSID) - I find that it is important to account for individual unobserved heterogeneity and dynamics also in the conditional variance, and that the dynamics are driven by job mobility. In line with those results, this paper develops a model that explicitly considers job changes in the dynamics of wages and in the heterogeneity pattern. In particular, the specifica-

[1]See, for example, Altonji and Shakotko (1987), Topel (1991), Topel and Ward (1992), Neal (1995), Altonji and Williams (1997), Dustmann and Meghir (2005), among others.

[2]A first group of studies uses a single wage equation and then applies instrument variable or control function methods to control for the endogeneity bias (Altonji and Shakotko, 1987; Topel, 1991; Altonji and Williams, 1997; Dustmann and Meghir, 2005). A second approach exploits information on firm closures (Neal 1995, Bonhomme and Jolivet, 2006). A third group suppose that workers' mobility decisions produce realized wage rates that are not random samples of the offered wage rates and estimate the returns to tenure taking into account the sample selection process (Topel, 1986; Marshall and Zarkin, 1987). Finally, other studies explicitly specify a simultaneous equation model with wage rate and job tenure as dependent variables, based upon a model in which they are jointly determined (Lillard, 1999; Abowd and Kang, 2002; Bagger, 2007; Amann and Klein, 2007).

tion proposed has two different parameters to capture dynamics within jobs and across jobs, and the unobserved heterogeneity shows a richer pattern as well, composed of both individual and job-specific effects.

As pointed out by Low *et al.* (2009), it is important to distinguish between movements in earnings that reflect choice and those which reflect uncertainty. Those authors address this issue by allowing for endogenous labour supply and job mobility which implies that a proportion of earnings fluctuations, usually interpreted as risk, are in fact attributed to choice. Here, the potential endogeneity of job mobility in relation to earnings is circumvented using an instrument variable estimation method that controls for individual and job-specific unobserved heterogeneity.

A recent empirical literature (Stevens, 2001; Leonardi, 2003) examines the contribution of job changes to the increasing male earnings inequality in the United States since the 1970. Following Gottschalk and Moffitt's 1994 and 1995 studies, these references have focused on the transitory component of the earnings variance (earnings instability). The problem with the models that they consider is that they are incapable of incorporating the effect of job mobility on permanent income because they parameterize *permanent income* as a fixed individual effect. However, this is a simplification as job mobility may also affect permanent income. In this paper, differently to Berry *et al.* (1988), Stevens (2001), and Leonardi (2003), I explicitly consider job-specific effects as well as individual unobserved characteristics, that is, the individual effects are time invariant whereas the job-specific or match effects change across jobs but remain constant within the same position[3]. Differently to Lillard (1999), Abowd and Kang (2002) and Low *et al.* (2009), I adopt a fixed effects perspective leaving the distribution for the unobserved heterogeneity components completely unrestricted and treating each effect as one different parameter to be estimated.

The paper contributes to the literature by more thoroughly describing the impact of job mobility on the dynamics and heterogeneity of individual wages than previous references. In particular, the proposed model: (i) permits that job changes may be correlated with individual and job specific unobserved characteristics, (ii) is agnostic regarding the distribution of these individual and job effects, (iii) can be estimated with no need to explicitly model the job mobility process, and (iv) allows us to calculate

[3]The importance of match effects in explaining wages has been stressed by Topel and Ward (1992), Abowd *et al.* (1999), Postel-Vinay and Robin (2002) and Bonhomme and Jolivet (2006).

different components of the variance within and across jobs.

In the empirical application, I use data on work histories drawn from the 1968-1993 PSID. These data allow me to establish the distinction between voluntary job-to-job changes (quits) and involuntary job-to-job changes (job losses). In the sample, once we control for individual and job-specific effects, the persistence within jobs is almost zero, whereas across jobs is significant but small. For the dynamics, the distinction between voluntary and involuntary transitions turns out to be irrelevant. However, this distinction matters in terms of risks. The estimated variance of the job-specific effects represents around one third of the variance for the individual fixed effects. However, if I consider a subsample that only includes involuntary job changes, the estimated variability across jobs increases up to two thirds with respect to the individual time-invariant component.

The rest of the paper is organised as follows. Section 2 describes the data. Section 3 presents the model. Section 4 explains the estimation strategy and section 5 shows the estimation results. Finally, section 6 concludes with a future research agenda.

2 The Data

The data come from the PSID for the period from 1968 to 1993[4]. The PSID began in 1968 by inteviewing over 5,000 families. Of these, about 3,000 families were representative of the US population as a whole (the core sample), and about 2,000 were low-income families (the Census Bureaus SEO sample). Thereafter, these same families have subsequently been interviewed every year, as have any new families formed from the original group of families[5]. The survey contains abundant information on individual characteristics, income and labour market status. The data set should follow individuals over a sufficiently long period of time to observe pre- and post- job changes earnings histories.

[4]Several changes have been implemented to the PSID since the mid-1990s. The most important is that the PSID switched to biannual interviewing in 1997. In addition, I exclude the 1994-1997 income files because, as explained by Kim et al. (2000), the continuity of the PSID data in those years was disrupted by a major revision of the survey that included a switch to computer-assisted telephone interviewing and to automated editing of the data, and changes in the structure of the income questions.

[5]A family member who moves out of a PSID family is eligible for interviewing as a separate family unit if he or she is a sample member and he or she is 18 years old or older and living in a different, independent household.

2.1 Sample Construction

In the empirical analysis, I use the core sample. I restrict my study to heads of households[6] since, during the sample period, survey questions regarding employment history are only asked to them[7]. In addition, to focus the analysis during the working life, I select males aged 25 to 55, with no missing records on race, education, region of residence or, if appropriate, reason of job change. I drop the self-employed, those with topcoded wages, and those with less than 8 years of usable data on earnings. Finally, I have an unbalanced panel that contains 2,013 individuals and 27,845 observations from 1968 to 1992.[8]

Step-by-step details on sample selection are reported in Appendix A. Sample composition by year, individuals by number of observations and demographic characteristics are presented in Appendix B.

2.2 Job Changes Definition

A **job change** takes place when current tenure of the worker is less than a year and there is information available regarding the type of change. The type of change is defined by the answer to the question: *"What happened to the job you had before - did the company go out of business, were you laid off, promoted, or what?"*. Therefore, I define a job change as an involuntary job separation or **job loss** in case of business or plant closing or due to being laid off or fired; and as **quit**, in case of voluntary change.

The question quoted above was only asked to individuals who report being with their present employer for less than twelve months (otherwise the question is skipped and coded as not applicable), so this make me feel confident regarding the variable tenure[9]. As pointed out by Polsky (1999), from 1984 to 1988 this question was asked to all respondents who reported that their current job started after January of the previous year. To correct for this possible inconsistency, no job change is reported for those with current tenure greater than one year.

The sample only includes annual job-to-job changes, because monthly calendar information, that

[6] A household head is defined as the adult of the family. When there is more than one adult in the family, the PSID assigns the primary male adult as the household head.

[7] The same information is available also for wives only from 1979.

[8] In practice, I use information only until 1992 because, in every survey wave, the time reference for wage records is the previous year.

[9] Since the PSID does not collect information on specific employers, the identification of job changes in this data set has been quite controversial. Many of the difficulties related to measuring job tenure in the PSID were evaluated by Brown and Light (1992). The tenure question also switched from being coded in intervals prior to 1976 to being measured in months, and from asking about *position* tenure to *employer* tenure. In any case, these difficulties are not so important here since I am not interested in the exact value of the variable but if tenure is less or more than one year.

would provide information regarding spells of unemployment lower than a year, is not available before 1984.

2.3 Descriptive Analysis of the Raw Data

The descriptive analysis will emphasize a number of salient facts about job mobility and the relationship between this and earnings dynamics.

Job mobility Among the 2,013 sample individuals, there are 699 individuals (around 35 percent) who never change job, whereas the remaining individuals change at least once (on average they have 3.40 different jobs).

As pointed out by Topel and Ward (1992), the most prominent and widely documented facts about job mobility are that average rates of job changing decline with age or experience and, specially, with current job tenure. These facts are consistent with the predictions of job-matching and search models[10] (Johnson, 1978; Burdett, 1978; Jovanovic, 1979).

Figure 1 shows those patterns in the sample. We can see how the probability of changing job decreases as age, or alternatively tenure, increases.

Regarding *vintage effects*, it is less clear if people entering the labor market more recently have patterns of labor mobility different from those of earlier cohorts. Table 1 presents the distribution of jobs by birth cohort. The 1921-1941 cohort contains a larger proportion of individuals who only have one job than individuals born between 1941-1960. Although sample selection may be relevant, since workers are more exposed to job changes as they grow older and more recent entrants are less likely to be observed in higher-order jobs, the results in the table suggest an increase in job instability for the most recent cohort in the sample.

With respect to the reason of change, if we look at average rates of job changing by cohorts we find that younger cohorts of workers are more likely to be laid off from their jobs than older cohorts but the difference is bigger in case of quit. More striking is the comparison across skill groups (see Figure 2).

For all groups the main reason for leaving job is quitting, but the difference with respect to layoff is

[10] In a matching model, job mobility is the consequence of a voluntary change to a better position where the worker is more productive and receives a higher pay. Search models are based on the existence of imperfect information. In these models, jobs are experience goods. As time goes by, the firm acquires more information and it can adjust the salary better. Under this approach, job mobility is the result of *poor* matchings looking for a better chance.

more important for graduate and - specially - for college people than for dropouts.

Job mobility and earnings dynamics In order to get a first impression of the impact that job changes have over the evolution of earnings, I calculate the cross-sectional sample correlations for consecutive logwage observations on years when no-change, a job loss or a job quit has happened[11]. Table 2 summarizes those calculations that work also as a check for the definitions above. As we would expect, when a job change occurs the correlation diminish, and that reduction is bigger in case of job loss than in case of a voluntary job change.

Table 3 displays average annual wage growth for workers within jobs and between jobs by type of exit. Within-job annual wage growth is lower than between-job annual wage growth in case of voluntary transitions. In case of job loss, real wages drop. I find the same qualitative patterns among different demographic groups.

As pointed out by Dustmann and Meghir (2005), the fact that within-job wage growth is lower than between-job wage growth does not imply that, on average, job quitters have higher wages than stayers. As they did, I regress log wages on dummies for the number of jobs workers have held up to then, also including age and year dummies.

Estimates for the first seven jobs, reported in the first column of Table 4, indicate that workers with more jobs have lower wages. Once I include individual fixed effects in the regression (column 4), the number of jobs is positively related with wages. In fact, if I exclude from the sample movers who transit only through job loss (columns 2 and 5), I obtain a positive relationship between number of jobs and wages. On the contrary, if I exclude those who change voluntary (columns 3 and 6), I obtain that workers with more jobs have lower wages even after including individual fixed effects.

3 The Model

In this section I propose an empirical model to study the dynamics of individual earnings over time, within a job and over the career of a worker in one or more different jobs.

[11]Nominal annual earnings are deflated by the GNP Personal Consumption Expenditure Deflator (base 1992).

3.1 Basic Specification

Building on the autoregressive model developed in Lillard and Willis (1978), for a worker i and time t, I consider the following more general specification

$$y_{it} = \alpha y_{it-1} + \beta d_{it-1} y_{it-1} + \mu_i + \phi_{i(t)} + \epsilon_{it};\ (t = 2, .., T_i), \tag{1}$$

where $\{y_{i1}, ..., y_{iT_i-1}\}_{i=1}^{N}$ are the observed log earnings data, d_{it} is an indicator of working i ending current job[12] at time t, the parameter α or, alternatively, $\alpha + \beta$ measures the persistence on the level of those earnings to shocks, ϵ_{it} is a purely transitory component, μ_i is an unobserved time-invariant individual component, like ability, and $\phi_{i(t)}$ is an unobserved individual-job component, such that,

- it remains constant whithin a position: $\phi_{i(t)} = \phi_{i(t-1)}$ if $d_{it-1} = 0$, but
- it is different across jobs: $\phi_{i(t)} \neq \phi_{i(t-1)}$ if $d_{it-1} = 1$.

In particular, for a worker i that is observed for T_i periods always at the same job, the model would be the classical $AR(1)$ process with individual fixed effects

$$y_{it} = \alpha y_{it-1} + \mu_i + \phi_i + \epsilon_{it} = \alpha y_{it-1} + \eta_i + \epsilon_{it}.$$

Notice that I abstract from additive aggregate effects by regarding y_{it} as a deviation from a time effect[13].

The model in (1) departs from the standard one in two main features related to job mobility:

1. The dynamics captured by the autoregressive parameters is different in years when workers change job, $\alpha + \beta$, than within the same job, α.
2. The unobserved heterogeneity across individuals has a job-specific matching component. In other words, I consider individual and job specific effects, $\mu_i + \phi_{i(t)}$.

[12] I should formally have a j subscript for job on wages but since it does not add clarity I have dropped it.

[13] As is usual in the earnings dynamics literature, the variable y_{it} - strictly speaking - represents log earnings residuals from first stage regressions on some observed variables -apart from year dummies (that capture the aggregate conditions of the economy) - as age, race and other individual characteristics. So we would keep in mind the following structure:

$$\begin{aligned} w_{it} &= x_{it}\beta + u_{it} \\ u_{it} &= \gamma_i + \upsilon_{it} \\ \upsilon_{it} &= \alpha \upsilon_{it-1} + \epsilon_{it} \end{aligned}$$

where w_{it} is the log annual wages of an individual i in period t, x_{it} is a vector of exogenous variables, and u_{it} is a random error with two components , an unobserved individual heterogeneity component and an autoregressive component. The connection with the specification above would be $y_{it} = \hat{u}_{it}$ and $\eta_i = (1-\alpha)\gamma_i$.

Given the model, within job, the transitory shocks will be uncorrelated with lagged earnings, but not with present or future earnings. Similarly, I do not need to assume the strict exogeneity of the job changes, in the sense of being uncorrelated to past, present, and future time-varying shocks. Apart from possibly being correlated with the unobserved heterogeneity components, I will consider that job changes may be predetermined, that is, they might be correlated with errors at certain periods but not at others. In particular, we could think of d_{it} as a function of the past errors and individual observed and unobserved characteristics - that is, the individual's work history - but as being uncorrelated to present and future shocks. Formally, I am imposing that

$$E\left(\epsilon_{it}|y_i^{t-1}, d_i^t\right) = 0.\text{[14]} \tag{2}$$

Although it would be preferable to also allow for correlation between d_{it} and ϵ_{it}, that would lead us to consider selection models which is out of the scope of the paper. Even so, the model proposed here has several advantages. First, it permits the estimation of a specification in which job changes can be correlated with individual and job specific characteristics with no need to explicitly model the job mobility process or to do any assumption regarding the distribution of these individual and job effects. Moreover, note that neither time series or conditional heteroskedasticity are assumed. Therefore, as before, we could consider unobserved heterogeneity components in those conditional variances, both at the individual and job-specific level.

3.2 Specification by Type of Exit

In the empirical analysis I will also consider an extended specification that reflects different dynamics across individuals and time according to the type of job change

$$y_{it} = \alpha y_{it-1} + \beta_l d_{it-1}^{loss} y_{it-1} + \beta_q d_{it-1}^{quit} y_{it-1} + \mu_i + \phi_{i(t)} + \epsilon_{it}, \tag{3}$$

where d_{it}^{loss} is a dummy variable equal to one if worker i at time t ends current job due to an involuntary job separation or job loss; and d_{it}^{quit} equal one if worker i at time t ends current job because she has decided to moved to a new job.

I consider the kind of individual and stochastic effects which preserve the same properties as the basic specification.

[14] In the sequel, for any random variable (or vector of variables) Z, z_{it} denotes observation for individual i at period t, and $z_i^t = \{z_{i1}, ..., z_{it}\}$, i.e. the set of observations for individual i from the first period to period t.

4 Identification and Estimation Method

In this section I discuss the conditions under which I achieve parameter identification. In the model, wages are observed conditional on individuals working; within-job wages, which identifies the parameter α, are only observed if the individual does not change job; between-job wage growth, which helps to identify differences on dynamics on years of change, β, is observed only for job movers. Further, participation and mobility decisions can be all endogenous and if this is ignored we risk biasing the estimates of the model[15]. Regarding participation, given the type of individuals considered in the sample, it does not seem such a big issue in this setting so I will ignore it. The potential endogeneity of job mobility is circumvented by controlling for possibly correlated individual and job-specific heterogeneity, without observing it, and by means of a instrument variable estimation method[16].

4.1 Orthogonality Conditions

As a matter of notation, I assume that the first observation occurs at $t = 1$, so that the earnings equation (1) rewritten in first differences is defined from $t = 3$

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta \Delta \left(d_{it-1} y_{it-1} \right) + \left(\phi_{i(t)} - \phi_{i(t-1)} \right) + \Delta \epsilon_{it};\ (i = 1, ...N; t = 3, .., T_i).$$

Given (2), the following moment conditions hold

$$E\left(y_i^{t-2} (1 - d_{it-1}) \Delta \epsilon_{it} \right) = 0;\ (t = 3, .., T_i), \tag{4}$$

and so

$$E\left(y_i^{t-2} (1 - d_{it-1}) \left(\Delta y_{it} - \alpha \Delta y_{it-1} - \beta \Delta \left(d_{it-1} y_{it-1} \right) \right) \right) = 0.$$

Then, we can consider a GMM estimator for $\theta = (\alpha, \beta)'$ that used all the available lags at each period as instruments for the equations in first differences (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991). Notice that GMM estimation will only consider the moment conditions with $d_{it-1} = 0$, and that β would be identified thanks to those with $d_{it-1} = 0$ but $d_{it-2} = 1$.

[15] As pointed out by Low *et al.* (2009) this, implicitly, has been the assumption made in papers estimating the covariance structure of earnings (MaCurdy, 1982; Abowd and Card, 1989; Meghir and Pistaferri, 2004).

[16] Low et al. (2009) use a similar sample selection procedure and consider a specification for the wage process fully parametric. Given the distributional assumption, in the estimation they control for selection into employment and for job mobility using the Heckman 2-step method. They claim that: “It is clear that what really matters is the firm mobility decision. Indeed, neglecting the participation correction reduces the variances of interest but the effects are minuscule.”

4.2 GMM Estimation

The GMM estimator of θ based on the corresponding sample moments for (4) with weight matrix A_N is given by

$$\hat{\theta}_{GMM} = \arg\min_{\theta} \left[\sum_{i=1}^{N} \Delta v_i' Z_i \right] A_N \left[\sum_{i=1}^{N} Z_i' \Delta v_i \right],$$

where $v_i = y_i - W_i \theta$, with $y_i = (y_{i3}, \ldots, y_{iT_i})'$, $W_i = \begin{pmatrix} y_{i2} & d_{i2} y_{i2} \\ \vdots & \vdots \\ y_{iT_i-1} & d_{iT_i-1} y_{iT_i-1} \end{pmatrix}$, and

$$Z_i = \begin{pmatrix} y_{i1}(1-d_{i2}) & & & 0 \\ & (y_{i1}, y_{i2})(1-d_{i3}) & & \\ & & \ddots & \\ 0 & & & (y_{i1}, \ldots, y_{iT_i-2})(1-d_{iT_i-1}) \end{pmatrix}.$$

According to standard GMM theory, an optimal choice of the inverse weight matrix, $V_N = A_N^{-1}$, is a consistent estimate of the covariance matrix of the orthogonality conditions $E(Z_i' \Delta v_i \Delta v_i' Z_i)$. A one-step GMM estimator uses

$$\hat{V} = \sum_{i=1}^{N} Z_i' D D' Z_i,$$

where D is the first-difference matrix operator, and a two-step GMM estimator uses the robust choice

$$\tilde{V} = \sum_{i=1}^{N} Z_i' \Delta \hat{v}_i \Delta \hat{v}_i' Z_i,$$

where $\Delta \hat{v}_i$ are one-step residuals.

An estimate of the asymptotic variance of two-step GMM is given by

$$\widehat{Var}\left(\hat{\theta}_{GMM2}\right) = \left[\left(\sum_{i=1}^{N} \Delta W_i' Z_i \right) \tilde{V}^{-1} \left(\sum_{i=1}^{N} Z_i' \Delta W_i \right) \right]^{-1}.$$

5 Estimation Results

In this section I show the results corresponding to the GMM estimation of the specifications presented in Section 3 (equations 1 and 3). In the estimation, y_{it} are log annual real wages residuals from first stage regressions on year dummies, age, education, dummies for race, region of residence, and residence in a SMSA[17].

[17] In earnings dynamics research it is standard to adopt a two step procedure. In the first stage regression, the log of real wages is regressed on control variables and year dummies to eliminate group heterogeneities and aggregate time effects. Then, in the second stage, the unobserved heterogeneity and dynamics of the residuals are modelled.

5.1 Common Parameters Estimates

I begin by obtaining alternative estimates of a univariate AR(1) model (setting $\beta = 0$). Table 5 compares OLS in levels, first differences, and within- groups with those obtaining by GMM, using as instruments for the equation in first differences of the lags of wages up to $t - 2$.

Taking GMM as a benchmark (columns 4 and 5), OLS in levels is biased upward and OLS in differences biased downward, as we would expect for an AR data generating process with individual unobserved heterogeneity. However, the comparison with the WG is puzzling, since we would also expect a downward bias in that case. Although the system- GMM estimate is bigger than WG, the Sargan test rejects the mean stationarity. Finally, the two-step AR(2) estimates reported in the last column do not change the conclusions, that suggests misspecification as a likely reason for these results[18].

Model in equation (1) differs from the previous standard AR(1) model in two main aspects: the different dynamics within and between jobs and the individual-job specific unobserved heterogeneity. The first two columns in Table 6 report GMM estimates (one- and two-step) of the basic specification, and column 3 corresponds to the two-step GMM estimates of the specification by type of exit. For comparison, I also include GMM estimates for a specification setting $\beta = 0$ (column 4) and another ignoring job-specific heterogeneity (column 5).

Controlling for individual and job-specific effects, GMM estimates of the AR coefficient within groups, α, are almost zero; and across jobs, β, is significant but small (columns 1 and 2). The corresponding estimates for the AR coefficients when I distinguish between involuntary, β_l, and voluntary changes, β_q, are very close to each other (the difference is statistically insignificant). If I impose the same dynamics, both within and between jobs, but still allowing for individual and job-specific effects, the $\hat{\alpha}$ estimate increases capturing the effect of job mobility (column 4). Finally, if I ignore the possibility of heterogeneous match effects across jobs the results for $\hat{\alpha}$ and $\hat{\beta}$ show a marked discrepancy between columns 5 and 2 (my preferred specification). Although it is not possible to reject the latter specification in terms of the Sargan test, the variance estimates in the next section suggest that individual heterogeneity across jobs is not negligible for movers, that is, individuals who change job at least once in the sample.

[18]These results are in line with the ones in Alvarez and Arellano (2004).

5.2 Variance estimates

Optimal estimation of σ_μ^2 and σ_ϕ^2 requires consideration of the data covariance structure. The errors in levels, $v_{it} = \mu_i + \phi_{i(t)} + \epsilon_{it}$, satisfy

$$\begin{aligned} Var\left(v_{it}\right) &= Var\left(\mu_i + \phi_{i(t)}\right) + \sigma_t^2, \text{ and} \\ Cov(v_{it}, v_{is}) &= Cov(\mu_i + \phi_{i(t)}, \mu_i + \phi_{i(s)}). \end{aligned}$$

If we assume *no sorting*, that is, once we have controlled for μ_i it would not make much sense to consider correlations across jobs and correlations between individual and job effects, errors would satisfy

$$\begin{aligned} Var\left(v_{it}\right) &= \sigma_\mu^2 + \sigma_\phi^2 + \sigma_t^2, \text{ and} \\ Cov(v_{it}, v_{is}) &= \begin{cases} \sigma_\mu^2 + \sigma_\phi^2 & \text{if same job at time } t \neq s, \\ \sigma_\mu^2 & \text{if different job at time } t \neq s. \end{cases} \end{aligned}$$

Therefore, for large N simple consistent estimates can be obtained combining cross-sectional sample covariances as

$$\widehat{\left(\sigma_\mu^2 + \sigma_\phi^2\right)} = \sum_{r=1}^{T-2} \left[\frac{1}{T-r-1} \sum_{t=r+2}^{T} \frac{1}{\sum_{i=1}^{N} S_{itr}} \sum_{i=1}^{N} S_{itr} \hat{v}_{it} \hat{v}_{it-r} \right],$$

and

$$\widehat{\sigma}_\mu^2 = \sum_{r=1}^{T-2} \left[\frac{1}{T-r-1} \sum_{t=r+2}^{T} \frac{1}{\sum_{i=1}^{N} (1 - S_{itr})} \sum_{i=1}^{N} (1 - S_{itr}) \hat{v}_{it} \hat{v}_{it-r} \right],$$

where $S_{itr} = \prod_{s=1}^{r} (1 - d_{it-s}) = (1 - d_{it-1}) \cdot (1 - d_{it-2}) \cdot \ldots \cdot (1 - d_{it-r})$ indicates that individual i stays at the same job between $t - r$ and t, and $\hat{v}_{it} = y_{it} - \hat{\alpha} y_{it-1} - \hat{\beta} d_{it-1} y_{it-1}$.

Results are reported in Table 7. I find that in the whole sample (column 1) the estimated variance of the individual effects is 0.09, very close to the variance of the sum of these and the job-specific effects, mainly because for the stayers (people who never change job) it is not possible to discriminate among those two components (column 2). If I only consider individuals that change at least once (column 3), the estimated variance of the job-specific effects represents around one third of the variance for the individual fixed effects. Finally, if I only use those who suffer involuntary job changes (column 4) the estimated variance of the heterogeneity across jobs increases up to one half[19].

[19] Similar results are found in Berry *et al.* (1988).

6 Conclusions

This paper develops an error components model designed to describe the impact of job mobility on the dynamics and heterogeneity of individual wages, that is, on the persistence of individual wages due to shocks related to job changes.

In particular, the specification proposed has two different parameters to capture dynamics within jobs and across jobs, and the unobserved heterogeneity shows a richer pattern, as well, composed of both individual and job-specific effects. The potential endogeneity of job mobility in relation to earnings is circumvented using an instrument variable estimation method that controls for those unobserved heterogeneity components. The simple GMM method that I use allows me to easily obtain measures of persistence.

In the data, drawn from the PSID, I find that - once we control for individual and job-specific effects - the dynamics within jobs is almost zero, whereas across jobs is significant but small. For the dynamics, the distinction between voluntary and involuntary transitions turns out to be irrelevant. However, that distinction matters in the case of the components of the cross-sectional variance. The estimated variance of the job-specific effects represents around one third of the variance for the individual fixed effects. If I consider a subsample that only includes involuntary job changes, the estimated variance of the heterogeneity across jobs increases up to one half.

Further research is needed on the consideration in the model of the labour market participation decision and, thus, the inclusion of women and transitions job-to-nonemployment and nonemployment-to-job into the analysis.

APPENDICES

A Sample selection

Starting point: PSID 1968-1993 Family and Individual - merged files (53,005 individuals).

1. Drop members of the Latino sample (10,022 individuals) = Sample (42,983 individuals).

2. Keep only those who are continuously heads of their households = Sample (16,038 individuals).

3. Keep only males aged 25 to 55 over the period = Sample (8,190 individuals).

4. Drop those with a spell of self-employment = Sample (6,303 individuals).

5. Drop those with missing race, education and region of residence records = Sample (6,047 individuals).

6. Drop those with top-coded earnings records and those with missing earnings = Sample (5,479 individuals).

7. Drop those with outlying earnings records, that is, a change in log earnings greater than 5 or less than -3 = Sample (5,384 individuals).

8. Drop those with missing records on reason of job change question and those with noncontinuous data = Sample (5,345 individuals).

9. Keep only those who are in the sample for 8 years or more

= FINAL SAMPLE: Males, 1968-1992 (2,013 individuals and 27,845 observations).

B Sample composition and descriptive statistics

Table B.1. Distribution of observations by year

Year	Number of observations	Year	Number of observations
1968	613	1981	1,287
1969	668	1982	1,330
1970	726	1983	1,343
1971	762	1984	1,393
1972	815	1985	1,451
1973	885	1986	1,400
1974	965	1987	1,353
1975	1,046	1988	1,302
1976	1,072	1989	1,258
1977	1,104	1990	1,205
1978	1,146	1991	1,173
1979	1,201	1992	1,096
1980	1,251		

Table B.2. Distribution of individuals by number of observations

Number of Years	Number of Individuals	Number of Years	Number Individuals
8	245	17	84
9	211	18	84
10	153	19	79
11	179	20	68
12	143	21	54
13	151	22	35
14	150	23	41
15	130	24	32
16	112	25	62

Table B.3. Descriptive Statistics

	1968	1980	1992
Age	37.16	36.58	40.48
	(6.33)	(8.82)	(5.70)
HS Dropout	0.45	0.26	0.12
HS Graduate	0.40	0.55	0.61
Hours	2,272	2,149	2,197
	(524)	(502)	(489)
Married	0.74	0.80	0.86
White	0.66	0.64	0.69
# Children	2.83	1.45	1.44
	(2.08)	(1.32)	(1.19)
Family Size	4.95	3.60	3.56
	(2.03)	(1.66)	(1.38)
North-East	0.18	0.16	0.17
North-Central	0.26	0.24	0.23
South	0.42	0.46	0.44
SMSA	0.69	0.66	0.54

Note: Standard deviations of non-binary variables in parentheses.

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TABLES

Table 1. Distribution of Individuals over Jobs by Birth Cohort (percent)

	Maximum Number of jobs							
	1	2	3	4	5	6	>6	N
All	37.70	22.16	17.09	9.34	6.01	3.73	3.97	2,013
Before 1941	51.12	21.67	13.60	5.53	3.29	2.24	2.55	669
1941 on	31.03	22.40	18.82	11.24	7.37	4.46	4.68	1,344

Note: Percentages are computed on total number of individuals in the sample, N. Each cell represents the proportion of individuals who had at most x jobs.

Table 2. Sample Correlations across Individuals

Correlations	No-change at time t	Job loss at time t	Job quit at time t
(w_{it-3}, w_{it-2})	0.905	0.869	0.878
(w_{it-2}, w_{it-1})	0.907	0.713	0.865
(w_{it-1}, w_{it})	0.907	0.628	0.799
(w_{it}, w_{it+1})	0.901	0.834	0.904
(w_{it+1}, w_{it+2})	0.874	0.816	0.867

Table 3. Sample Wage Annual Growth

Wage growth	Within job	Job loss	Job quit
All	0.010	-0.101	0.035
	(0.271)	(0.716)	(0.444)
Workers<35 years	0.021	-0.022	0.075
	(0.268)	(0.725)	(0.398)
Workers≥35 years	0.002	-0.164	0.013
	(0.272)	(0.703)	(0.503)
Dropout	0.001	-0.113	0.012
	(0.332)	(0.810)	(0.506)
Graduate	0.009	-0.098	0.076
	(0.258)	(0.661)	(0.480)
College	0.024	-0.074	0.102
	(0.203)	(0.680)	(0.457)

Note: standard deviation in parentheses.

Table 4. Log wages on number of jobs

Number of jobs	OLS			Fixed effects		
	All	Voluntary movers	Involuntary movers	All	Voluntary movers	Involuntary movers
2	-0.017	0.069	-0.371	0.020	0.082	-0.177
	(−1.89)	(7.13)	(−20.45)	(2.84)	(10.80)	(−11.90)
3	-0.044	0.128	-0.442	0.068	0.195	-0.146
	(−3.94)	(9.00)	(−16.23)	(7.45)	(17.92)	(−6.93)
4	-0.076	0.146	-0.597	0.074	0.227	-0.329
	(−5.18)	(7.13)	(−9.86)	(6.29)	(14.92)	(−7.81)
5	-0.139	0.119	-0.740	0.076	0.258	-0.338
	(−6.67)	(3.45)	(−6.25)	(5.07)	(11.66)	(−4.68)
6	-0.175	0.282	-1.305	0.118	0.356	-1.166
	(−6.41)	(5.42)	(−2.41)	(6.31)	(11.00)	(−4.37)
7	-0.391	0.110	-0.997	0.028	0.268	-0.841
	(−9.62)	(1.44)	(−1.84)	(1.07)	(6.03)	(−3.15)

Note: t-ratios in parentheses. All regressions include age and time dummies.

Table 5. Autorregresive Model of Earnings

	OLS levels	OLS dif	WG	GMM1	GMM2	GMM System	GMM2 AR(2)
y_{it-1}	0.792	-0.313	0.389	0.331	0.321	0 .431	0.329
	(0.009)	(0.012)	(0.006)	(0.023)	(0.022)	(0.020)	(0.025)
y_{it-2}							0.048
							(0.014)
m1	-	-	-	17.25*	-14.55*	-15.58*	-13.83*
m2	-	-	-	2.09*	1.80	2.91*	-0.15
Sargan test	-	-	-	-	304.02	369.18*	295.48
(df)					(275)	(298)	(273)

Note: Heteroskedasticity robust standard errors in parentheses. m1 and m2 are serial correlation tests for differenced errors. * Rejection at the 5 percent.

Table 6. Autorregresive Model of Earnings with Job Changes

	GMM1 Basic	GMM2 Basic	GMM2 By type of exit	GMM2 Same dynamics within and across	GMM2 No job-specific heterogeneity
y_{it-1}	0.060	0.026	0.018	0.149	0.272
	(0.047)	(0.043)	(0.044)	(0.021)	(0.048)
$d_{it-1}y_{it-1}$	0.133	0.153			0.096
	(0.051)	(0.049)			(0.086)
$d_{it-1}^{loss}y_{it-1}$			0.175		
			(0.083)		
$d_{it-1}^{quit}y_{it-1}$			0.161		
			(0.066)		
m1	-7.52*	-7.32*	-7.02*	-12.51*	-14.24*
m2	-0.42	-0.76	-0.76	0.35	1.72
Sargan test	-	292.38	291.25	297.59	301.09
(df)		(274)	(273)	(275)	(274)

Note: robust t-ratios in parentheses. m1 and m2 are serial correlation tests for differenced errors. * Rejection at the 5 percent.

Table 7. Wage Variance Estimates

	Whole sample	Only stayers	Only movers	Only layoffs
$\left(\sigma_\mu^2+\sigma_\phi^2\right)$	0.104	0.094	0.124	0.156
σ_μ^2	0.090	-	0.091	0.104
σ_ϕ^2	0.014	-	0.033	0.052
Obs.	19,069	9,064	10,005	2,014

Note: σ_μ^2 and σ_ϕ^2 are the variances of the individual and job effect. $\hat{\sigma}_\phi^2$ is obtained as the difference between $\widehat{\left(\sigma_\mu^2+\sigma_\phi^2\right)}$ and $\hat{\sigma}_\mu^2$. Obs.: number of sample $\hat{u}_{it}$ available for calculation. I drop observations if consecutive changes for the same worker, and any sample covariance with less than 25 observations.

FIGURES

Figure 1. Probability of Job Change

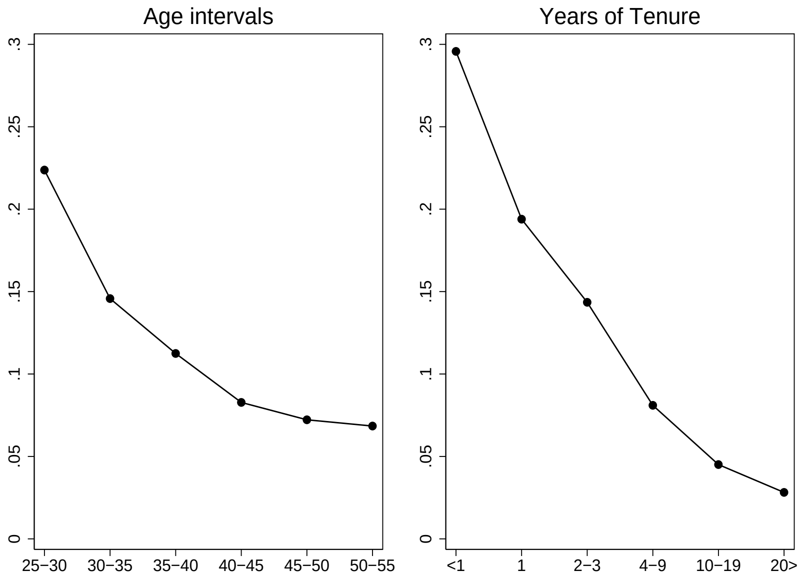

Figure 2. Probability of Job Change