Paired movers: A new test of (log) additive separability

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Abstract

Consider a pair of workers who both move from firm A to firm B. In a model with additively separable firm and worker effects, the pay gap between them at the origin firm should perfectly predict the gap at the destination firm (a forecast coefficient of 1). Using data from Brazil and Italy, we find forecast coefficients of 0.70 and 0.82, rejecting additive separability and indicating the presence of match effects. Under exogenous mobility, these estimates imply that the variance of match effects is about 40% of the variance of firm effects. In a model with endogenous mobility, these estimates imply a larger role for match effects. In simulated data, we show that standard specification tests are often biased or underpowered, and that extrapolating earnings patterns from observed to unobserved job offers can be misleading when match effects are important.

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A large literature is based on the Abowd, Kramarz, and Margolis (1999) (AKM) wage equation where the (log) wage can be written as the sum of a person effect, a firm effect, and an independent error term (e.g., Card, Heining, and Kline (2013), Card, Cardoso, and Kline (2016), Sorkin (2018), and Gerard et al. (2021)). A causal interpretation of the firm effect is justified either by the assumption of exogenous mobility or of additive separability.

This equation is controversial because it conflicts with many canonical models of wage determination and mobility (see, e.g., Gibbons et al. (2005), Eeckhout and Kircher (2011), and Borovičková and Shimer (2024)). Nonetheless, three pieces of evidence are supportive of this specification. First, Card, Heining, and Kline (2013) introduce what we call the event study test for exogenous mobility, and show that for movers across firms the change in the firm effects does a good job of predicting changes in earnings. Second, Card, Heining, and Kline (2013) look at the change in adjusted-R^2 from an additively separable model (AKM) to a non-additively separable model and find that the change is small, suggesting a minimal role for match effects. Finally, Bonhomme, Lamadon, and Manresa (2019) develop a way of estimating interactions in the wage equation and find minimal deviations from additive separability.

In this paper, we revisit this evidence by developing a new test of additive separability. The basis of the test is to consider a pair of workers (*paired movers*) who both move from firm A to firm B. Additive separability implies that on average the gap between the earnings of the workers should be determined only by the difference in their person effects and thus that this difference should be stable across firms. We formulate this test as a forecast bias test and document meaningful deviations from additive separability. We estimate a model and use a combination of the model and the forecast bias test to revisit each of the three pieces of evidence we described in the last paragraph. In each case, we find evidence that these are less compelling than previously thought.

We begin by explaining how additive separability, the assumption that this paper is testing, is stronger than exogenous mobility, the assumption needed to interpret a two-way fixed effects estimator as capturing average firm effects. Exogenous mobility says that workers can move on the basis of the firm effects, the worker effects, and non-wage related factors. Workers cannot move on the basis of match effects or the error term. Additive separability says that there are not permanent worker-firm interactions in the wage equation. To see the distinction, suppose that there are match effects in the wage equation but there is random assignment of workers to firms. In this case, we can consistently estimate the average treatment effects of firms because the match effects average out. So exogenous mobility is satisfied. But it is clear that additive separability is not satisfied because there are match effects in the wage equation. Thus, rejecting additive separability does not necessarily imply that exogenous mobility fails. Nonetheless, we present additional evidence that challenges the exogenous mobility assumption.

We then introduce the paired movers test, which relies on the idea that earnings gaps between workers should be stable across firms. When additive separability holds and the errors are independent, the regression of the gap between the paired movers at firm A on the gap at firm B is just a regression of the difference in worker effects on itself. Even when additive separability holds, however, the OLS estimator is downward biased because of measurement error. Therefore, in our implementation we only use workers where we have two observations of earnings at the origin firm so that we can instrument and correct for measurement error.

Assuming exogenous mobility, we develop an estimator for the variance of match effects. The estimator combines the paired mover coefficient with the absolute earnings gap between the paired movers. In most models of endogenous mobility, this estimate will be a lower bound. The reason is that endogenous mobility will tend to introduce a positive correlation between match effects across successive jobs. Thus, given the same underlying variance of match effects, the earnings gap will appear more stable under endogenous mobility than under exogenous mobility. Therefore, to match a given paired mover coefficient, a model with endogenous mobility will need a larger variance of match effects than a model with exogenous mobility.

We use administrative data from two countries: Italy and Brazil. For the Italian data, we use the Veneto Worker History data and exactly follow the data construction in Kline, Saggio, and Sølvsten (2020). For the Brazilian data, we use the RAIS data and we follow Gerard et al. (2021), except for the geographic restrictions. Because the Brazilian dataset is much larger (and less noisy), we focus on the results from Brazil. In the body of the paper, we briefly discuss where results in Veneto differ from those in Brazil.

In terms of descriptive statistics, we focus on how selected the paired movers are. Paired movers make up about 5% of all movers. Paired movers are older, earn more, and have higher tenure than all movers. The most important difference between paired movers and all movers is that paired movers start from—and end up at—much larger firms. We show that given mobility patterns, the number of paired movers that we have in the data is close to what we would expect by chance. So in this sense while the paired movers are a narrow subset of the data, it is roughly as narrow as we would expect based on the distribution of mobility that we observe. Therefore, we view it as plausible to extrapolate from the paired mover sample.

In our main results, we document substantial deviations from additive separability. To develop a reasonable benchmark, we show that among stayers at the same firm, the forecast bias coefficient is 0.97. Among all firm switchers, the coefficient is 0.70.

Under the assumption of exogenous mobility, our estimator implies that the variance of match effects is around 40% of the variance of the Kline, Saggio, and Sølvsten (2020) (KSS) corrected variance of firm effects in the full sample. Our estimator uses the earnings gap between the paired movers as a key moment. All else equal, a larger earnings gap implies a larger variance of match effects. We show that there are corners of the data with a much larger role for match effects because the paired mover coefficient is stable as the earnings gap increases. Because the estimator aggregates nonlinearly, when we implement our estimator in deciles of the earnings gaps we find an overall variance of match effects to be over two times larger than the pooled estimator, or the same size as the variance of firm effects. Our baseline estimate of the variance of match effects is substantially larger than that implied by comparing the adjusted-R^2 in the AKM model and an interacted model, a point we return to below.

We then develop subgroup analyses that are suggestive of violations of exogenous mobility. We find lower coefficients for moves across contexts than within contexts, which is what we expect if there were context-specific match effects. For within-sector moves the coefficient is 0.73, and for across sector moves it is 0.67. In the Veneto data, these differences are starker. One important feature of the data is that workers are disproportionately likely to remain in the same context, rather than switch. Such a pattern is consistent with workers taking match effects into account when deciding whether to move, which would violate exogenous mobility. This pattern occurs in models of match effects where the importance of match effects implies that much mobility is not realized.

To develop an estimate of the variance of match effects taking into account endogenous mobility, we estimate a simple random job search model where workers are heterogeneous in productivity and move on the basis of both a firm effect and a match effect. We match the KSS-corrected variance of the firm effects, the earnings gap between paired movers (which depends on person effects and match effects), the paired mover regression coefficients, as well as Employer to Employer (EE), Employer to Unemployment (EU) and Unemployment to Employment (UE) rates.

Quantitatively, the model finds that the variance of match effects in the steady state distribution is just over half the variance of firm effects in the full sample and is about 25% larger than that implied by our exogenous mobility benchmark. In the model, match effects are positively correlated across matches within person and so the lower bound logic applies.

In the model, the presence of match effects means that the average wage changes experienced by workers who accept offers are a poor predictor of the wage changes of other potential movers. Specifically, we forecast the earnings changes of the rejected offers using the earnings changes of the accepted offers and find that there is a large negative intercept and the slope departs from 1 (it is around 0.8). Thus, in the context of the model accepted offers are a poor guide to average treatment effects in the population.

Turning to the first piece of evidence supporting the AKM specification, this simple model of mobility based on match quality and a firm effect—which thus violates exogenous mobility—generates an event study coefficient of 0.56 on employer to employer (EE) transitions and 0.99 on employer to unemployment to employment (EUE) transitions. This sample split is supportive of the basic logic of the event study test and its ability to detect deviations from exogenous mobility. Despite the fact that the EE transitions are about 40% of the moves in the model-generated data, when we pool, we find an event study coefficient of 0.99. This result is explained mainly by the fact that the means differ between the two samples so Simpson's paradox effects are present. Even when the share of EE moves is over 90% the event study coefficient is still above 0.9.

We show evidence of this between-sample effect in the data: in the Brazilian data the event study coefficient is 1.07. But when we split moves by whether there was an increase or decrease in the firm effect, we find coefficients of 1.25 and 1.47, which are less supportive of the exogenous mobility assumption. Thus, the event study test is low-powered against alternative hypotheses that include an important role for endogenous mobility.

Turning to the second piece of evidence supporting the AKM specification, in the model the comparison of the adjusted-R^2 from AKM and an uninteracted model is a severely downward biased estimator of the variance of match effects. There are two sources of bias: endogenous mobility and short panels. With endogenous mobility and short panels, this estimator is downward biased by almost an order of magnitude. Thus, the small implied variance of match effects from this estimator is consistent with a much larger role for match effects than previously thought.

Turning to the third piece of evidence supporting the AKM specification, we implement the static Bonhomme, Lamadon, and Manresa (2019) estimator in our data. Typically, the BLM estimator finds some deviations from additive separability and so we want to translate their deviations into our metrics. We simulate data from their estimated model and then run the paired mover test in the simulated data. The BLM estimator is unable to accurately recover the paired mover coefficient. We thus conclude that our test points to a new feature of the data that has been missed by previous work.

Literature: The most closely related paper is an unpublished paper, Kantenga and Law (2016). Section 6 of that paper develops a statistical test for additive separability based on the same feature of the data that this paper exploits: two workers observed at the same two firms (albeit, not restricted to the same years) should have constant earnings gaps up to concerns about measurement error. Compared to Kantenga and Law (2016), this paper develops a more transparent approach to looking at this implication. By formulating it as a forecast bias test, this paper also connects to other features of the data that researchers studying the AKM model have explored.

Woodcock (2015) is another paper that develops an estimate of match effects in the context of the AKM model. The paper pursues multiple estimation approaches. The easiest to explain is the orthogonal match effects model where the match effect is the mean residual of the AKM model within firm-worker match. As Kline (2024) emphasizes, the estimation of many parameters in the AKM model relies on indirect contrasts where it is less transparent what feature of the data is driving results. The present paper builds from the minimal feature of the data that identifies match effects.

Kline (2024) uses Veneto data and Table 1 looks at the edges where there are two or more movers, which is the same feature of the data that this paper relies on. It shows that the AKM model captures 84% of the variance of edge effects generated by looking directly at the movers. This paper looks at these same edges but looks at a different feature of these edges: whether the earnings gaps between workers are stable with the moves. In this sense, the exercise in this paper is reminiscent of a pre-processing step in Hagedorn, Law, and Manovskii (2017) where they find that the ranking of workers across firms is not stable and they develop an approach to average this out (see their section 4.2).

A number of "AKM" papers present evidence that is consistent with match effects. Most directly, Beauregard et al. (2025) develop a U-AKM model, where the worker's fixed effect is allowed to depend on whether they are matched to a union or non-union firm. A number of papers ask whether the change in the firm effects can explain the change in earnings for a select subset of workers. In this sense, these exercises are reminiscent of the event study test. A typical finding is that the firm effects do a poor job of explaining these changes. For example, Lachowska, Mas, and Woodbury (2020) find that the change in firm effects does not on average explain the earnings losses of displaced workers. Relative to this literature which relies on having a specific shock to mobility or a particular model of match effects, this paper presents an omnibus approach to testing for and quantifying the role of match effects.

Conceptually, this paper is also related to Borovičková and Shimer (2024). The main thrust of that paper is to develop a model with endogenous mobility because of selective hiring. The paper shows that the model implies a wage equation that is additively separable in levels (and approximately so in logs). Most provocatively, the paper develops analytical and numerical evidence that the model passes the event study test of Card, Heining, and Kline (2013), despite an economic structure that violates exogenous mobility. We show using data simulated from their model that the reason the event study test passes is due to the between-sample effect that we emphasized above. More broadly, while the point of Borovičková and Shimer (2024) is to show analytically that it is possible for an economic structure featuring match effects to deliver additively separable wage equations (since prior work had supported this functional form restriction), our goal is to develop a direct test of this functional form restriction.

1 Additive separability versus exogenous mobility

In this section, we discuss the difference between exogenous mobility and additive separability, which is important to interpreting our results.

1.1 Informal discussion

The basis of much empirical work in labor (and applied) economics is the following two way fixed effects specification (Abowd, Kramarz, and Margolis (1999)):

$$y_{it} = \alpha_i + \psi_{\mathbf{j}(i,t)} + \beta X_{it} + \epsilon_{it}, \tag{1}$$

where y is log earnings, i is an individual, $\mathbf{j}(i,t)$ is the firm that employers worker i at time t, α is a worker fixed effect, ψ is a firm effect, X_{it} is a set of time-varying worker covariates, and ϵ is an error term. This equation looks like it imposes additive separability in that there is no term for interactions between firms (j) and workers (i). We will see, however, that the conventional assumption deviates from additive separability.

For expositional purposes, we depart from the conventional equation and explicitly write the wage equation to include match effects:

$$y_{it} = \alpha_i + \psi_{\mathbf{j}(i,t)} + \beta X_{it} + m_{ij} + \tilde{\epsilon}_{it}, \tag{2}$$

where $m_{ij} \equiv \mathbb{E}[\epsilon_{it}|i,j]$ so that m_{ij} is defined as the mean of the error term over all draws of the error term, not just the periods in which i and j actually match and $\tilde{\epsilon}_{it} \equiv \epsilon_{it} - m_{ij}$. This definition of a match effect as a permanent component of the match parallels the way person and firm effects are defined, and parallels the definition in equation (3) in Woodcock (2015). Below, we characterize the time series properties of the match effect. Note that $\tilde{\epsilon}_{it}$ is mean zero, while the potential ϵ_{it} for a particular worker i at firm j may not be. We refer to the m_{ij} as match effects in what follows, though the m_{ij} are a statistical—and not an economic—object.

Conventionally, researchers impose an exogenous mobility assumption. Informally, exogenous mobility says that workers do not, on average, select a firm based on the error term.

To see the distinction between exogenous mobility and additive separability, suppose that we see each worker at all firms for an extended period of time. Then we can estimate the average treatment effect of each firm on earnings in the whole population (relative to some omitted firm). For example, suppose that there are N people, J firms and T time periods. Posit asymptotics where N and T grow large. Assume that $\frac{T}{J}$ (the number of periods that each worker spends at each firm) is an integer. Suppose we index firms by numbers and normalize the 0^{th} firm to have firm effect of 0, i.e., $\psi_0 \equiv 0$. Then the plug-in estimator for the firm j effect is:

$$\hat{\psi}_j = \frac{J}{NT}\sum_i\sum_t y_{it|\mathbf{j}(i,t)=j} - \frac{J}{NT}\sum_i\sum_t y_{it|\mathbf{j}(i,t)=0}. \tag{3}$$

Substituting in for the definition of y, we have:

$$\hat{\psi}_j = \frac{J}{NT}\sum_i\sum_t \left[\alpha_i + \psi_{\mathbf{j}(i,t)=j} + \beta X_{it} + m_{i\mathbf{j}(i,t)=j} + \tilde{\epsilon}_{it}\right] - \frac{J}{NT}\sum_i\sum_t \left[\alpha_i + \psi_{\mathbf{j}(i,t)=0} + \beta X_{it} + m_{i\mathbf{j}(i,t)=0} + \tilde{\epsilon}_{it}\right]. \tag{4}$$

We can see that the α_i cancel, the assumption that the m_{ij} and $\tilde{\epsilon}_{it}$ are mean zero for each $i-j$ combination means that these cancel out. So then $\hat{\psi}_j = \frac{J}{NT}\sum_i\sum_t \psi_{\mathbf{j}(i,t)=j} - \frac{J}{NT}\sum_i\sum_t \left[\psi_{\mathbf{j}(i,t)=0}\right]$, where $\psi_{\mathbf{j}(i,t)=0} \equiv 0$ because of the normalization.

While ψ_j captures the average effect of firm j on earnings, this effect averages over arbitrary heterogeneity. For worker i, the average change in earnings of going from firm j' to j is

$$\psi_j + m_{ij} - \psi_{j'} - m_{ij'}.$$

Exogenous mobility allows the treatment effect of a firm to be heterogeneous and thus is consistent with the presence of match effects. The key implication of exogenous mobility is that matches are not formed on the basis of the match effects.

The relevant takeaway for interpreting our resuls is that exogenous mobility is an assumption which allows the researcher to estimate the average treatment effect of the firm, while additive separability is an assumption which implies that the treatment effect of the firm is constant. Thus, exogenous mobility can hold without additive separability holding. More deeply, specification tests for exogenous mobility do not directly test additive separability. Below, however, we use our machinery to develop some auxiliary evidence about the plausibility of exogenous mobility.

1.2 (More) Formal discussion

Once we decompose the error term into a permanent component (the match effects) and an idiosyncratic component, exogenous mobility says that on average workers do not select firms on the basis of either component (this assumption uses notation from Kline (2024, pg. 14)):

Assumption 1. *Assume that:*

$$\mathbb{E}[\tilde{\epsilon}_{it}|\mathbf{j}(i,s), X_{is} = x] = 0, \tag{5}$$

and

$$\mathbb{E}[m_{ij}|\mathbf{j}(i,s), X_{is} = x] = 0, \tag{6}$$

where $\mathbf{j}(i,s)$ *is the employer of worker* i *in time period* s*, for all workers* $i \in \{1,...,N\} \equiv [N]$*, all time periods,* $(s,t) \in [T]^2$ *(where* $t \in \{1,....,T\} \equiv [T]$*), and all possible firm assignments* $j \in [J]$ *(where* $j \in \{1,...,J\} \equiv [J]$*.*

This assumption still allows workers to select firms on the basis of the ψ, and thus is consistent with arbitrary patterns of sorting because workers with different α can select firms (or firms can select workers) differently.

Additive separability pairs the same assumption on the idiosyncratic component of the error term with a stronger statement about m_{ij}:

Assumption 2. *Assume that:*

$$\mathbb{E}[\tilde{\epsilon}_{it}|\mathbf{j}(i,s), X_{is} = x] = 0, \tag{7}$$

and

$$m_{ij} = 0 \ \forall \ i, j, \tag{8}$$

where $\mathbf{j}(i,s)$ *is the employer of worker* i *in time period* s*, for all workers* $i \in \{1,...,N\} \equiv [N]$*, all time periods,* $(s,t) \in [T]^2$ *(where* $t \in \{1,....,T\} \equiv [T]$*), and all possible firm assignments* $j \in [J]$ *(where* $j \in \{1,...,J\} \equiv [J]$*.*

Exogenous mobility says that, on average, the match effects in realized matches are zero. Additive separability says that the permanent component of the match effects are all zero.

The paired mover test assesses additive separability. It is logically possible to reject additive separability but for exogenous mobility to hold. In this case, the firm effects are average treatment effects. There are many questions for which it is interesting to know the average treatment effect of a firm.

2 A test of (log) additive separability

In this section, we introduce the paired movers test. We compare the paired movers test to the event study test. We discuss important implementation issues, and how to interpret deviations of the forecast bias coefficients in both tests from the benchmark value of 1. We also show that under exogenous mobility we can use the paired mover coefficient to estimate of the variance of match effects.

2.1 The paired movers test

We consider workers i and i' who both work at firm A and B. For expositional simplicity, we replace the time subscript with the firm subscript and drop the covariates, but in implementation we keep track of both time and covariates. Then the difference between worker i and i''s earnings at firm A is given by:

$$y_{iA} - y_{i'A} = (\alpha_i - \alpha_{i'}) + (m_{iA} - m_{i'A}) + (\tilde{\epsilon}_{iA} - \tilde{\epsilon}_{i'A}). \tag{9}$$

By differencing across workers within firm, the firm effect drops out. Additive separability implies that $\mathbb{E}[\tilde{\epsilon}_{iA} - \tilde{\epsilon}_{i'A} | \mathbf{j}(i,s) = A, \mathbf{j}(i',s) = A] = 0$ and $m_{iA} = m_{i'A} = 0$. Hence, $\mathbb{E}[y_{iA} - y_{i'A}] = (\alpha_i - \alpha_{i'})$. Now consider the difference between worker i and i' at firm B:

$$y_{iB} - y_{i'B} = (\alpha_i - \alpha_{i'}) + (m_{iB} - m_{i'B}) + (\tilde{\epsilon}_{iB} - \tilde{\epsilon}_{i'B}). \tag{10}$$

To construct the test, we consider whether the earnings *gaps* at firm A predict earnings *gaps* at firm B:

$$(y_{iB} - y_{i'B}) = \beta_0 + \beta_1 (y_{iA} - y_{i'A}) + \varepsilon_{i,i',A,B}. \tag{11}$$

We can substitute in for the definitions of the earnings gaps to write:

$$(\alpha_i - \alpha_{i'} + (m_{iB} - m_{i'B}) + \tilde{\epsilon}_{iB} - \tilde{\epsilon}_{i'B}) = \beta_0 + \beta_1((\alpha_i - \alpha_{i'}) + (m_{iA} - m_{i'A}) + \tilde{\epsilon}_{iA} - \tilde{\epsilon}_{i'A}) + \varepsilon_{i,i',A,B}. \tag{12}$$

Under the assumption of additive separability, the probability limit of β_1 is 1 because this regression is effectively a regression of $\alpha_i - \alpha_{i'}$ on itself. Thus, deviations from 1 are indicative of deviations from additive separability which implies the presence of match effects. Below, we solve for the regression coefficient in terms of variances and covariances and discuss their economic interpretation.

2.2 Interpretation of paired movers test

To interpret deviations from 1 in the forecast coefficient, we compute the probability limit of the forecast coefficient. The asymptotic thought experiment is that the number of paired movers grows.

Then the probability limit is given by:

$$\begin{aligned}\text{plim } \hat{\beta}_1 = &\frac{Var(\alpha_i - \alpha_{i'}) + Cov(m_{iA} - m_{i'A}, m_{iB} - m_{i'B})}{Var(\alpha_i - \alpha_{i'}) + 2Cov(\alpha_i - \alpha_{i'}, m_{iA} - m_{i'A}) + Var(m_{iA} - m_{i'A})} \\ &+ \frac{Cov(\alpha_i - \alpha_{i'}, m_{iB} - m_{i'B}) + Cov(\alpha_i - \alpha_{i'}, m_{iA} - m_{i'A})}{Var(\alpha_i - \alpha_{i'}) + 2Cov(\alpha_i - \alpha_{i'}, m_{iA} - m_{i'A}) + Var(m_{iA} - m_{i'A})}. \end{aligned} \tag{13}$$

The covariance terms correspond to different forms of selection. For example, for the $Cov(\alpha_i - \alpha_{i'}, m_{iB} - m_{i'B})$ term, some forms of selection would imply that these terms would tend to be negative: the firm will only hire a worker if she is good enough, which is the sum of the person and match effect. So conditional on two people ending up at the same firm, these are negatively related. The $Cov(m_{iA} - m_{i'A}, m_{iB} - m_{i'B})$ term is about the persistence of match effects.

2.3 Interpretation of paired movers in the special case of exogenous mobility

Under exogenous mobility, workers do not select employers on the basis of match effects. Therefore, the only source of selection is the across-firm sorting of workers. Suppose that within a firm the variance of worker types is given by $\alpha \sim N(0, \sigma_\alpha^2)$, the variance of match effects is given by $m \sim N(0, \sigma_m^2)$, and the variance of the (independent) errors is given by $\tilde{\epsilon} \sim N(0, \sigma_{\tilde{\epsilon}}^2)$. Workers then move randomly.

In this case, we can map the paired mover coefficient into an estimate of the role of match effects. The probability limit simplifies to:

$$\text{plim } \hat{\beta}_1 = \frac{Var(\alpha_i - \alpha_{i'})}{Var(\alpha_i - \alpha_{i'}) + Var(m_{iA} - m_{i'A})}. \tag{14}$$

The probability limit reflects the dispersion of person effects between the paired movers relative to the dispersion in the match effects among the movers.

To convert this coefficient into an estimate of the variance of match effects, we need a second moment that tells us about the dispersion of within-firm person effects. To do so, consider the gap between the paired movers at the origin firm:

$$y_i - y_{i'} = \alpha_i + m_i + \tilde{\epsilon}_i - \alpha_{i'} - m_{i'} - \tilde{\epsilon}_{i'},$$

where the firm effects difference out. Since the gap is a function of six normal random variables the gap itself is normal random variable, $Z \sim N(0, 2\sigma_m^2 + 2\sigma_\alpha^2 + 2\sigma_{\tilde{\epsilon}}^2)$. Under exogenous mobility the mean of this gap is zero. A function of this gap that is non-zero is the mean of the absolute value of the gap. The absolute value of a normal distribution is known as the half-normal distribution, and its mean is known in closed form. Hence, the mean of the absolute value of the gap is:

$$\mathbb{E}[|Z|] = 2\sqrt{\frac{\sigma_m^2 + \sigma_\alpha^2 + \sigma_{\tilde{\epsilon}}^2}{\pi}}. \tag{15}$$

We can combine equations (14) and (15) to solve for σ_m^2 in closed form:

$$\hat{\sigma}_m^2 = (1 - \hat{\beta}_1)\frac{\pi}{4}\hat{\mathbb{E}}[|Z|]^2\mathcal{A}, \tag{16}$$

where $\mathcal{A}$ is an adjustment term reflecting the measurement error term, $\tilde{\epsilon}$.[1] These equations show that the paired mover coefficient maps linearly into the variance of the match effects. A smaller paired mover coefficient, $\hat{\beta}_1$, implies a larger variance of match effects. And, similarly, a larger mean absolute gap, $\hat{\mathbb{E}}[|Z|]$, implies a larger variance of match effects.

Under one natural form of endogenous mobility, this estimator is likely to generate a lower bound on the variance of match effects. The intuition is that exogenous mobility rules out a covariance term of match effects across matches. In most models of endogenous mobility, match effects will be positively correlated across matches because workers have the option of keeping their old match effect. Relative to exogenous mobility, this positive correlation will generate a higher paired mover coefficient and thus imply a smaller role for match effects than this estimator. Hence, the true variance of match effects is likely larger than implied by this estimator.

This estimator is instead an upper bound if within-firm there is a negative relationship between match effects and person effects as arises in the case of selective hiring discussed above. The model we work with below only features the mechanism discussed in the previous paragraph.

2.4 The event study test

The test that launched the modern Abowd, Kramarz, and Margolis (1999) literature is the seminal event study analysis in Card, Heining, and Kline (2013). This analysis tests the implication of exogenous mobility that the change in the firm effects on average predict the change in earnings when workers switch firms.

To write the event study test in the same notation, consider worker i at firm A and B:

$$y_{iA} = \alpha_i + \psi_A + m_{iA} + \tilde{\epsilon}_{iA} \tag{17}$$

and

$$y_{iB} = \alpha_i + \psi_B + m_{iB} + \tilde{\epsilon}_{iB}. \tag{18}$$

The basis of the event study test is to ask whether changes in the firm effects (or mean co-worker earnings) predicts changes in earnings within worker. The regression version is:

$$y_{iA} - y_{iB} = \beta_0 + \beta_1(\psi_A - \psi_B) + \varepsilon. \tag{19}$$

[1] In Appendix A, we solve for this term while allowing the $m + \alpha$ to follow an $AR(1)$ process.

Plugging in for the definition of y_{iA} and y_{iB} we have:

$$(\psi_A - \psi_B) + (m_{iA} - m_{iB}) + (\tilde{\epsilon}_{iA} - \tilde{\epsilon}_{iB}) = \beta_0 + \beta_1(\psi_A - \psi_B) + \varepsilon. \tag{20}$$

Under the assumption of exogenous mobility and abstracting from difficulties in estimating the ψ, the probability limit of β_1 is 1 because this regression is effectively a regression of $\psi_A - \psi_B$ on itself (on average, the m and $\tilde{\epsilon}$ terms are zero). Deviations from 1 are indicative of deviations from exogenous mobility. In implementation below, we address concerns about measurement error by splitting the sample on the basis of workers and computing two measures of the ψ_A and the ψ_B so that we can instrument.

Using the notation in equation (20) the probability limit is given by:

$$\text{plim } \hat{\beta}_1 = \frac{Var(\psi_A - \psi_B) + Cov(m_{iA} - m_{iB}, \psi_A - \psi_B)}{Var(\psi_A - \psi_B)}. \tag{21}$$

If mobility is exogenous, then this coefficient equals 1. The forecast coefficient is below 1 when the differences in match quality are negatively correlated with the differences in firm effects, and positive when the differences in match quality are positively correlated with the differences in firm effects. This natural way of generating a coefficient above 1 differs from the paired movers test.

3 Data

3.1 Brazilian data

We use *Relação Anual de Informações Sociais* (RAIS) data from Brazil, which is a matched employer-employee data set that contains information on all formal job contracts. Each observation in the data is a job spell and the notion of employer is an establishment within a firm. We start from the universe of spells from 2006 to 2022 and obtain a single observation per worker per year by keeping the job with the highest earnings (average monthly wage $\times$ months worked) in each year. Each year, we drop workers on temporary contracts, public servants, and those with zero earnings. Finally, we focus on workers aged 18 to 64. We refer to this sample as the sample of *all workers*.

We define a mover as a worker who changes employers between two consecutive years and (i) separated from the previous employer and (ii) such separation was either voluntary (employee-initiated) or involuntary (employer-initiated). The first condition excludes workers who change their dominant job, the job from which they earned the most in a given year, but remain employed at the original firm. The second condition excludes workers who transfer within establishments of the same firm. We often refer to this sample as the sample of *all movers*.

To construct the sample of *paired movers*, we make a few restrictions. First, we focus on paired movers where the workers are present for two years in the origin firm. This restriction allows us to instrument the earnings at the origin firm. We also explore the time series properties of the gaps and so restrict to samples where the paired workers are both present for more years in both the origin and destination firms. Second, we want to ensure that the paired movers are actually moving firms, and so we require that no more than 30% of the workers in the origin firm go to the destination firm, and that no more than 30% of employment in the destination firm came from the origin firm (Benedetto et al. (2007)). By construction, we also need to observe the worker at least once at the destination firm, and she must move with at least one co-worker. A move is defined by origin, destination, and year. In many cases, there are more than two workers who leave a firm in a particular year. In this case, we randomly match workers and keep only one pair per worker per move. Workers can appear multiple times if they move between different firm pairs in different years.

We also construct a sample of *paired stayers*, where A and B is the same employer. Since the resulting sample is too large, we take a random sample of 10%.

We construct three other samples to estimate AKM models. We start from the sample of *all workers* defined above in 2015. Due to the large size of the data, we take a random sample of 25% of the workers and construct a panel of these workers from 2012 to 2017. Building on this first sample, the second sample includes only workers who change employers at least once between 2012 and 2017—that is, we drop the stayers. The third sample includes only workers in the second sample who are in the paired movers sample (and her move in the paired movers sample is between 2012 and 2017).

The main variables we report from the data are gender, age, years of education, tenure, occupation, earnings, and firm-level variables such as sector, size, average pay, and location.

Our baseline notion of earnings is the average log hourly wage through the year. Job contracts in Brazil are defined by monthly wages and weekly working hours. We deflate values to 2019 BRL and compute earnings as the average monthly wage divided by an estimate of monthly hours (weekly hours $\times$ 30/7) (Gerard et al., 2021). We compute firm size as the number of workers employed on December 31st of each year.

Age is age on December 31st of the year. Years of education is the highest level of education completed using the *Instituto Brasileiro de Geografia e Estatística* (IBGE) classification. Tenure is measured in months as the difference between the date of hire and the date of separation (or Dec. 31st). Occupation is classified using three-digit *Classificação Brasileira de Ocupações* (CBO) codes. Sectors are defined using two-digit *Classificação Nacional de Atividades Econômicas* (CNAE) codes. We observe the establishment's municipality and use IBGE's *regiões geográficas imediatas*, which are similar to commuting zones in the U.S., as geographic units.

For most of the analysis, we work with residualized earnings. Conceptually, if one worker is young and on the steep part of her lifecycle earnings profile and the other worker is old and on the flat part of her lifecycle profile, then we would not find stable earnings gaps across firms. This instability would just be about the lifecycle earnings profile, and not about match effects. We construct residualized earnings in two steps. First, we estimate the role of covariates using only within-firm-worker match variation in wages:

$$y_{it} = X_{it}\beta + d_{ij(i,t)} + \epsilon_{it},$$

where d_{ij} is a dummy for the interaction of worker i and firm $j(i,t)$. Our baseline set of covariates is a fourth degree polynomial in age, interacted with gender and four education categories (no primary education, primary education, high school, and some college or more). Second, we construct residualized earnings by subtracting off the estimated effect of covariates:

$$\tilde{y}_{it} = y_{it} - X_{it}\hat{\beta}.$$

We use residualized earnings throughout the analysis except that in the AKM analysis we show how the conventional AKM regression compares to the results using residualized earnings.

When we construct paired movers we arbitrarily order them such that sometimes the earnings gap is positive and sometimes it is negative. In Appendix B we present simulation evidence that if two workers draw earnings from distributions with a different mean (as would be the case in the presence of individual effects), then sorting workers to ensure that the gaps are all the same sign creates a mechanical upward bias relative to the truth. Thus, we do not sort workers to ensure that the gap is always positive.

3.2 Veneto data

The Veneto Worker History data in its full version runs from 1976 to 2001.

In terms of cleaning the data, we use cleaning code used in Kline, Saggio, and Sølvsten (2020) and so our description follows their computational appendix. The wage record consists of a start date, end date, number of days worked in a given year, and the total wage compensation paid in a given year. We can thus compute a notion of a daily wage in each year.

We focus on workers aged 18 to 64. We focus on the worker's dominant job. We also exclude workers with implausibly low wages (below 5 euros or zero days worked), implausibly large wage changes (more than doubling), or those employed in the public sector, having more than ten jobs or missing gender.

We use the data from 1985 to 2001 because the view is that data on days worked is unreliable before this date.

Based on the description of the Veneto data in Card, Devicienti, and Maida (2014) the industry codes are five-digit ATECO 91 codes. The employers in the Veneto data are described as firms.

To construct the set of paired movers, we make analogous restrictions to what we did in the Brazilian data. In many cases, there are more than two workers who leave a firm in a particular year. In this case, we form all possible pairs.

4 Results

In this section, we first discuss descriptive statistics on our sample. The key question is understanding who the paired movers are and how they are selected. We then present the main results documenting meaningful deviations from additive separability and present extensive robustness. We show that under exogenous mobility the estimate of the variance of match effects is substantial. Finally, we show that the deviations from additive separability are stronger in moves across contexts.

4.1 Descriptive statistics

Table 1 shows summary statistics in three samples. The first sample is all workers. The second sample is all workers who switch firms. The third sample is the set of paired movers. In general, movers are negatively selected relative to all workers in terms of tenure and earnings. In contrast, paired movers are positively selected. Relative to all movers, paired movers come from much larger employers and higher-paying employers. Movers are a younger and more male than all workers.

The paired movers come from larger firms and go to larger firms, which suggests that the dominant form of selection into paired mobility is simply chance. To assess the chance hypothesis, we take the origin firms and compute the empirical distribution of the destination firms of movers over a one year window—not including the paired movers. Using these empirical probabilities, we then simulate mobility year by year using the number of movers we see each year and compute the number of paired movers, where a paired move has to occur in the same year. As can be expected from the fact that paired movers have disproportionately large origin and destination firms, Table 2 shows that this simple logic explains over 70% of the paired movers. We interpret this evidence as reassuring that the paired movers are not too unusual and so it is plausible to extrapolate from them to other movers.

As another way of comparing paired movers to all movers, Table 3 shows the AKM decomposition in four samples, including those of paired and all movers. Columns (1) and (2) show the decomposition in the sample of all workers, where the columns differ by whether we use raw earnings or the residualized earnings. The reason to show these two columns is to display the minimal role of working with residualized earnings on the decomposition. Column (3) reports the decomposition among all movers, and column (4) reports results for the paired movers. The reason to show all movers is that this sample is most comparable to the paired movers sample. The baseline finding is that the adjusted-R^2—and thus the fit of the AKM model—is similar in the all mover sample and the paired mover sample. Where there are slight differences is that the variance of firm effects (and the share of the variance of earnings explained) is larger in the all mover sample than the paired mover sample: in the all mover sample it is 0.064, which is about 15% of the variance of earnings, whereas in the paired mover sample it is 0.048, which is about 10% of the variance of earnings in the sample. Below, when we compare the variance of match effects to the variance of firm effects, we are conservative and compare to the largest variance of firm effects in the table.

As we emphasized above in the quantitative interpretation of the paired mover test, the absolute earnings gaps between the paired movers is an important moment for understanding the magnitude of match effects. In Table 4 we report statistics about the distribution of the absolute gap in earnings at the origin firm among the paired movers. The mean of the absolute gap is around 36 log points. The table also shows that this gap in a set of paired stayers: we look at random pairs of workers who are observed at the same firm for two years and then we see again for at least a year (either in the origin firm, or at a different firm). The stayers have more dispersion than the paired movers (45 log points, versus 36 log points for the paired movers). Because of these differences, below we consider how our results differ if we focus on subsets of the data where the absolute earnings gaps are larger.

Figure 1 shows that the distribution of earnings changes among the paired movers are broadly similar compared to all movers.

Veneto data: The Veneto data differs in a few ways from the Brazilian data. First, as in the Brazilian data the movers are negatively selected relative to all workers. But the paired movers do not fully undo that selection and are still lower earning than all workers. In addition, the paired movers are more rare than in the Brazilian data. Second, the mean earnings gaps are surprisingly similar.

4.2 Main results

Figure 2 shows the graphical version of our main IV results. The x-axis shows the gap in earnings between a pair of workers in period t, and the y-axis shows the gap in earnings in the next period. The red dots show the first stage of the gap in earnings in two consecutive periods in the paired mover sample at the origin firm. The dots are approximately linear and lie very close to the 45 degree line, indicating that earnings gaps are quite stable. The blue squares show earnings gaps from the year before the move to the year after the move. These dots are also approximately linear, but the slope is much shallower than between the years when the workers do not move. This indicates that earnings gaps are not stable across contexts.

Table 4 shows the main IV results in a table. We first show results for paired stayers. Paired stayers provide a quantitative benchmark that is perhaps more empirically realistic than forecast unbiasedness in that it allows for the possibility of deviations from the assumptions of the benchmark additively separable specification that are different from match effects. For example, if there is drift in the individual effects, then the paired movers test would interpret this as evidence for match effects, whereas in the paired stayers setting we would know that persistent match effects are not the explanation. Panel A shows the second stage estimates. For the stayers, the coefficient is 0.97, indicating minimal drift in match effects between periods. In contrast, for paired movers the coefficient is 0.70, which is meaningfully different from 1 and from the stayers coefficient. Consistent with the first stage dots lying close to the 45 degree line, Panel B shows that the first stage coefficient is around 0.93 for the baseline paired movers and 0.94 for the stayers.

Robustness to residualization: In our benchmark results, we residualize for a fourth degree polynomial in age interacted with gender and education. Appendix Table A1 shows that our results are similar if we instead just residualize for the age polynomial interacted with gender. Rather than residualizing earnings, we can also match workers on age and gender. Appendix Figure A1 shows similar coefficients when matching on 10-year age bins or 1-year age bins, with the coefficient ranging from 0.70 to 0.73. We prefer to focus on the residualized approach because it preserves sample sizes and parallels the treatment of covariates in the AKM literature.

Time series properties: In Section 1, we defined match effects to be a permanent feature of the match. The implication of this assumption is that up to measurement error the gap should be stable *within* the match. We already presented some evidence on this aspect of match effects by looking at paired stayers and finding a forecast coefficient of 0.97, which indicates small deviations from permanence.

Table 5 presents further evidence that the gaps are quite persistent by zooming in on the sample of paired movers and computing the correlation between the gaps at various horizons and in various samples (balanced panel and full sample) at both the origin and destination firms. To help interpret these correlations, we convert them to implied AR(1) coefficients at each horizon[2] Panels B and D of Table 5 shows these coefficients range from 0.93 to 0.98.

We follow Lachowska et al. (2023, Footnote 9) and pool the autocorrelation coefficients using a regression.[3] For the full sample, we find an estimate of the persistence parameter of around 0.96 (see Appendix Table A2). This estimate compares to 0.976 that Lachowska et al. (2023, pg. 387) find for firm effects. Thus, the match effects are almost as persistent as the firm effects.

As another way to show the relative stability of match effects, Figure 3 shows that our results are not very sensitive to which year we measure the earnings gaps. It provides an event study representation of our main results. The left-side of the graph looks at paired movers who are at their origin firm and plots stayer coefficients. The dot at -3 is workers who are at their origin firm in -5, -4, and -3 and we instrument the gap at -4 with the earnings in -5 and see how related they are to -3. We then repeat the exercise in -2, -1 and 0. The figure shows this regression coefficient for both a balanced panel and for the full sample of paired movers. The basic message of the figure is that the earnings gaps are quite stable over time at the origin firm. The right-side of the graph instruments for gap at 0 with the gap at -1 and then looks at outcomes in different years at the destination firm. The first thing to note is the dramatic drop from the left- to the right-hand side: gaps are much less stable when switching firms than staying within firms. The second thing to note is that the gaps are quite stable regardless of which year we use in the destination firm. This evidence is consistent with the match effects being quite persistent.

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[2] Let $\rho_{t,t+n}$ be the correlation of the gap between the paired workers at time t and $t+n$. Then under the $AR(1)$ model the persistence coefficient is given by $\frac{\rho_{t,t+2}}{\rho_{t,t+1}}$.

[3] For completeness, we reproduce the logic here. Let $y_t = \delta + \nu y_{t-1} + u_t$ so that the autocorrelation of y_t and y_{t-k} is $\rho(k) = \nu^k$. To estimate ν, fit $\ln(\rho(k)) = \beta k + \epsilon(k)$ where k is the lag order. The antilog of $\hat{\beta}$ is an estimate of ν.

For our primary results, we ask whether earnings gaps at the origin firm predict gaps at the destination firm. Conceptually, we could also do the test in reverse, and ask whether the gaps in the destination firm predict the gaps in the origin firm. In Appendix C we show that our results are robust to reverse versions of the test or using alternate periods.

Veneto data: The Veneto data generates a paired mover coefficient that is quite similar to that in Brazil: 0.82 versus 0.70. The stayer coefficient is slightly lower: 0.94 rather than 0.97. Notably, and indicating that the data are noisier, the first stage coefficients are much lower.

4.3 Quantitative interpretation under exogenous mobility

As we showed in Section 2, the probability limit of the regression coefficient of 0.70 is a complicated function of variances and covariances, which reflect patterns of sorting of workers across firms on the basis of person effects and match effects. In the special case of exogenous mobility, we showed that we can solve for the variance of match effects in closed form by combining the paired mover coefficient and the mean of the absolute gap between the paired movers. Using equation (16) and the estimate of the mean absolute value of the gap between paired movers in Table 4, we find the variance of match effects is 0.029.[4] This estimate is about 40% of the variance of (KSS-corrected) firm effects that we found in Table 3.[5]

An alternative way of learning about the variance of match effects comes from examining the change in adjusted R^2 from a model with additively separable firm and worker effects, or allowing for interactions. Versions of this exercise are standard in the literature (e.g., Card, Heining, and Kline (2013, pg. 995) and Bonhomme, Lamadon, and Manresa (2019, pg. 718-9). Using numbers in Table 3, this calculation implies a variance of match effects of 0.014.[6] This number is smaller than we found above. We return to this calculation in Section 5.

The conversion from the paired mover coefficient to the variance of match effects under exogenous mobility relies on the earnings gap between the paired movers. Figure 4 shows that if we focus on subsets of the data where the earnings gap is larger that we find a (much) larger role for match effects. Panel (a) shows the CDF of the absolute mean gap. While the median is around 0.36, there is a wide support. For the remainder of the figure we divide the paired movers into 10 deciles based on the size of the earnings gap.

One might suspect that the paired mover coefficient is driven by the instability of small earnings gaps at the origin firm. Panel (b) shows instead that the IV coefficient is *declining* in the size of the gap at the origin firm. The panel only shows 8 deciles because for the two smallest deciles there is so much implied noise that the IV coefficient is very large and coefficients in the top half of the

[4] $\sigma_m^2 = (1-\hat{\beta}_1)\frac{\pi}{4}\mathbb{E}[|Z|]^2 = (1-0.699)\frac{\pi}{4}0.364^2\frac{1}{1+\frac{0.95-0.83}{2\times 0.83}} = 0.029.$

[5] Our estimate of the variance of firm effects is 0.072. Gerard et al. (2021, Table 3) report estimates separately by demographic group and find variances of firm effects ranging from 0.056 to 0.086.

[6] $(0.934-0.907)\times 0.506 = 0.014$. This calculation uses the full sample. The calculation using only the paired movers is $(0.924-0.877)\times 0.473 = 0.022$.

gap distribution would not be visible. The key point is that paired mover IV coefficient is smallest where the gap is largest.

A related concern is that the earnings gaps are less stable when they are larger. We repeat the exercise of computing the implied AR(1) coefficient on earnings gaps, but now by the decile. Panel (c) shows that in fact earnings gaps are *more* stable the larger they are.

Panel (d) combines the estimates from Panel (b) and (c) and computes the implied variance of match effects under exogenous mobility. The panel only shows this calculation for the top 6 deciles, because these are the deciles where the paired mover coefficient is less than 1, which is required by the formula. The basic message from this figure is that there are corners of the data with a very large implied variance of match effects. For example, in the top decile the implied variance of match effects is over 0.40, which is more than 10 times the overall number. If we sum the six estimates and divide by ten, we get an implied variance of match effects of 0.07, which is over twice as large as what we found by pooling. Thus, this procedure aggregates in a non-linear way and implies a much larger variance of match effects than the overall number.

4.4 Heterogeneity

Table A3 shows additional summary statistics on the paired movers, and all of the subsamples of paired movers that we discuss below.

We first split by whether the paired movers are moving across sector or within sector. We define sector as a two digit CNAE code. Appendix Table A3 shows how the sector stayers compare to the sector movers. Sector stayers are older, higher paid, higher tenure, and have more schooling than sector movers. In terms of what would be predicted by chance Table 2 shows that the mobility patterns of other workers would predict that about 48% of paired movers would be within sector, whereas in the data 46% of them are. Thus, the notable feature of the data is that mobility patterns are relatively concentrated within sector, rather than that the paired movers are unusual.

Columns (3) and (4) of Table 4 show that the forecast bias coefficient is higher for the stayers than the movers: 0.73 versus 0.67. The finding that earnings gaps are more stable for small sector moves can be generalized. For each origin sector, we rank destination sectors by the frequency with which workers arrive. Panel (a) of Figure 5 shows that as we move from the most frequent sector move to less frequent moves, the paired mover coefficient falls from 0.74 (for the stayers) to around 0.64 for sectors that are 11th and down in terms of likelihood. Inspection of the data reveals that retail trade is a very common destination sector in almost all origin sectors. Separating out retail trade, we get a coefficient of 0.73 for the closest sector, falling to 0.63 for the least likely sectors, and 0.59 for retail trade.

Columns (5) to (8) of Table 4 shows heterogeneity where we split moves on the basis of mean pay at the firm and we split firm pay at the median of the distribution. Appendix Table A3 shows important differences by whether workers are staying or switching between different parts of the pay distribution. Those originating in high-paying firms have higher tenure and earn more than those originating in low paying firms. Columns (6) through (9) of Table 2 shows that again the distribution of paired movers in terms of staying at the same level of firm pay or changing is similar to what would be predicted by chance. And, again, the notable feature of the data is the low share of switchers. Turning to the regression results, Columns (5) to (8) of Table 4 shows that earnings gaps are more stable for workers staying in the same context than switching. This gap is especially large for workers starting in high-paying firms, where those who move to another high-paying firm have a paired mover coefficient of 0.72 whereas those who switch to low-paying firm have a coefficient of 0.62.

Columns (9) and (10) of Table 4 shows that the paired mover coefficient is 0.74 for the cluster stayers and 0.68 for the cluster switchers. (We discuss how we construct the clusters of firms in Section 6).)

Another way of measuring context is by occupation. In columns (11) through (13) we consider moves where neither worker changes occupation, one worker changes occupation or both change occupation. Here we find the starkest differences: the paired mover coefficient is 0.77 for moves where both workers keep their occupations but only 0.60 where both workers switch their occupations.

Columns (14) through (16) show, interestingly, that the earnings gaps are more stable for high-tenure paired movers than for low-tenure paired movers. Perhaps surprisingly, columns (17) and (18) show that there are minimal differences for paired movers within or across geography.

Across these splits, workers are more likely to stay in the context than to switch. Table 2 shows that 53% of moves switch sectors, whereas random mobility would say that 96% of moves should switch sectors. 68% of moves switch clusters, whereas random mobility would say that close to 90% of moves should switch clusters. Similar patterns apply to the earnings stayers.

These patterns of heterogeneity are consistent with violations of exogenous mobility. If workers take match effects into account, then they should be less likely to switch across contexts that encode match effects. In Section 5, we develop a model that formalizes this intuition.

In Appendix Tables A4 and A5 we explore how the paired mover coefficient differs by the reason for separation as well as the time between employment spells.

Veneto data: The results on heterogeneity in Veneto are generally more stark than in Brazil. For example, the sector stayers have a coefficient of 0.86 whereas the switchers have a paired mover coefficient of 0.72.

5 Model-based interpretation of the results

Assuming exogenous mobility, we converted the paired mover coefficient into an estimate of the variance of match effects. In this section, we develop and estimate a partial equilibrium search model to do so in the presence of endogenous mobility. We then show why the presence of match effects matters.

5.1 The model

The model is a standard partial equilibrium search model. Workers have a fixed effected $h_i \sim N(0, \sigma_w^2)$. Firms have a firm effect $p_j \sim N(0, \sigma_f^2)$. This distribution is also the offer distribution, denoted by F. The match effects distribution is $\mu_{ij} \sim N(0, \sigma_m^2)$. Denote this distribution by M. A worker's payoff to working at a firm j with firm effect h_j and match effect μ_{ij} is given by

$$h_i + p_j + \mu_{ij}.$$

As we formalize in the next paragraph, the worker sees the μ_{ij} before making her mobility decision, so this model violates both additive separability and exogenous mobility.

The value of unemployment for a worker i is:

$$U_i = b + \beta \left(\lambda_0 \int_\mu \int_p \max\{W_i(p', \mu'), U_i\} dF(p') dM(\mu') + (1 - \lambda_0) U_i \right). \tag{22}$$

This equation says that a worker receives the flow value of unemployment of b. Then the worker receives an offer with probability λ_0, and accepts it if it increases her value. If she does not receive an offer, then she remains unemployed. The notable feature is that the offer includes both the firm effect and the match effect.

The value of an employed worker with person effect α_i at a firm with firm effect p and with match effect μ is:

$$\begin{aligned} W_i(p_j, \mu_{ij}) = \alpha_i + p_j + \mu_{ij} + \beta \Big(\lambda_1 (1 - \delta) \int_\mu \int_p \max\{W_i(p_j, \mu_{ij}), W_i(p', \mu')\} dF(p') dM(\mu') \\ + (1 - \lambda_1)(1 - \delta) W_i(p_j, \mu_{ij}) + \delta U_i \Big). \end{aligned} \tag{23}$$

This equation says that an employed worker receives the flow payoff of her match. If her job is not destroyed, she can receive an outside offer, and she makes a maximizing decision whether or not to accept it. If she does not receive an offer (and her job is not destroyed) she remains in her job. With probability δ her job is destroyed.

5.2 Estimation

We estimate the model by the method of simulated moments. For simplicity, we assume that b is negative infinity so that all offers from unemployment are accepted. We simulate the model forward until steady state where steady state means that the distribution of the firm effects, worker effects, and match effects among employed workers is stable.

Estimation proceeds in two steps. We estimate the EU rate (δ) and UE rate (λ_0) by matching quarterly flow rates computed in survey data. We are then left with four unknowns: λ_1 and the variance of person, firm and match effects. We match four empirical moments: the EE rate, the paired mover regression coefficient, the variance of firm effects (estimated using AKM and the

Kline, Saggio, and Sølvsten (2020) correction), and the mean absolute earnings gap between paired movers that we documented in Table 4, though we correct for measurement error (see Appendix A). The reason to target the earnings gap between paired movers is that this parallels the conversion we did in the exogenous mobility exercise. Targeting the gap is also a way of capturing the extent to which workers are sorted across firms.[7] We search the parameter space using Metropolis-Hastings.

5.3 Model fit

The first part of Table 6 shows that we are able to closely replicate the four moments that we match. The paired mover coefficient is 0.69 in the data and 0.70 in the model, the variance of firm effects is 0.07 in both, and the mean absolute gap is 0.35 in the data and 0.36 in the model. Finally, the EE rate is 0.04 in both.

Appendix D discusses how model parameters map into the paired mover coefficient.

5.4 Results

The main take-away from Table 6 is that the variance of the match effects in the offer distribution is just over half of the variance of firm effects which is about 25% larger than the calculation under exogenous mobility.

The fourth part of Table 6 shows the mean and variances of the structural match effects, person effects and firm effects in the steady state distribution. The steady state distribution differs from the offer distribution because workers reject offers. Despite these rejections, the variance of the firm effects and match effects in the steady state distribution are quite similar to those in the offer distribution. Hence, our main estimate is that the variance of the match effects is about 50% of the variance of the firm effects. This result quantifies the role of match effects implied by the paired mover coefficient while taking into account endogenous mobility.

To understand where this estimate of the role of match effects comes from, recall that above we showed that under exogenous mobility the variance of match effects is about 40% of the variance of firm effects. As discussed above, natural forms of endogenous mobility will generate a positive covariance of match effects and so the exogenous mobility benchmark will be a lower bound. Appendix Table A6 displays the model-based components of equation (13) and shows that the term that contributes to the gap is the positive covariance in the gaps of match effects across firms.

The estimates are calibrated to match both the paired mover coefficient and the average earnings gap among paired movers. As we saw in Figure 4, the paired mover coefficient is stable or decreasing in the size of the gap. So if we calibrated our model to these corners of the data, then we would find a much larger role for match effects.

In the presence of match effects, predictions of changes in earnings based on accepted offers provides a poor guide to the changes in earnings for other workers, specifically, workers who rejected offers. Panel (a) of Figure 6a shows that earnings changes on accepted offers do a poor job of

[7] This model has no way of generating a correlation between person effects and firm effects. The way to generate such a correlation would be to allow the arrival rate of offers to be increasing in the worker type, as in Lentz (2010).

predicting earnings changes on rejected offers. At the firm-level, the x-axis computes the mean change in earnings for workers who move from A to B on EE moves (and thus all earnings changes are positive). The y-axis considers for those same firm pairs the change in earnings for the rejected offers. We then bin the firms. The notable feature of the Figure is first that the intercept is negative, consistent with the fact that offers that would lead to earnings cuts are rejected in this model. Second, the slope is not 1 (even when we split the sample and instrument). Thus, the presence of match effects means that the magnitude of earnings changes among accepted offers is a poor guide to the earnings changes among other potential moves (the rejected offers).

5.5 Extended model with a notion of context

Our results above suggest that the paired mover test looks quite different for "larger" and "smaller" moves, and that the larger moves are relatively rarer. Combined, this evidence heuristically points to violations of exogenous mobility in that workers are taking into account match effects in mobility.

To formalize this logic, consider an extended version of the model that is the same as above except that the match component has two dimensions: a "sector" component and a firm-specific component. If the worker stays in the same sector, then they retain their sector component. If the worker switches sectors, then they get a new draw of the sector component. (In this sense, the model is identical to Neal (1999)). We use 20 sectors. Appendix Table A7 shows that when we target the difference between the paired mover coefficient for within- and between-sector moves we qualitatively replicate the relative rarity of between- versus within sector moves in that workers are twice as likely to accept within sector as between sector offers. Similarly, fewer moves are cross-sector than a random mobility benchmark would predict.

6 Revisiting specification tests in the literature

So far we have developed evidence indicating a large role for match effects in the data both as a share of the variance of earnings, as well as in driving mobility. This evidence is inconsistent with the results of three exercises in the literature that are supportive of both exogenous mobility and additive separability. In this section, we use a combination of the estimated model and the paired mover regression to revisit this evidence.

6.1 Event study test

We construct the event study test in the following way. We randomly split the sample of workers and estimate two sets of firm effects. We then instrument the measurement of the change in firm effects estimated in the first sample with the change in firm effects estimated in the second sample.

Event study test in the model: Panel (b) of Figure 6 shows that the event study test matches intuitions about how it should work when we divide the model-generated data into EE and EUE moves (Appendix Table A8 shows regression versions). Intuitively, EE moves give more scope to select on match effects than EUE moves and so should generate a much lower event study coefficient. Consistent with this intuition, on EE moves the coefficient is 0.59 and on EUE moves it is 0.99.[8] Thus, with this sample split the event study works exactly how researchers expect it to and would detect that there are deviations from exogenous mobility on the EE moves where workers select firms on the basis of match effects.

What is surprising, however, is that when we aggregate all moves and run the event study test in the full sample we find a coefficient of 0.99. In the model, 41% of moves are EE moves, and so we might expect that the overall coefficient would be in between the coefficient on the EE split and the EUE split. Instead, the coefficient is (very slightly) above the coefficient on the EUE split.

To explain this result, in Appendix E we derive the standard result of how OLS combines the two lines (in the simulated data the first stages are essentially 1 in each of the subsamples), which depends on three things: relative sample sizes, the within-group variances, and the between-group differences in sample means. The relative sample size and variance logic implies that the pooled coefficient should lie in between the coefficients in the two sample separately. The difference in sample means can generate unintuitive behavior; for example, an extreme example of this logic is known as Simpson's paradox where the pooled coefficient is a different sign than the coefficient in each subsample.

Panels (b) of Figure 6 show the reduced form corresponding to these event study tests since the first stages are identical. The variance weighting logic pushes for more weight on the EUE moves because on EE moves there are relatively few moves to lower paying firms. The between-sample logic pushes for a coefficient above one.

Panel (c) of Figure 6 shows that the event study test fails to find convincing evidence against exogenous mobility for a wide range of the shares of moves that are EE. We vary the share of EE moves by increasing the arrival rate of offers on the job, λ_1. As the share of EE moves rises both the EE and EUE event study coefficients fall. The explanation for both is the same: a higher share of EE moves means that workers are more selected on match effects in any job. For workers making EE transitions, there is thus very strong selection on match effects in the origin job that persists into the destination job. For workers making EUE transitions, the strong selection on match effects still exists at the origin job even though in the destination job there is no selection on match effects. What is striking in this figure is that the event study coefficient remains above 0.90 even as the coefficients on the separate regressions both decrease. Indeed, as the share of EE moves gets high enough the pooled event study coefficient *exceeds* the coefficient in the EE or EUE samples. The reason why is that the between-sample slope is around 1.4 for a low share of EE moves and rises to 1.8 as the share of EE moves grows large. Thus, the between-sample comparison pushes up the overall coefficient. Panel (d) looks at the simulated data for the highest share of EE moves where it is visually easy to see the role of the between-sample comparison.

[8] We note that our attempts to separate EE and EUE moves in the data do not generate this distinction.

Event study test in the data: Appendix Table A9 shows that the forecast coefficient in the event study test is 1.07. The standard errors are tight enough that we can reject 1, but we do not interpret this deviation as economically large. In the Veneto data, the event study coefficient is also 1.07.[9]

Panel (e) of Figure 6 shows that this between-sample logic is present in the data. In the Brazilian data, e split the moves based on whether there are increases or decreases in the firm fixed effects on the move. The panel shows that in these two subsamples the event study coefficient *exceeds* the coefficient in the pooled regression: it is 1.25 on the increases and 1.47 on the decreases. Thus, the event study test looks less "good" in these subsamples and pooling makes the event study test look better. In Appendix Figure A2 we repeat this sample split in the model generated data in an endogenous mobility version of the model (what we introduced above) and an exogenous mobility version of the model (the model above with the same parameters, except there are no rejected offers). In the exogenous mobility version of the model, in both subsamples we find an event study coefficient of 1 (and in the pooled regression). In the endogenous mobility version of the model the split is 0.87 on the increases and 1.12 on the decreases. Quantitatively, the gap between the coefficients on the increases and decreases is very similar to what we find in the data.

Discussion: We interpret this result to say that unless the researcher ex-ante knows the corner of the data where exogenous mobility fails, the event study test is unlikely to detect this failure. If researchers can isolate the corner of the data where moves on match effects are a big deal, then the event study test will fail. But even if there are large corners of the data where workers move on the basis of match effects, the test might not fail if there are also non-trivial corners where workers do not move on the basis of match effects.

This discussion of the reasons why the event study test can fail to reject differ from those in the literature. Bonhomme, Lamadon, and Manresa (2019) emphasize that it can fail to reject for reasons similar to the distinction between exogenous mobility and additive separability discussed in Section 1: even if there are match effects (and additive separability does not hold), if mobility is exogenous then symmetry will hold. When the EE rate is low, the BLM critique is illustrated in the EUE sample because mobility is exogenous and so the event study coefficient is 1. Relatedly, Borovičková and Shimer (2024) emphasize that if the wage equation is additively separable then the data will pass the event study test. As we discuss below, there is clear evidence of deviations from additive separability in data generated from their model.

6.2 Adjusted-R^2 in AKM and the interacted model

Besides the event study test, one important piece of evidence in Card, Heining, and Kline (2013) against the importance of match effects is the small change in adjusted R^2 in going from the additively separable model to one with match fixed effects. For example, as we discussed above

[9] The Brazilian and Veneto data differ in the event study coefficient in the paired mover sample: in the Brazilian data it is 1.05 while in Veneto it is 0.65. The reweighting exercise in columns (3) through (5) shows that this difference can be explained by the set of firms we are considering.

Table 3 shows that in our data going from an additively separable model to a model with arbitrary firm and worker interactions increases the adjusted-R^2 from 0.90 to 0.93, which implies variance of match effects of 0.014 (in the paired mover sample it is 0.022).

In this section, we use the model to assess how compelling this evidence is. We hold fixed the parameters of the model and simulate data under two assumptions on mobility and two panel lengths. The two assumptions on mobility are exogenous mobility—where we assume that workers accept all offers—and endogenous mobility, which is the baseline model. The two panel lengths are 100 periods (which numerical experiments suggests is stable) and 7 periods (which is the number of periods in Card, Heining, and Kline (2013)). We interact the mobility assumption and the panel length.

We report three ways of estimating the variance of match effects. We report two versions of the adjusted R^2 calculation. The first version compares the adjusted-R^2 from the interacted and uninteracted model and multiplies this by the variance of earnings to get an estimate of the variance of match effects. The second is similar to the first but uses the KSS variance components to construct an implied R^2 of the uninteracted model, and then assigns an R^2 of 1 to the interacted model because there is no error term. The third way of estimating the variance of match effects uses the paired mover coefficient and the absolute earnings gap.

Table 7 shows that under exogenous mobility and long panels there are versions of the adjusted R^2 calculation that works. Specifically, in column (1) the KSS version matches the structural variance of match effects of 0.036. Similarly, the paired mover estimator is also able to exactly recover the structural variance of match effects. In contrast, the adjusted- R^2 estimator that is common in the literature is biased down by about 15% relative to the truth.

With endogenous mobility (but retaining the long panels), KSS approach is approximately unbiased, while the adjusted-R^2 approach is now biased down by 30% and the paired mover estimator is biased down by 17%.

With short panels, the adjusted-R^2 logic is quite biased. With exogenous mobility it is biased down by 67% and with endogenous mobility it is biased down by an order of magnitude: the implied variance of match effects is only 11% of the truth. The KSS-based estimator is also quite biased, while the paired mover estimator has identical bias (or its absence) in short panels as in long panels.

The take-away from these simulations is that the in the presence of realistic data generating processes the adjusted-R^2 logic is a downward biased estimate of the variance of match effects.

6.3 Bonhomme, Lamadon, and Manresa (2019)

Bonhomme, Lamadon, and Manresa (2019) (BLM) develops methods designed to detect deviations from additive separability. In this section, we show that the BLM approach does not reliably detect the deviations that our paired mover test detects.

The BLM model and estimation procedure: We consider the static model in BLM. In the static model, firms are assigned to classes, and workers are assigned to types. The static model in

BLM parallels the AKM model in its key assumptions. Where the static model is richer than the AKM model is that it allows for interactions in the wage equation.

Estimation proceeds as in BLM. The key step is that we give the k-means clustering algorithm 30 percentiles of the log-earnings distribution among stayers. We use 10 firm clusters and 6 worker types. The static model implies a set of worker-type specific transition probabilities (a transition matrix) across firm classes.

We compute the steady state distribution implied by this transition matrix. From this steady state distribution, we then simulate a set of moves. By firm class, we then pair workers up. To construct wages, we use the fact that the estimation also gives us an additive error term and we draw from this error term to construct wages. For the origin firm, we draw two error terms in order to be able to exactly replicate what we do in the data and instrument.

Based on the estimates, we simulate a dataset. In this simulated dataset, we then run the paired movers regression and construct the mean absolute earnings gap between paired movers.

We estimate the BLM model in two different ways. First, we use all movers. This parallels the standard implementation of BLM. Second, we use only the paired movers. This enable an apples-to-apples comparison to the paired mover test, in that the BLM estimator is looking at the exact same data as the paired movers test.

For each of these exercises, we draw 100 random subsamples of the data in order to show the distribution of BLM-implied estimates of the paired mover coefficient (and mean absolute earnings gaps) compare to what we find in the data. For all movers, we use subsamples of 500,000. For paired movers, we use subsamples of 50,000.

The paired movers test in simulated data: Figure 7 shows that the data simulated from BLM estimates does not reflect the underlying patterns in the data and the direction of the bias cannot be signed. Looking first at estimates based on all movers, Panel (a) shows that the BLM-implied estimates of the paired mover coefficient are centered at a lower value than what is in the data. Moreover, they are much more dispersed. In contrast, Panel (c) shows that using only the paired movers the BLM-implied estimates of the paired mover coefficients are centered at a much higher value than what is in the data. Panels (b) and (d) show that in both samples the BLM-implied estimates of absolute mean gap are much larger than what is in the data.

We interpret this evidence as indicative that the deviations from additive separability that the paired mover test documents are different from what the literature has previously found.

6.4 Quantitative comparison to Borovičková and Shimer (2024)

Borovičková and Shimer (2024) calibrate their model to match Kline, Saggio, and Sølvsten (2020)'s result on Veneto data. The argument of the paper is that a model of selective hiring generates a model that is approximately (log) additively separable. Relatedly, the paper argues that this approximate additive separability is why the model in the paper generates an event study coefficient close to 1.

In Appendix Table A10 we report results of the paired mover and event study tests using data simulated from their model. The paired mover coefficient is 0.62. Thus, there is evidence against additive separability in the model-generated data. The event study coefficient is around 0.96. We run the event study test splitting the data by EE and EUE moves. Both coefficients are below the coefficient in the pooled sample (0.95 in the EUE sample and 0.35 in the EE sample). Therefore, the between-sample logic that we have emphasized explains why the model-generated data passes the event study test in their model, rather than the approximate additive separability.

7 Discussion

The idea of this paper is that paired movers—that is, workers who both move from firm A to firm B—are the simplest feature of the data that allows us to see the presence of match effects. These match effects represent a deviation from the wage equation that is additively separable in firms and workers that is popular in empirical work. We formulate this paired mover test as a forecast bias test. Under exogenous mobility, we show how to translate this coefficient into an estimate of the variance of match effects, which is a lower bound under plausible forms of endogenous mobility.

We study these paired movers in administrative data from two countries and find meaningful deviations from additive separability in the sense that the forecast bias coefficient is well below 1. Strikingly, there are larger deviations for statistically rarer moves, which are those across contexts: sector, firm-pay level, cluster or occupations. This link between match effects and mobility is consistent with deviations from exogenous mobility.

Under exogenous mobility, we find a variance of match effects that is about 40% of the variance of firm effects. We show that the estimator is non-linear such that if we split the sample and aggregate we find a variance that is over twice as large.

We then estimate a simple job search model to do the conversion with endogenous mobility. The variance of match effects is about a quarter larger than under exogenous mobility. An implication of the important role for match effects is that extrapolating from the earnings changes we see in the data to the earnings changes that other workers would experience if they made similar moves is misleading. Specifically, the earnings changes on accepted offers are a different sign than those on rejected offers, and the differences in earnings changes across accepted offers are a poor guide to those on rejected offers.

Finally, we revisit three pieces of evidence taken as evidence supportive of the AKM specification. We first show that even though the model violates exogenous mobility, data simulated from the model passes the event study test, which is typically taken as evidence in favor of exogenous mobility. We show that this is due to combinations of the variance weighting properties of OLS and Simpson's paradox. We then show that the adjusted-R^2 logic produces a severely downward biased estimate of the variance of match effects given endogenous mobility and short panels. Finally, we show that the Bonhomme, Lamadon, and Manresa (2019) approach does not reliably detect deviations from additive separability using our paired mover test.

This paper suggests two exciting avenues for future work. First, the results in this paper suggest that—since they are large—trying to understand the structure and determinants of match effects is an important task. Second, while this paper has developed results in the context of an additively separable wage equation, there are numerous other applied contexts where researchers have used movers designs (e.g., Finkelstein, Gentzkow, and Williams (2016), Chetty and Hendren (2018), and Lachowska, Sorkin, and Woodbury (2025)). Studying the paired mover sample could be informative as to the presence of match effects in these contexts as well.

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Table 1: Summary statistics

	All workers (1)	All movers (2)	Paired movers (3)
A. Brazil			
Avg. age	34.09	30.90	32.37
Share female	0.40	0.35	0.31
Years of schooling	11.30	11.10	10.90
Tenure (months)	46.97	23.27	38.13
Avg. log earnings	2.34	2.19	2.39
# of Worker-Years	555,346,010	79,856,352	3,962,382
Avg. (origin) firm size	14.08	27.21	78.82
Avg. (origin) firm pay	2.41	2.45	2.47
# of (origin) Firm-Years	46,405,377	18,220,954	883,078
B. Veneto			
Avg. age	34.17	30.14	35.51
Share female	0.37	0.37	0.38
Avg. log earnings	10.10	9.64	10.01
# of Worker-years	15,158,383	1,897,250	22,187
Avg. (origin) firm size	8.35	15.79	225.14
Avg. (origin) firm pay	10.10	10.11	10.17
# of (origin) Firm-years	1,815,553	676,890	6,291

This table shows descriptive statistics of different subsamples of the Brazilian (Panel A) and Veneto (Panel B) data, described in Section 3. Column 1 displays all workers in the data regardless of mobility status and reports statistics over all employment spells. Columns 2 and 3 display different groups of workers who change firms and report statistics of the spell prior the move in the origin firm. Column 2 shows all movers in the data and Column 3 shows the sample of paired movers that we use in estimation. Panel A uses the universe of spells in RAIS from 2007 to 2021, while Panel B uses Veneto Worker History data from 1985 to 2001. As described in the text, in the Brazilian data we keep only one pair per worker per moving event in the paired movers sample, while in the Veneto data we form all possible pairs due to the small number of movers.

Table 2: Paired movers *vs.* what would be predicted by chance

		% of total moves							
	N (1)	Sector Stayers (2)	Sector Movers (3)	Cluster Stayers (4)	Cluster Movers (5)	Low - Low (6)	Low - High (7)	High - High (8)	High - Low (9)
A. Brazil									
Paired Movers	1,981,191	45.5	54.5	31.7	68.3	36.5	13.5	36.5	13.5
All Movers		33.3	66.7	22.7	77.2	33.1	16.8	33.7	16.4
Eligible Movers		48.5	51.5	32.5	67.5	38.4	11.6	38.6	11.4
A. Year-specific distributions									
Simulated Movers	1,402,411	47.5	52.5	32.1	67.9	35.5	12.2	36.0	11.7
p5 (200 draws)	1,402,132	47.5	52.5	32.1	67.9	35.5	12.2	36.0	11.7
p95 (200 draws)	1,403,071	47.5	52.5	32.1	67.9	35.5	12.2	36.0	11.7
B. Single distribution									
Simulated Movers	1,233,808	48.6	51.4	32.7	67.2	31.7	10.8	32.2	10.4
p5 (200 draws)	1,232,589	48.5	51.3	32.7	67.2	31.7	10.8	32.2	10.4
p95 (200 draws)	1,234,106	48.7	51.5	32.8	67.3	31.7	10.8	32.3	10.5
C. Random Benchmark									
Paired Movers		3.8	96.2	9.8	90.2	25.0	25.0	25.0	25.0
All Movers		6.0	94.0	5.0	95.0	25.0	25.0	25.0	25.0
Eligible Movers		4.0	96.0	9.8	90.2	25.0	25.0	25.0	25.0
B. Veneto									
Paired Movers	8167	60.7	39.3	27.1	70.4	36.5	13.3	36.7	13.5
All movers									
D. Year-specific distributions									
Simulated Movers	6804	57.7	42.3	26.5	71.8	37.1	12.7	37.4	12.7
p5 (200 draws)	6627	56.9	41.2	25.6	70.8	36.7	12.5	36.7	12.5
p95 (200 draws)	7025	58.8	43.1	27.3	72.6	37.5	13.3	37.6	13.3
E. Single distribution									
Simulated Movers	4525	59.0	41.0	23.2	74.2	33.9	16.0	34.1	16.0
p5 (200 draws)	4406	57.3	40.2	22.7	72.8	32.9	15.6	33.0	15.6
p95 (200 draws)	4577	59.8	42.7	24.7	74.8	34.4	17.1	34.4	17.1
F. Random benchmark									
Paired movers		10.1	89.9	12.3	87.7		25.2		23.4
All movers		7.5	92.5	9.6	90.4		25.2		24.7

This table shows sample sizes of paired movers that would be obtained by chance as implied by the mobility patterns in the data. We take the sample of eligible movers (as defined in Section 3) and drop workers in the final paired movers sample (Column 3 in Table 1). We then compute, for each origin firm, the empirical distribution of the destination firms over a one-year period. We use these distributions to simulate a sample of movers of the same size as in the data, and then create a paired movers sample as we do with the real data. In Panel A, we do these steps year by year, while in Panel B we use a single distribution for each origin firm, pooling years. The table shows the number of paired movers in the simulated samples, as well as the 5th and 95th percentiles of the distribution of the number of paired movers across 200 draws. In Column 1 we show the number of paired moves obtained, and columns 2 to 9 show the share of these moves that are within or across sectors, clusters, and pay levels. The first row shows the actual sample of paired movers in the data, while the second row shows the sample of all movers. In Panel C, we compare those with a random benchmark formed by either the sample of paired movers or all movers. The benchmark is formed as follows. For example, for sectors, we compute the likelihood in the data of a move being from each sector and the likelihood of a move being to each sector. The probability of a move being within sector is the product of these two probabilities summed over sectors.

Table 3: AKM Estimates (KSS-corrected)

	All Workers (1)	All workers* (2)	All movers* (3)	Paired movers* (4)
A. Brazil, 2012–2017				
Var(Y)	0.506	0.486	0.430	0.473
Var(α)	0.283	0.271	0.224	0.295
Var(ψ)	0.072	0.071	0.064	0.048
Cov(ψ, α)	0.050	0.047	0.041	0.035
Var(ε)	0.051	0.050	0.060	0.059
R^2	0.929	0.927	0.895	0.907
Adj. R^2	0.907	0.904	0.861	0.877
Adj. R^2, interactions	0.934	0.933	0.920	0.924
Observations	40,950,644	40,950,644	22,599,194	1,061,171
# Firms	911,755	911,755	911,755	49,927
# Workers	8,764,893	8,764,893	4,598,015	211,831
# Movers	4,598,015	4,598,015	4,598,015	211,831
# of Moves	14,585,164	14,585,164	14,585,164	644,314
B. Veneto, 1996–2001				
Var(Y)	0.7655	0.7784	0.7277	0.8282
Var(α)	0.3174	0.3256	0.2365	0.4239
Var(ψ)	0.1259	0.1292	0.1114	0.0507
Cov(ψ, α)	0.0438	0.0425	0.0370	0.0714
Var(ε)	0.2347	0.2386	0.3057	0.2107
R^2	0.8200	0.8231	0.7112	0.8165
Adj. R^2	0.7525	0.7567	0.6150	0.7576
Adj. R^2, interactions		0.8070	0.7609	0.8100
Observations	5,111,991	5,111,991	1,702,650	17,725
# Firms	61,638	61,638	61,638	627
# Workers	1,332,729	1,332,729	363,959	3,679
# Movers	363,959	363,959	363,959	3,679
# of Moves	988,088	988,088	988,088	9,258

This table shows the results of the AKM estimation with the KSS correction in Brazilian (Panel A) and Veneto (Panel B) data. (Abowd, Kramarz, and Margolis, 1999; Kline, Saggio, and Sølvsten, 2020). The asterisk ($*$) indicates residualized earnings. Columns 1 and 2 show the results for "all workers," where column 2 shows the residualized earnings. In Brazil, we use a 25% random sample of workers followed from 2012–2017, while in Veneto we use all work spells from 1996–2001. Column 3 restricts the samples only to workers that move at least once in the period, and Column 4 further restricts the sample to workers in the paired movers sample (and whose associated move in the paired movers sample is in the same period as the AKM estimation). We report the KSS-corrected variance terms, the R^2 and adjusted R^2 of the AKM model, and the adjusted R^2 of a regression of the log earnings on fully interacted worker and firm fixed effects. The last five rows show the number of observations, firms, workers, movers, and moves in the connected set of data used in the estimation. Following Kline, Saggio, and Sølvsten (2020), we construct the "strongly-leave-one-out-match" connected set of firms and workers.

Table 4: The Paired Mover Test

	Baseline (1)	Stayers (2)	Within Sector (3)	Across Sector (4)	Gap in Origin Low - Low (5)	Low - High (6)	High - High (7)	High - Low (8)	Cluster Stayers (9)	Cluster Switchers (10)
A. Brazil, 2^{nd} Stage										
Gap in Origin	0.699	0.967	0.733	0.666	0.709	0.681	0.718	0.619	0.740	0.683
	(0.0007)	(0.0003)	(0.0010)	(0.0010)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Mean absolute Gap (Z)	0.364	0.450	0.375	0.355	0.288	0.319	0.454	0.372	0.404	0.363
$\frac{\rho - Corr(Z_t, Z_{t-1})}{2Corr(Z_t, Z_{t-1})}$	0.050		0.056	0.059	0.052	0.056	0.059	0.058	0.056	0.058
Var(m_{ij}) - Ex. mobility	0.030	0.005	0.028	0.031	0.018	0.024	0.043	0.039	0.032	0.031
Observations	1,981,191	1,302,157	900,977	1,080,214	723,590	267,048	723,497	267,056	418,334	901,398
p-value, equality test			0.0000		0.0000		0.0000		0.0000	
B. Brazil, 1^{st} Stage										
Gap in Origin (lag)	0.925	0.941	0.925	0.924	0.920	0.915	0.929	0.922	0.934	0.931
	(0.0005)	(0.0003)	(0.0007)	(0.0007)	(0.0010)	(0.001)	(0.0008)	(0.002)	(0.001)	(0.0008)
F-statistic	3,133,829.8	10,611,459.4	1,590,750.9	1,545,680.3	931,451.9	378,268.1	1,345,544.8	361,093.4	793,000.8	1,440,341.2
C. Veneto, 2^{nd} Stage										
Gap in origin	0.816	0.938	0.858	0.715	0.848	0.580	0.832	0.871	0.908	0.781
	(0.009)	(0.0008)	(0.010)	(0.018)	(0.017)	(0.028)	(0.011)	(0.029)	(0.017)	(0.011)
p-value, equality test			0.0000		0.0000		0.1596		0.000	
Observations	49,040	1,021,944	31,854	17,186	17,740	6,002	18,754	6,544	13,910	33,984
D. Veneto, 1^{st} Stage										
Gap in Origin (lag)	0.473	0.637	0.499	0.420	0.403	0.479	0.568	0.477	0.476	0.473
	(0.003)	(0.0005)	(0.004)	(0.006)	(0.005)	(0.012)	(0.005)	(0.009)	(0.006)	(0.004)
F-statistic	19,560.5	1,520,530.4	15,379.9	4,699.1	5,912.0	1,582.6	11,076.7	2,760.9	6,169.4	12,982.7

This table shows different versions of the paired movers test. We estimate a 2SLS regression where the log earnings gap in the destination firm is regressed on the log earnings gap in the origin firm, instrumented by the lagged earnings gap in the origin firm. Panels A and B show the second and first stages of the test in Brazilian Data, respectively. Panels C and D show the second and first stages in Veneto data. Column 1 shows the baseline estimate using the full paired movers sample (Column 3, Table 1). Column 2 shows the estimate using a benchmark sample of paired stayers. Columns 3 and 4 show the estimate using the sample of paired movers split by whether they stay in the same sector or move to a different sector (2-digit CNAE code for Brazil and ATECO 91 code for Veneto). Columns 6 to 9 show the estimate using the sample of paired movers across different pay bins. We define low/high pay as the bottom/top 50% of the firm pay distribution among firms in the estimation sample. Columns 9 and 10 show the estimate using the sample of paired movers split by whether they stay in the same cluster or move to a different cluster. Clusters are estimated using the entire data following Bonhomme, Lamadon, and Manresa (2019). The clusters are only defined in the connected set, which is why the sample sizes fall. For Columns 3 to 10, we report the p-value of the equality test of the coefficients across columns for the relevant heterogeneity. Finally, in Panel A we also report the mean absolute gap in origin, the measurement error correction term, and the variance of match effects net of exogenous mobility as described by Equation 16. For the stayers we assume there is no measurement error.

Table 4: The Paired Mover Test in Brazilian Data (cont.)

	None change ocup (11)	One change ocup (12)	Both change ocup (13)	Both low tenure (14)	One low tenure (15)	Both high tenure (16)	CZ Stayers (17)	CZ Switchers (18)
A. 2^{nd} Stage								
Gap in Origin	0.768	0.723	0.602	0.706	0.680	0.716	0.700	0.698
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0008)	(0.001)
Observations	746,586	532,681	701,924	787,939	626,757	566,495	1,505,131	476,060
B. 1^{st} Stage								
Gap in Origin (lag)	0.907	0.943	0.919	0.906	0.927	0.940	0.928	0.914
	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0006)	(0.001)
F-statistic	1,026,008.2	1,140,317.1	930,876.4	867,467.7	1,125,726.9	1,206,425.1	2,433,827.8	702,763.0

This table shows different versions of the paired movers test in Brazilian data. We estimate a 2SLS regression where the log earnings gap in the destination firm is regressed on the log earnings gap in the origin firm, instrumented by the lagged earnings gap in the origin firm. Panel A shows the second stage of the test, while Panel B shows the first stage. Columns 11 to 13 show the estimate using the sample of paired movers split by whether none, one or both workers change occupation (3-digit CBO code). Columns 14 to 16 show the estimate using the sample of paired movers split by whether both workers have low tenure (less than 30 months), one has low tenure and the other has high tenure, or both have high tenure. Columns 17 and 18 show the estimate using the sample of paired movers split by whether they stay in the same commuting zone (CZ) or move to a different CZ. The CZs are defined as IBGE's immediate geographic regions (Regiões Geográficas Imediatas). For Columns 11 to 18, we report the p-value of the equality test of the coefficients across columns for the relevant heterogeneity.

Table 5: Earnings gap autocorrelation and implied AR(1) coefficients

	Balanced Panel					Full Sample				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Origin Firm, autocor.										
Time lag	-1	-2	-3	-4	-5	-1	-2	-3	-4	-5
0	0.83	0.804	0.768	0.732	0.693	0.794	0.778	0.744	0.717	0.686
-1		0.956	0.906	0.862	0.813		0.947	0.884	0.842	0.803
-2			0.934	0.887	0.837			0.921	0.872	0.831
-3				0.929	0.875				0.92	0.87
-4					0.923					0.921
B. Origin Firm, AR(1) coef.										
Time lag	-1	-2	-3	-4	-5	-1	-2	-3	-4	-5
0		0.969	0.955	0.953	0.947		0.980	0.956	0.964	0.957
-1			0.948	0.951	0.943			0.933	0.952	0.954
-2				0.950	0.944				0.947	0.953
-3					0.942					0.946
C. Destination Firm, autocor.										
Time lead		2	3	4	5		2	3	4	5
1		0.918	0.871	0.835	0.778		0.847	0.815	0.789	0.767
2			0.933	0.89	0.827			0.88	0.846	0.819
3				0.934	0.865				0.893	0.86
4					0.904					0.903
D. Destination Firm, AR(1) coef.										
Time lead		2	3	4	5		2	3	4	5
1			0.949	0.959	0.932			0.962	0.968	0.972
2				0.954	0.929				0.961	0.968
3					0.926					0.963

This table shows the autocorrelation and implied AR(1) coefficients of the log earnings gap between paired movers at origin and destination firms for different time lags/leads. Panels A and C show the autocorrelation of the log earnings gap at origin and destination firms, respectively. Hence, the first row of Column 1 in Panel A shows the correlation between the log earnings gap at the last year at the origin firm ($t = 0$) and one year before that ($t = -1$). Panels B and D show the implied AR(1) coefficients at origin and destination firms, respectively, calculated as the ratio of the autocorrelation at time lag/lead k and $k + 1/k - 1$. We show results for both a balanced panel where all paired movers stay at the origin firm from $t = -4$ to $t = 0$ and at the destination firm from $t = 1$ to $t = 5$ (Columns 1 to 5) and the full sample of paired movers observed in a given time lag/lead (Columns 6 to 10).

Table 6: Model results

	(1)	(2)	(3)	(4)	(5)
	EE rate	β_1	Mean gap	$Var(\psi_j)$	$Var(\alpha_i)$ (untargeted)
Empirical Moments (Data)	0.038	0.699	0.352	0.071	0.271
Simulated Moments (Model)	0.040	0.703	0.356	0.074	0.066
	λ_0 (UE rate)	δ (EU rate)			
Calibrated Parameters	0.072	0.076			
	λ_1	$Var(\mu_{ij})$	$Var(h_i)$	$Var(p_j)$	
Estimated Parameters	0.121	0.036	0.067	0.083	
Steady-state (employed)		μ_{ij}	h_i	p_j	
Mean		0.062	0.000	0.114	
Variance		0.035	0.067	0.074	
Correlation (μ_{ij},p_j)	0.003				

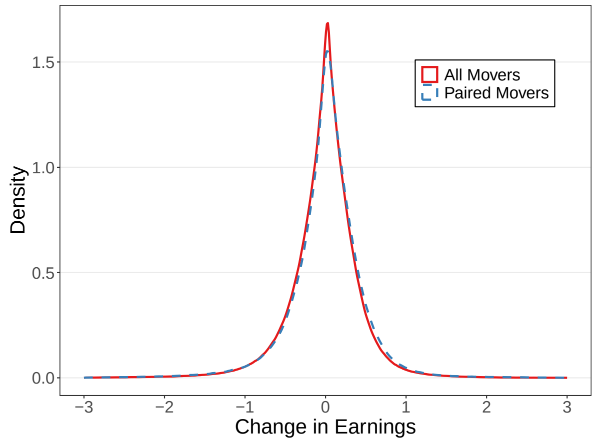
This table shows the results of the model estimation. We estimate the model using the simulated method of moments (SMM) on the empirical moments of the data. We fix the λ_0 and δ parameters to quarterly UE and EU rates in Brazil, measured using labor force surveys (PNAD). We estimate the four remaining parameters of the model, λ_1, $Var(\mu_{ij})$, $Var(h_i)$, and $Var(p_j)$, to match empirical moments of the data: the EE rate, the β_1 coefficient in the paired movers test, the absolute mean gap at the origin, and the variance of firm effects. We search the parameter space using a Metropolis-Hastings algorithm with 10 chains of 250 iterations each. At each iteration, we simulate 200,000 workers and 200 firms over 200 periods. The first two rows in each panel show the empirical moments in the data and the simulated moments in the estimated model. The next two rows show the calibrated and estimated parameters of the model. The last three rows show the steady-state moments of employed workers in the model.

Table 7: Recovering the variance of match effects under different mobility assumptions

	Long Panel ($T = 100$)		Short Panel ($T = 7$)	
	Exogenous (1)	Endogenous (2)	Exogenous (3)	Endogenous (4)
A. Structural parameters				
Var(Y)	0.183	0.180	0.184	0.180
Var(h_i)	0.067	0.067	0.067	0.067
Var(p_i)	0.079	0.079	0.081	0.079
Var(μ_{ij})	0.036	0.035	0.036	0.035
B. Variance components estimates				
Var(α_i) - AKM	0.073	0.078	0.095	0.100
Var(ψ_i) - AKM	0.079	0.077	0.081	0.070
Var(α_i) - KSS	0.067	0.066	0.084	0.095
Var(ψ_i) - KSS	0.079	0.077	0.081	0.070
C. Intermediate statistics				
R2	0.836	0.862	0.954	0.982
Adj. R2	0.833	0.860	0.937	0.975
Adj. R2, interactions	1.000	1.000	1.000	1.000
Paired mover coefficient (β)	0.652	0.706	0.652	0.700
Absolute Mean Gap (Z)	0.362	0.357	0.363	0.357
D. Implied variance of match effects under exogenous mobility				
Var(m_{ij}) - KSS	0.036	0.037	0.019	0.015
Var(m_{ij}) - Adj. R2	0.030	0.025	0.012	0.004
Var(m_{ij}) - Equation 16	0.036	0.029	0.036	0.030

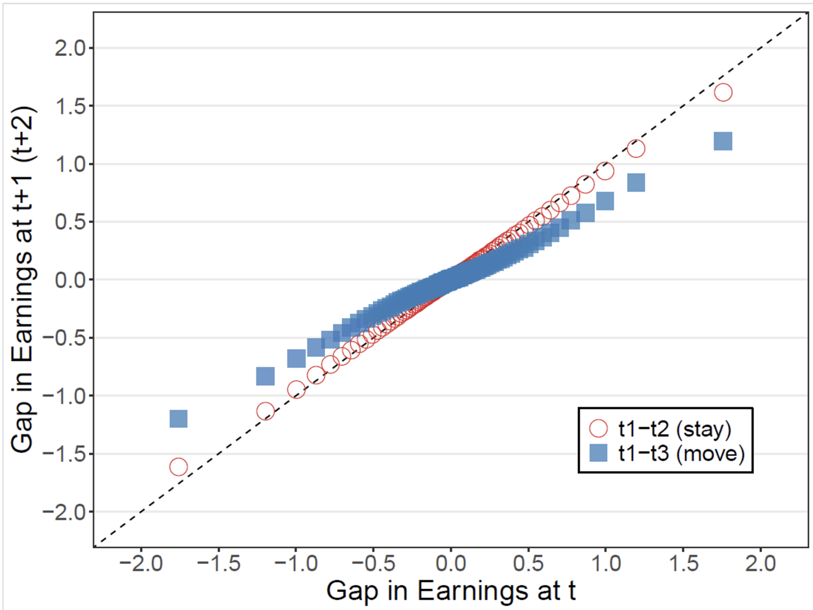
This table shows the ability of different methods to recover the variance of match effects ($Var(m_{ij})$) under different panel lengths and mobility assumptions. We simulate data from the model in Table 6 under two scenarios: exogenous mobility, where workers accept any outside offer, and endogenous mobility, where workers only accept higher-value outside offers (as in the estimated model). We simulate two panel lengths: a long panel with 100 periods (Column 1 and 2) and a short panel with 7 periods (Column 3 and 4). Panel A shows structural parameters: the true variances of wages, worker effects, firm effects, and match effects in the simulated data. Panel B shows the variance of worker and firm effects estimates using the AKM and KSS methods. Panel C shows intermediate statistics: the (adjusted) R^2 of the two-way fixed effects regression, the adjusted R^2 of a fixed effects regression with worker-firm interactions, the paired mover coefficient, and the absolute mean gap between paired movers in the simulated data. Finally, Panel D shows the variance of match effects implied by the KSS estimates, $Var(Y) \times \left(1 - \frac{Var(\alpha_i)+Var(\psi_j)}{Var(Y)}\right)$, the adjusted R^2 estimates $(1 - \text{Adj. } R^2) \times Var(Y)$, and the formula in Equation 16 (which assumes exogenous mobility). All results are averaged over 100 simulations.

Figure 1: Change in Earnings around the Move, Brazil



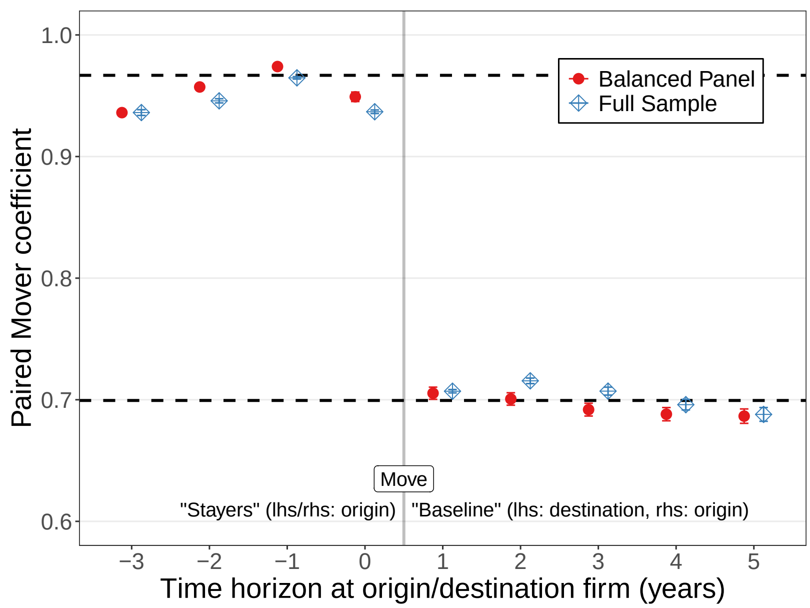
This figure shows the distribution of the change in log earnings between the destination and origin firms for all movers (Column 2, Table 1) and the final sample of paired movers (Column 3, Table 1).

Figure 2: Changes in Gap in Earnings, Paired



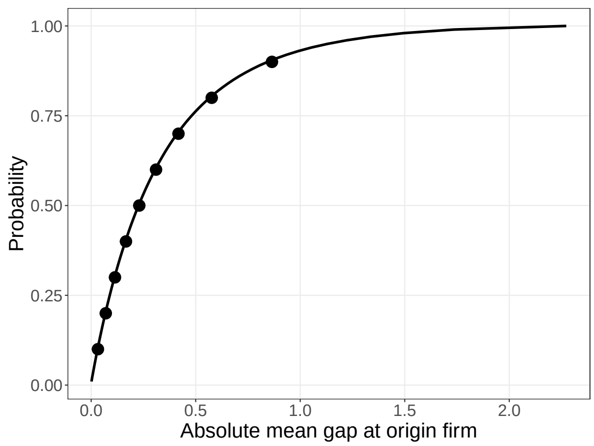
This figure shows the graphical version of the paired movers test. The x-axis shows the gap in earnings in the second-to-last period in the origin firm. We split the gap in earnings into 100 bins. The red circles show the first stage, so the y-axis represents earnings in the last period at the origin firm. The blue squares show the reduced-form, so the y-axis represents earnings in the in the first period at the destination firm. The dashed line shows the 45-degree line.

Figure 3: Temporal Stability

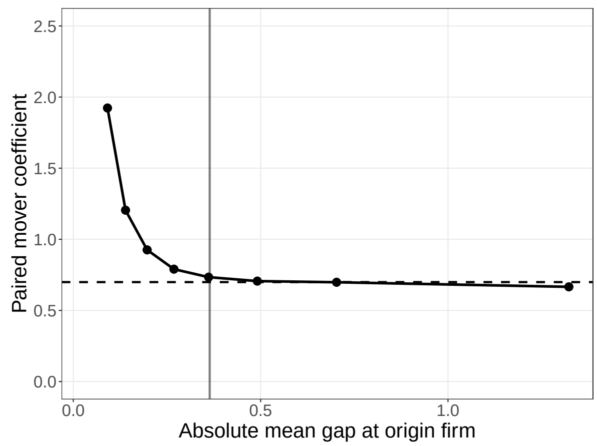


This figure shows different versions of the paired movers test. The lower dashed horizontal line shows the baseline estimate from Column 1 of Table 4. The higher dashed horizontal line shows the estimate from Column 2 of Table 4 ("stayers" placebo). The gray vertical line marks the timing of the move between origin and destination firms. To the left of the vertical line, the sample is paired movers who move between 2012 and 2019 that are observed for at least three years at the origin firm. We report the second-stage coefficient of a regression of the gap in earnings at the origin at t on the gap in earnings at the origin at $t-1$ instrumented by the lagged gap in earnings at the origin at $t-2$. Time t runs from $t=0$ (last year at the origin) to $t=-3$. Thus, these are "stayers" regressions similar to Column 2 of Table 4. To the right of the vertical line, the sample is paired movers who move between 2012 and 2019. Here, we report the second-stage coefficient of the baseline paired movers regression: the outcome is the gap in earnings at the destination at t and the endogenous variable is the gap in earnings at the origin at $t=0$, instrumented by the lagged gap in earnings at the origin at $t=-1$. At each period from $t=1$ (first year at the destination) to $t=5$, we change the outcome variable to the gap in earnings at the destination at t. At each period, both prior and post the move, we report the coefficients from regressions using the full sample (all paired movers observed at that period) and a balanced panel (only paired movers observed at all periods).

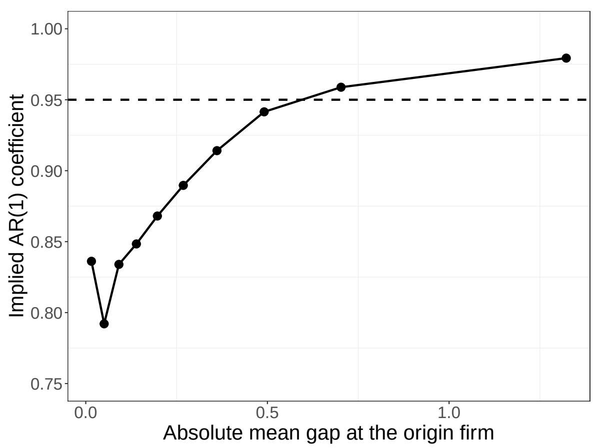
Figure 4: Paired Movers across the Gap Distribution



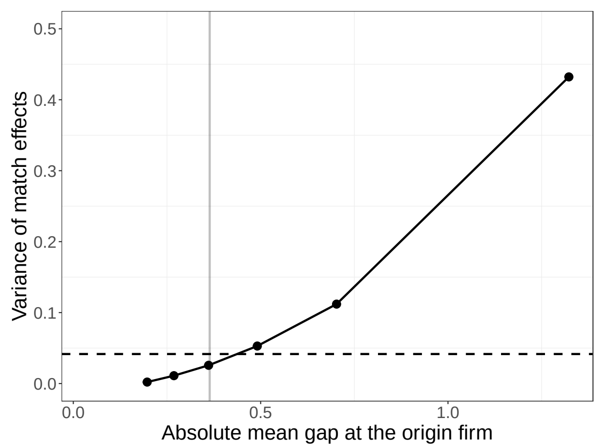
(a) Gap in earnings distribution



(b) Paired movers coefficient by gap decile



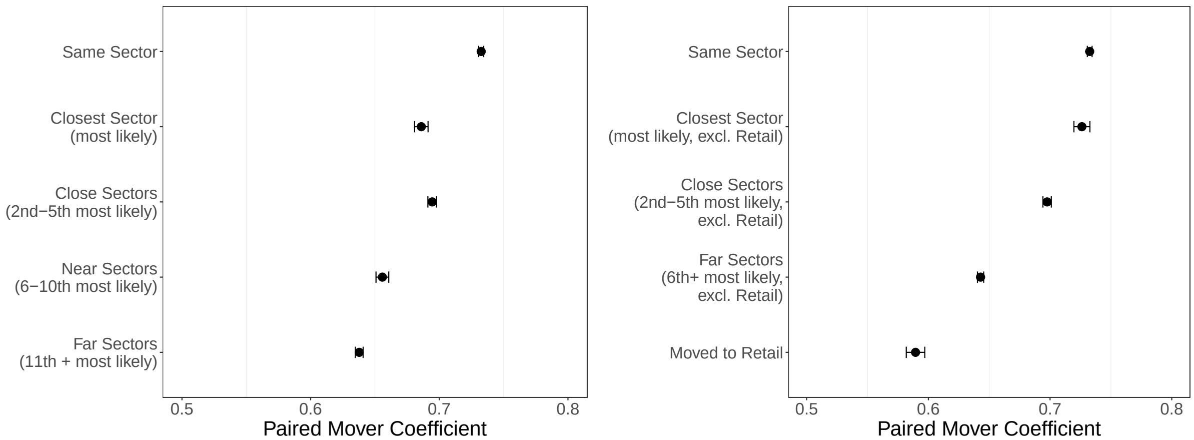
(c) Implied AR(1) by gap decile



(d) Var(m_{ij}) by gap decile (exogenous mobility)

This figure shows the paired movers' statistics across the distribution of the absolute gap in earnings at the origin firm. Panel A shows the cumulative distribution of the absolute gap in earnings at the origin firm at $t = 0$ (last year at the origin), where the dots mark the cutoff of each decile. Panel B shows the paired movers' coefficient estimated using only movers within a given decile of the gap in earnings at the origin firm. The first 2 deciles are excluded due to large estimates. The dashed horizontal line shows the baseline estimate from Column 1 of Table 4, and the vertical line shows the average absolute gap in the sample. Panel C shows the implied AR(1) coefficient of the log earnings gap at the origin firm calculated as the ratio of the autocorrelations at lags -1 and -2, using only movers within a given decile of the gap in earnings at the origin firm. The dashed horizontal line shows the AR(1) coefficient estimated using the full sample (Appendix Table A2). Panel D shows the variance of match effects under the assumption of exogenous mobility according to Equation 16. The first 4 deciles are not shown since the implied variance is negative. The dashed horizontal line shows the variance of match effects implied by the model (Table 6). In Panel D, if we sum up the variances across the six deciles and divide by ten the mean implied variance is 0.067. Appendix Table A11 shows the numbers underlying Panels A–D.

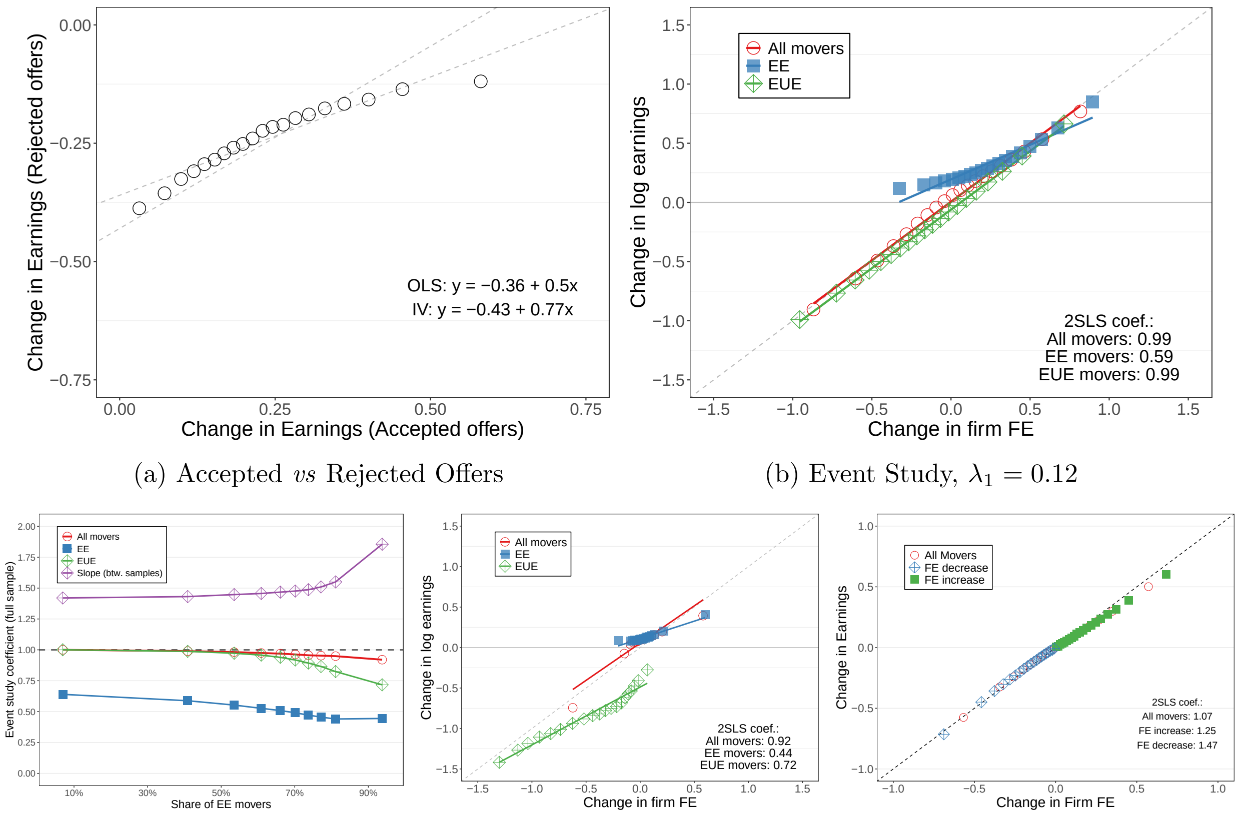
Figure 5: Large *vs* Small Moves



(a) By move likelihood (b) By move likelihood, excl. Retail

This figure shows the second stage of the paired movers test for different types of moves in the Brazilian data. In Panel A, we report the coefficient for movers who stay in the same sector (2-digit CNAE code), as in Column 3 of Table 4, and then moves by decreasing "likelihood", defined as the share of moves from a given sector that go to the destination sector. We first show the coefficient for movers that go to the most likely destination sector, then the second to fifth most likely, and so on. Since the most likely destination sector for half of the sectors is Retail (the largest employer), in Panel B we replicate the exercise by categorizing Retail separately.

Figure 6: Model Simulated Data



(a) Accepted *vs* Rejected Offers

(b) Event Study, $\lambda_1 = 0.12$

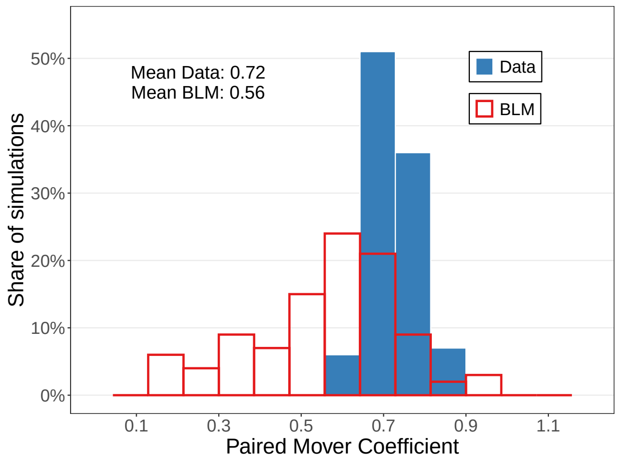
(c) Event study by share EE

(d) Event Study, $\lambda_1 = 0.99$

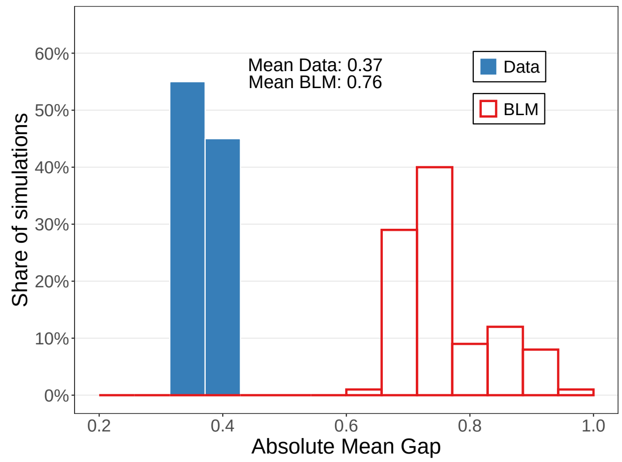
(e) Event Study, data

This figure shows results using data simulated from the model estimated in Brazilian data. In Panel A, we compare the change in log earnings for accepted and rejected offers. We match workers who moved from firm i to firm j with workers who were in firm i and received an offer from firm j but did not accept it and compute the mean change in log earnings between the destination and origin firms for accepted and rejected offers for each origin-destination pair. We then split the data in 20 bins based on the change for accepted offers and plot the average change for rejected offers. We also report the slope of the regression line in the underlying individual-level data. The IV coefficient comes from splitting the sample randomly. In Panels B and D we show the event study test. We plot the change in log earnings between destination and origin firms against the change in firm effects. Panel B uses the baseline parameter $\lambda_1 = 0.12$, while Panel D sets $\lambda_1 = 0.99$. We show the coefficient for all moves, EE moves, and EUE moves. Finally, in Panel C, we vary the parameter λ_1 from 0 to 0.99 to obtain increasing shares of EE moves in the simulated data and plot the event study coefficient estimated in each case. We again show the coefficient for all moves, EE moves, and EUE moves. We also plot the between-sample slope of the change in log earnings on the change in firm effects between EE and EUE moves. Panel E shows the event study estimated in Brazilian data (Column 1, Appendix Table A9), split by whether the move has an increase in firm effects or not. In Panels B, C and E we split the sample randomly to generate two estimates of the firm effects to be able to instrument for the change in the firm effects.

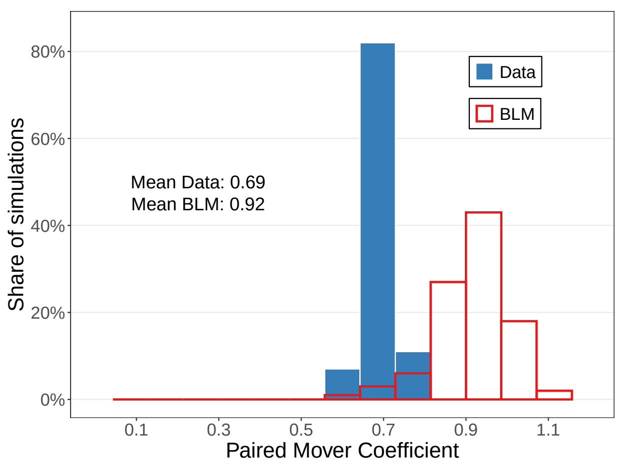
Figure 7: Paired Movers Test across BLM estimations



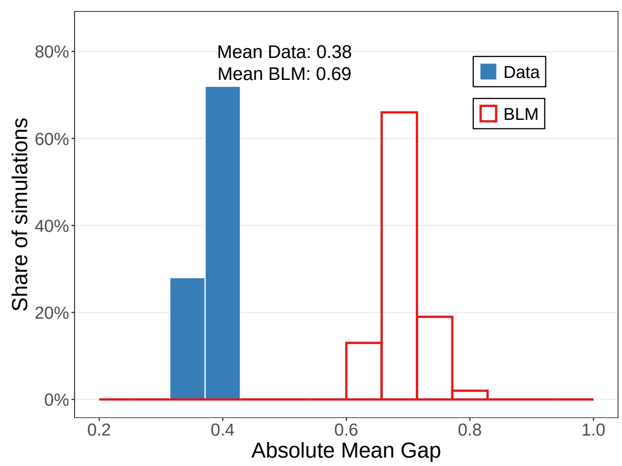
(a) Paired Movers Coefficient, All Movers



(b) Absolute Mean Gap, All Movers



(c) Paired Movers Coefficient, Paired Movers



(d) Absolute Mean Gap, Paired Movers

This figure shows the distribution of the paired movers test statistics across BLM estimations. In Panels A and B, we draw 100 subsamples of 500,000 workers from the full Brazilian data (Columns 1–2 of Table 3) and estimate the BLM model in each subsample (Bonhomme, Lamadon, and Manresa, 2019). We plot the distribution of the paired movers coefficient (Panel A) and the absolute mean gap (Panel B) within each subsample and from data simulated from the estimated BLM model. In Panels C and D, we repeat the exercise using only the paired movers sample (Column 4 of Table 3). We draw 100 subsamples of 50,000 paired movers from the full paired movers sample and repeat the exercise.

A An estimator for the variance of match effects under exogenous mobility

Note that in the paper we observe repeated observations of the gap between workers within the firm. Let $Z = G + \nu$ where $G = \alpha_i - \alpha_{i'} + m_{iA} - m_{i'A}$ and $\nu = \epsilon_{iA} - \epsilon_{i'A}$.

In the paper we imposed an AR(1) structure G:

$$G_t = \rho G_{t-1} + \iota. \tag{A1}$$

We are interested in learning about the variance of ν. Consider the correlation between two observations of Z:

$$Corr(Z_t, Z_{t-1}) = \frac{Cov(G_t + \nu_t, G_{t-1} + \nu_{t-1})}{\sqrt{Var(G_t + \nu_t)}\sqrt{Var(G_{t-1} + \nu_{t-1})}}. \tag{A2}$$

Let's analyze the numerator first:

$$Cov(G_t + \nu_t, G_{t-1} + \nu_{t-1}) = Cov(G_t, G_{t-1}) \tag{A3}$$
$$= Cov(\rho G_{t-1} + \iota, G_{t-1}) = \rho Var(G_{t-1}), \tag{A4}$$

because the ν are independent.

Now analyze the denominator:

$$Var(G_t + \nu_t) = Var(G_t) + Var(\nu_t) \tag{A5}$$
$$= Var(G) + 2Var(\epsilon), \tag{A6}$$

since we assume these processes are stationary.

Hence:

$$Corr(Z_t, Z_{t-1}) = \frac{Cov(Z_t, Z_{t-1})}{\sqrt{Var(Z_t)}\sqrt{Var(Z_{t-1})}} \tag{A7}$$
$$= \frac{\rho Var(G)}{Var(G) + 2Var(\epsilon)}. \tag{A8}$$

Now $Var(G) = 2Var(m) + 2Var(\alpha) = 2\sigma_\alpha^2 + 2\sigma_m^2$. Note that we have estimates of $Corr(Z_t, Z_{t-1})$ and we have estimates of ρ.

Rearranging the above, we have:

$$Corr(Z_t, Z_{t-1}) = \frac{\rho Var(G)}{Var(G) + 2Var(\epsilon)} \tag{A9}$$
$$Corr(Z_t, Z_{t-1}) = \frac{\rho(\sigma_\alpha^2 + \sigma_m^2)}{\sigma_\alpha^2 + \sigma_m^2 + \sigma_\epsilon^2} \tag{A10}$$
$$\sigma_\epsilon^2 = \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}(\sigma_\alpha^2 + \sigma_m^2). \tag{A11}$$

Note that:

$$\frac{\pi}{4}\mathbb{E}[|Z|]^2 = \sigma_m^2 + \sigma_\alpha^2 + \sigma_\epsilon^2$$
$$= \left(\sigma_m^2 + \sigma_\alpha^2\right)\left(1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}\right) \tag{A12}$$
$$\frac{\frac{\pi}{4}\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}} = \sigma_m^2 + \sigma_\alpha^2. \tag{A13}$$

Hence,

$$\hat{\beta}_1 = \frac{\sigma_\alpha^2}{\frac{\pi}{4}\mathbb{E}[|Z|]^2}\left(1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}\right) \tag{A14}$$
$$\sigma_\alpha^2 = \hat{\beta}_1 \frac{\frac{\pi}{4}\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}}. \tag{A15}$$

Hence,

$$\sigma_m^2 = \sigma_\alpha^2 \frac{1 - \hat{\beta}_1}{\hat{\beta}_1} \tag{A16}$$
$$\sigma_m^2 = (1 - \hat{\beta}_1)\frac{\pi}{4}\frac{\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}}. \tag{A17}$$

Hence, we can write our moments of interest in terms of estimable quantities as:

$$\sigma_\alpha^2 = \hat{\beta}_1 \frac{\pi}{4}\frac{\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}} \tag{A18}$$
$$\sigma_m^2 = (1 - \hat{\beta}_1)\frac{\pi}{4}\frac{\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}}. \tag{A19}$$

These formulas are intuitive: a smaller paired mover coefficient, $\hat{\beta}_1$, implies a larger variance of match effects. And a larger mean gap, $\mathbb{E}[|Z|]$, implies a larger variance of match effects.

We can also use the above formulas to derive a measurement error corrected mean of the absolute earnings gaps. In the above notation, we are interested in

$$\mathbb{E}[|G|] = \sqrt{4\frac{\sigma_m^2 + \sigma_\alpha^2}{\pi}} \tag{A20}$$
$$= \sqrt{\frac{\mathbb{E}[|Z|]^2}{1 + \frac{(\rho - Corr(Z_t, Z_{t-1}))}{Corr(Z_t, Z_{t-1})}}}. \tag{A21}$$

B Pairing workers randomly *vs.* sorting

In the baseline implementation of the paired movers test, we pair workers and compute their gap in (residualized) earnings randomly, i.e., without sorting which worker is the highest earner in the origin firm. One alternative implementation is to sort paired workers so that the gap in earnings at the origin firm is always positive. Appendix Table A12, column (1) shows that doing so yields a larger paired movers coefficient of 0.87, which is larger than the 0.70 in the baseline. (Column (2) shows that the stayers coefficient is more stable).

Appendix Figure A3 presents Monte Carlo evidence that sorting workers creates a mechanical upward bias in the paired movers coefficient when the income process of the two workers have different means, which would be the case in the empirically realistic setting where there are differences in individual effects. In particular, we simulate the income process of two workers by drawing two correlated random variables, one for the origin firm and one for the destination firm. We add an independent mean-zero shock to each. We create a lagged variable for the origin firm using an AR(1) process. We either leave the order of workers random, or sort them so that the gap in earnings at the origin firm is positive. We compute the paired movers coefficient using the same IV regression as in the baseline. We repeat this exercise 1,000 times.

The figure shows that when the two workers have the same mean, sorting does not create any bias. However, when there is a difference in the means, sorting creates a mechanical upward bias in the paired movers coefficient. Therefore, we prefer the baseline implementation of the paired movers test, which does not sort workers.

C Forward, Backward, and Donut Paired Movers Tests

In the baseline implementation of the paired movers test, we regress the gap in earnings at the destination firm at $t = 1$ (first year at the destination) on the gap in earnings at the origin firm at $t = 0$ (last year at the origin), instrumenting with the lagged gap in earnings at the origin firm at $t = -1$. However, the test can be implemented in any three periods in which we observe two workers in two firms. These three periods do not need to be consecutive, and the test can be implemented in either direction (regressing the gap at the destination on the gap at the origin, or vice-versa). In this context, one could be worried that our results are due to the specific way we implement the test. In particular, if the years around the move are special in some way, then our results could be driven by this specific choice.

To address this concern, we show results from alternative implementations of the paired movers test. Panel A of Appendix Table A13 shows results from the baseline, or forward, version of the test, where we regress the gap in earnings at the destination firm on the gap in earnings at the origin firm. Column 1 replicates the baseline results from Column 1 of Table 4 – where the outcome is the gap in earnings at the destination firm at $t = 1$ and the endogenous variable is the gap in earnings at the origin firm at $t = 0$, instrumented with the lagged gap in earnings at the origin firm at $t = -1$.

Column 2 shows results when we keep the outcome the same but change the right hand side variable. Instead of the last year at the origin firm ($t = 0$), we use the gap in earnings at the origin firm at $t = -1$ (second to last period at the origin firm) instrumented with the lagged gap in earnings at the origin firm at $t = -2$ (third to last period at the origin firm). Column 3 shows results when we exclude the first year at the destination ($t = 1$) from the sample, using as the outcome the gap in earnings at the destination firm in the second year, $t = 2$, and as the regressor the gap in earnings at the origin firm at $t = 0$, instrumented with the lagged gap in earnings at the origin firm at $t = -1$.

Finally, Column 4 shows results from a donut version of the test, combining Columns 2 and 3 so that we omit the last year at the origin firm and the first year at the destination firm. Columns 5 to 8 replicate Columns 1 to 4 within a fixed sample of movers observed in all periods. The results are very similar across all specifications, with coefficients ranging from 0.699 to 0.720.

Panel B of Appendix Table A13 shows results from the backward version of the paired movers test, where we regress the gap in earnings at the origin firm on the gap in earnings at the destination firm. Across specifications, the coefficient is larger than the baseline when the regressor is the gap in earnings at the first year at the destination—around 0.8—and smaller than the baseline when the regressor is the gap in earnings in the second year at the destination—around 0.65. This pattern is consistent with the idea that earnings in the first year at the destination are noisier, which can also be seen in Table 5. Overall, the results suggest that our findings are not driven by the specific way we implement the paired movers test.

D Heuristic identification

Appendix Figure A4 shows heuristic identification plots, which explains how model parameters map into the paired mover coefficient. Under exogenous mobility, we showed that the paired mover coefficient is directly proportional to the variance of match effects. In panel (a) of the Figure we hold fixed our estimated parameters, vary the variance of the match effects and plot the resulting paired movers coefficient. The paired movers coefficient is decreasing in the variance of the match effects. Panel (b) shows that all else equal the paired mover coefficient is increasing in the variance of worker effects. Holding fixed the variance of match effects, the larger is the variance of person effects the more stable are earnings gaps across firms.

Because the model does not generate any sorting on the basis of person effects, all of the covariance terms between person effects and match effects are zero. So the only term that matters is $Cov(m_{iA} - m_{i'A}, m_{iB} - m_{i'B})$, the covariance in match effects gaps between workers i and $i\prime$ across firms. This covariance depends on how long the job ladder is.

The "length" of the job ladder depends on how many job-to-job transitions a worker makes before re-entering unemployment. It is increasing in λ_1 (the arrival rate of offers on the job) and decreasing in δ (the job destruction rate). Panels (c) and (d) show that these two parameters move the implied paired mover coefficient in opposite directions. As δ increases and workers have fewer jobs (all else equal) the paired mover coefficient declines. The reason is that with fewer jobs the match effects distribution is unselected and so the covariance term of the match effects across firms is smaller. Similarly, as λ_1 increases and workers have more jobs the paired mover coefficient increases because the covariance of match effects across jobs increases. In contrast, the job finding rate when unemployed (λ_0) has no impact on the length of the job ladder and so varying λ_0 has no impact on the estimated paired mover coefficient.

E Regression coefficient from pooling two samples

Let $G \in \{1, 2\}$ denote the sample indicator, with

$$\Pr(G = 1) = \omega, \qquad \Pr(G = 2) = 1 - \omega. \tag{A22}$$

Within sample g, the data generating process (DGP) is

$$Y = a_g + b_g X + \varepsilon, \qquad \mathbb{E}[\varepsilon | G = g] = 0, \qquad \text{and} \qquad X | G = g \sim \mathcal{N}(\mu_g, \sigma_g^2). \tag{A23}$$

We are interested in the population OLS slope when we *pool* both samples:

$$\beta^{\text{pool}} = \frac{\text{Cov}(X,Y)}{\text{Var}(X)}. \tag{A24}$$

The denominator is:

$$\text{Var}(X) = \underbrace{\omega\sigma_1^2 + (1-\omega)\sigma_2^2}_{\text{within-group variance}} + \underbrace{\omega(1-\omega)(\mu_1-\mu_2)^2}_{\text{between-group variance}}. \tag{A25}$$

The numerator is:

$$\text{Cov}(X,Y) = \underbrace{\omega b_1\sigma_1^2 + (1-\omega)b_2\sigma_2^2}_{\text{within-group covariance}} + \underbrace{\omega(1-\omega)(\mu_1-\mu_2)\big[(a_1+b_1\mu_1)-(a_2+b_2\mu_2)\big]}_{\text{between-group covariance}}. \tag{A26}$$

Hence,

$$\beta^{\text{pool}} = \frac{\omega b_1\sigma_1^2 + (1-\omega)b_2\sigma_2^2 + \omega(1-\omega)(\mu_1-\mu_2)\big[(a_1+b_1\mu_1)-(a_2+b_2\mu_2)\big]}{\omega\sigma_1^2 + (1-\omega)\sigma_2^2 + \omega(1-\omega)(\mu_1-\mu_2)^2}. \tag{A27}$$

The within-group covariance generates a coefficient that is in the convex hull of the two subsample estimates. When $\mu_1 \neq \mu_2$ and there are different means in the two samples, then the between-group covariance can generate parameter estimates that are outside the convex hull.

Table A1: Paired Movers Test, Residualization Approach

	Age and gender	Age, gender, and education
	(1)	(2)
A. Second Stage		
Gap in Origin	0.690	0.719
	(0.0007)	(0.0007)
Observations	2,137,179	2,137,179
B. Brazil, 1st Stage		
Gap in Origin (lag)	0.923	0.933
	(0.0005)	(0.0005)
F-statistic	3,403,026.1	3,666,801.9

This table shows estimates based on different residualization approaches.

Table A2: Earnings Gap AR(1) Coefficients

	Full sample (1)	Destination (2)	Origin (3)
A. Balanced Panel			
k	-0.054	-0.057	-0.049
	(0.001)	(0.003)	(0.003)
AR(1) Coefficient	0.948	0.944	0.952
B. Full Sample			
k	-0.040	-0.035	-0.042
	(0.005)	(0.001)	(0.007)
AR(1) Coefficient	0.960	0.966	0.959
Observations	25	10	15

This table shows the results of the regression $\ln(\rho_k) = \beta k + \varepsilon_k$, where ρ_k is the autocorrelation of the log earnings gap between paired movers at time lag/lead k. The coefficient β can be interpreted as an estimate of $\ln(\nu)$ in the AR(1) process $y_t = \nu y_{t-1} + u_t$. Hence, $\exp(\beta)$ is the AR(1) coefficient of the log earnings gap. The regressed autocorrelations are the same as those shown in Table 5. Panel A shows the results for the balanced panel of paired movers, while Panel B shows the results for the full sample. Column 1 shows the results using all available autocorrelations, while Columns 2 and 3 show the results using only the autocorrelations at destination and origin firms, respectively. All regressions are weighted by the number of observations used to calculate each autocorrelation. Standard errors are shown in parentheses.

Table A3: Summary statistics: paired movers

	All pairs (1)	Sector stayers (2)	Sector movers (3)	Low-Low (4)	Low-High (5)	High-High (6)	High-Low (7)	Cluster stayers (8)	Cluster movers (9)
A. Brazil									
Avg. age	32.37	33.02	31.84	32.21	31.26	32.72	33.01	32.59	31.97
Share female	0.31	0.34	0.29	0.38	0.31	0.25	0.27	0.30	0.32
Years of schooling	10.90	10.89	10.90	10.16	10.81	11.83	10.48	11.30	10.91
Tenure (months)	38.13	39.47	37.00	33.59	34.75	43.37	39.58	41.31	38.13
Avg. log earnings	2.39	2.41	2.37	1.99	2.18	2.86	2.37	2.61	2.37
Avg. log gap origin	0.35	0.36	0.35	0.27	0.31	0.46	0.36	0.40	0.35
Var. log gap origin	0.18	0.19	0.17	0.11	0.14	0.24	0.17	0.21	0.17
p90 - p10 log gap origin	0.85	0.88	0.83	0.64	0.74	1.05	0.84	0.95	0.85
# of Worker-years	3,962,382	1,801,954	2,160,428	1,447,180	534,096	1,446,994	534,112	836,668	1,802,796
Avg. origin firm size	78.82	98.83	107.68	68.62	117.02	144.43	174.41	181.25	121.35
Avg. origin firm pay	2.47	2.48	2.49	2.09	2.14	2.75	2.61	2.56	2.49
Avg. destination firm size	77.06	95.05	106.17	67.80	180.97	138.10	111.06	175.15	117.44
Avg. destination firm pay	2.49	2.49	2.52	2.11	2.70	2.79	2.16	2.58	2.52
# of Firm-Years	1,579,661	916,911	939,525	776,810	313,236	505,591	315,767	393,130	757,674
B. Veneto									
Avg. age	35.51	36.30	34.44	37.23	33.45	35.11	34.96	36.29	35.30
Share female	0.38	0.37	0.39	0.63	0.37	0.18	0.33	0.37	0.37
Avg. log earnings	10.01	10.06	9.94	9.50	9.84	10.44	10.20	10.02	10.00
Avg. log gap origin	0.40	0.41	0.39	0.41	0.42	0.38	0.43	0.41	0.40
Var. log gap origin	0.24	0.24	0.24	0.23	0.33	0.21	0.25	0.24	0.24
p90 - p10 log gap origin	0.93	0.93	0.93	0.95	0.99	0.86	0.96	0.94	0.92
# of Worker-years	22,187	12,743	9,444	7,049	3,358	8,272	3,508	5,801	15,563
Avg. origin firm size	225.14	256.82	244.71	171.63	199.78	305.61	315.52	329.27	235.38
Avg. origin firm pay	10.17	10.18	10.14	9.47	9.68	10.50	10.33	10.22	10.12
Avg. destination firm size	240.49	272.63	283.94	197.18	389.43	325.47	220.50	352.25	259.71
Avg. destination firm pay	10.24	10.24	10.25	9.56	10.47	10.57	9.84	10.28	10.22
# of Firm-years	12,081	7,204	6,197	3,909	2,380	4,800	2,483	3,615	9,252

This table shows descriptive statistics of the paired movers sample. Panel A displays the Brazilian data, while Panel B displays the Veneto data. Column 1 displays all paired movers and uses the same samples as Column 3 in Table 1. Columns 2 and 3 display movers split by whether they stay in the same sector or move to a different sector (2-digit CNAE code for Brazil and 2-digit ATECO 91 code for Veneto). Columns 4 to 7 display movers across different pay bins. We define low/high pay as the bottom/top 50% of the firm pay distribution among firms in the sample. Firm pay is computed yearly across all workers, not only paired movers. Columns 8 and 9 display movers split by whether they stay in the same cluster or move to a different cluster. Clusters are estimated using the entire data (Column 1, Table 1) following Bonhomme, Lamadon, and Manresa (2019). Clusters are only estimated in the connected set of firms.

Table A3: Summary statistics: paired movers (cont.)

	No ocup. change (1)	1 ocup. change (2)	2 ocup. change (3)	Both Low Tenure (4)	Both High Tenure (5)	One Low Tenure (6)	CZ stayers (7)	CZ switchers (8)
C. Brazil, cont.								
Avg. age	33.98	32.59	30.50	31.41	34.22	31.92	32.00	33.55
Share female	0.31	0.30	0.31	0.27	0.33	0.34	0.34	0.21
Years of schooling	10.54	11.09	11.13	10.41	11.35	11.11	11.04	10.44
Tenure (months)	36.85	39.44	38.49	16.88	67.94	37.89	39.71	33.11
Avg. log earnings	2.37	2.47	2.34	2.26	2.57	2.38	2.36	2.48
Avg. log gap origin	0.30	0.45	0.34	0.32	0.36	0.38	0.35	0.35
Var. log gap origin	0.15	0.21	0.17	0.16	0.18	0.19	0.18	0.17
p90 - p10 log gap origin	0.74	1.00	0.82	0.79	0.88	0.91	0.85	0.86
# of Worker-years	1,493,172	1,065,362	1,403,848	1,575,878	1,132,990	1,253,514	3,010,262	952,120
Avg. origin firm size	111.26	125.47	123.85	108.73	130.20	120.28	82.73	175.49
Avg. origin firm pay	2.48	2.50	2.50	2.45	2.53	2.49	2.47	2.52
Avg. destination firm size	108.99	122.03	120.85	111.37	122.02	119.04	80.83	172.19
Avg. destination firm pay	2.51	2.53	2.53	2.49	2.54	2.52	2.49	2.55
# of Firm-Years	762,490	638,164	706,312	779,079	650,597	696,432	1,382,675	394,431

This table shows descriptive statistics of the Brazilian paired movers sample. Columns 1 to 3 display movers split by whether they change occupation or not (3-digit CBO codes). Column 1 shows moves in which both workers in the pair remain in the same occupation, Column 2 shows moves in which one worker changes occupation and Column 3 shows moves in which both workers change occupation. Columns 4 to 6 display movers split by whether they have low or high tenure at the origin firm. We define low tenure as tenure below the median tenure of all paired movers (30 months). Column 4 shows pairs where both workers have low tenure, Column 5 shows pairs where one worker has low tenure and Column 6 shows pairs where both workers have high tenure. Finally, Columns 7 and 8 display movers split by whether they stay in the same commuting zone (CZ) or not. There are 510 CZs, defined as the “immediate regions” designated by the Brazilian Institute of Geography and Statistics (IBGE), which have a similar logic to the US commuting zones.

Table A4: Paired Mover Test by Reason of Separation

	Gap in Destination				
	Baseline	Without cause	Both Involuntary	Both Voluntary	Mixed
	(1)	(2)	(3)	(4)	(5)
A. Second Stage					
Gap in Origin	0.699	0.702	0.692	0.735	0.712
	(0.0007)	(0.0007)	(0.0009)	(0.002)	(0.002)
Observations	1,981,191	1,906,985	1,360,054	222,400	324,531
B. First Stage					
Gap in Origin (lag)	0.925	0.924	0.923	0.916	0.934
	(0.0005)	(0.0005)	(0.0007)	(0.001)	(0.001)
F-statistic	3,133,829.8	3,061,911.9	1,990,405.5	492,634.7	586,976.5

This table shows different versions of the paired movers test by reason of separation. We estimate a 2SLS regression where the log earnings gap in the destination firm is regressed on the log earnings gap in the origin firm, instrumented by the lagged earnings gap in the origin firm. Panel A shows the second stage of the test, while Panel B shows the first stage. Column 1 shows replicates the baseline estimate using the full paired movers sample (Column 1, Table 4). Column 2 shows the estimate using the sample of paired movers where we exclude workers whose separation was with cause. Columns 3 to 5 show the estimate using the sample in Column 2 split by whether both workers were separated involuntarily (employer-initiated), both workers separated voluntarily (employee-initiated), or one worker separated voluntarily and the other involuntarily.

Table A5: Paired Mover Test by Reason of Separation and Time to Re-employment

	Gap in Destination							
	Involuntary				Voluntary			
	Full sample (Same duration pairs)	Within 1 month	Btw. 2–6 months	After 6 months	Full sample (Same duration pairs)	Within 1 month	Btw. 2–6 months	After 6 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Second Stage								
Gap in Origin	0.671	0.801	0.699	0.620	0.736	0.743	0.692	0.690
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.009)	(0.009)
Observations	835,395	131,395	149,509	554,491	145,425	113,446	13,329	18,650
B. First Stage								
Gap in Origin (lag)	0.919	0.913	0.911	0.923	0.910	0.914	0.870	0.894
	(0.0009)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.006)	(0.007)
F-statistic	1,116,888.0	427,650.5	300,665.8	573,687.0	361,198.2	345,770.1	22,587.7	16,521.8

This table shows different versions of the paired movers test by reason of separation and time to re-employment. We estimate a 2SLS regression where the log earnings gap in the destination firm is regressed on the log earnings gap in the origin firm, instrumented by the lagged earnings gap in the origin firm. Panel A shows the second stage of the test, while Panel B shows the first stage. Columns 1 and 5 show the estimate using the sample of paired movers who did not separate with cause (Column 2 of Table A4) and additionally both workers take the same (discrete) amount of time to re-employment. Time to reemployment is defined as the difference between the hiring date at the destination firm and the separation date at the origin firm. Columns 1 and 5 show the results for involuntary and voluntary separations, respectively, benchmarking the results in Columns 3 and 4 of Table A4. Columns 2–4 and 6–8 show the results for involuntary and voluntary separations, respectively, split by whether both workers found a new job within one month of the month of separation between 2 and 6 months after separation, or after 6 months of separation.

Table A6: β_1 Decomposition: Equation 13

Term	Value
$Var(h_i - h_{i'})$	0.134
$Cov(\mu_{iA} - \mu_{i'A}, \mu_{iB} - \mu_{i'B})$	0.006
$Var(\mu_{iA} - \mu_{i'A})$	0.066
$Cov(h_i - h_{i'}, m_{iA} - \mu_{i'A})$	0.000
$Cov(h_i - h_{i'}, m_{iB} - \mu_{i'B})$	0.000

This Table uses the model-estimated parameters to decompose how the model arrives at its paired mover coefficient, following Equation 13. The table reports the structural counterparts to the reduced-form parameters in the equation.

Table A7: Multi-sector Model results

	(1)	(2)	(3)	(4)	(5)	(6)
	EE rate	β_{Stayer}	β_{Switcher}	Abs. Mean Gap	$Var(\psi_j)$	$Var(\alpha_i)$ (untargeted)
Empirical Moments (Data)	0.0384	0.733	0.666	0.352	0.071	0.271
Simulated Moments (Model)	0.0400	0.757	0.652	0.352	0.059	0.058
	λ_0 (UE rate)	δ (EU rate)				
Calibrated Parameters	0.072	0.076				
	λ_1	$Var(\mu_{ij})$	$Var(\mu_{is})$	$Var(h_i)$	$Var(p_j)$	
Estimated Parameters	0.121	0.039	0.004	0.060	0.083	
Mobility (EE)	% Offers Accepted	% Offers Cross-Sector	% Within-Sector Offers Accepted	% Cross-Sector Offers Accepted	% Moves Cross-Sector	
	0.215	0.963	0.367	0.209	0.938	

This table shows the results of the multi-sector model estimation. We estimate the model using the simulated method of moments (SMM) on the empirical moments of the data. We estimate the model similarly to the baseline model (Table 6), but now allowing for sector-specific match effects μ_{is}, in addition to firm-specific match effects μ_{ij}. We use the same moments as in Table 6, but now we split the paired movers' coefficients by whether the paired movers switch sectors or not (β_{Stayer} and β_{Switcher}).

Table A8: Event Study Test in Model Simulated Data

	All movers (1)	EE moves (2)	EUE moves (3)
A. Brazil			
Change in $\hat{\psi}$ (IV)	0.991	0.586	0.990
	(0.0007)	(0.001)	(0.0009)
Observations	997,061	411,299	585,762
B. Veneto			
Change in $\hat{\psi}$ (IV)	1.05	0.333	0.941
	(0.011)	(0.008)	(0.020)
Observations	17,704	12,361	5,343

This table shows the event study test in data simulated from the estimated model (Table 6). We estimate firm effects in two randomly split samples of the data and run a 2SLS regression as in Table A9. Column 1 shows the results for all movers, while Columns 2 and 3 show the results for EE and EUE moves, respectively. A graphical version of this table is shown in Figure 6b.

Table A9: Event Study Test

	Change in $\hat{\psi}_1$ / Change in Log Earnings				
	All movers	Paired movers	Weight (1) to match ... in Paired Movers:		
			Origin Firms	Destination Firms	Origin-Destination Pairs
	(1)	(2)	(3)	(4)	(5)
A. Brazil, 2nd Stage					
Change in $\hat{\psi}_1$	1.07	1.05	0.977	0.992	0.987
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
Observations	3,574,659	390,178	3,124,563	3,158,568	900,960
B. Brazil, 1st Stage					
Change in $\hat{\psi}_2$	0.761	0.815	0.884	0.882	0.879
	(0.0003)	(0.0009)	(0.0003)	(0.0003)	(0.0005)
F-statistic	4,845,767.8	762,862.2	10,880,588.9	10,872,954.4	3,110,841.6
C. Veneto, 2nd Stage					
Change in $\hat{\psi}_1$	1.07	0.647	0.893	0.853	0.674
	(0.007)	(0.027)	(0.008)	(0.007)	(0.029)
Observations	281,075	10,274	110,470	130,813	23,255
D. Veneto, 1st Stage					
Change in $\hat{\psi}_2$	0.520	0.715	0.776	0.765	0.781
	(0.002)	(0.007)	(0.002)	(0.002)	(0.004)
F-statistic	106,863.3	10,636.7	159,587.8	157,401.3	47,581.7

This table shows the results of the standard event study test using AKM estimates. We first estimate two sets of firm fixed effects by randomly splitting the full data (Column 1, Table 1) in two samples. We then use a sample of movers to estimate a 2SLS regression where the change in the log earnings between destination and origin firms is regressed on the change in the estimated firm effect across origin-destination firms, where we use the firm effects estimated in the first sample to instrument the firm effects in the second sample. Column 1 shows the results for all movers used in the AKM estimation. Column 2 subsets the sample for movers in the final paired movers sample (Column 3, Table 1). Columns 3 to 5 show the results the sample in Column 1 when we weight the observations to match the distribution of origin firms, destination firms, and origin-destination pairs in the paired movers sample. Panel A shows the second stage of the test in Brazilian data, while Panel C shows the second stage in Veneto data. The first stage is shown in Panels B and D.

Table A10: Simulated Borovičková and Shimer (2024) data

	Paired Mover	Event Study		
		All movers	EE moves	EUE moves
	(1)	(2)	(3)	(4)
Gap in origin	0.622			
	(0.002)			
Change in $\hat{\psi}$ (IV)		0.958	0.347	0.950
		(0.002)	(0.002)	(0.003)
Observations	180,560	2,516,273	1,338,002	1,178,271
Abs. Mean Gap	0.102			
Var(m_{ij}) – Exog. mobility	0.003			

This table shows the results using data simulated from the model of Borovičková and Shimer (2024), with the same parameters as estimated in the original paper. We report the paired movers and event study tests (split by EE and EUE moves), as well as the absolute mean gap and the variance of match effects implied by the paired movers test under exogenous mobility (Equation 16), without a correction for measurement error ($\mathcal{A} = 1$).

Table A11: Var(m_{ij}) along the Gap Distribution

Decile	Mean Gap (1)	β (2)	Cor(Z_t, Z_{t-1}) (3)	ρ (4)	Var(m_{ij}) (5)
5	0.197	0.925	0.587	0.868	0.002
6	0.269	0.790	0.680	0.890	0.012
7	0.361	0.734	0.756	0.914	0.027
8	0.491	0.706	0.812	0.941	0.056
9	0.703	0.698	0.850	0.959	0.117
10	1.323	0.666	0.828	0.979	0.459

This Table shows the underlying numbers for Figure 4. Column 1 shows the mean log earnings gap at origin firms for each decile of the gap distribution (deciles 5 to 10). Column 2 shows the paired movers test coefficient β estimated separately for each decile. Column 3 shows the autocorrelation of the log earnings gap at origin firms, estimated separately for each decile. Column 4 shows the AR(1) coefficient ρ implied by Column 3. Finally, Column 5 shows the variance of match effects m_{ij} implied by the estimates in Columns 1–4 using equation (16).

Table A12: Paired Movers Test, Sorting

	Positive gap at $t = 0$	
	Baseline	Stayers
	(1)	(2)
A. Second Stage		
Gap in Origin	0.871	0.974
	(0.001)	(0.0005)
Observations	1,981,191	1,302,157
B. Brazil, 1st Stage		
Gap in Origin (lag)	0.706	0.852
	(0.0006)	(0.0004)
F-statistic	1,587,311.8	5,394,925.8

This table shows results from a robustness exercise in which we sort paired movers so that the gap in earnings at the origin firm at $t = 0$ is always positive.

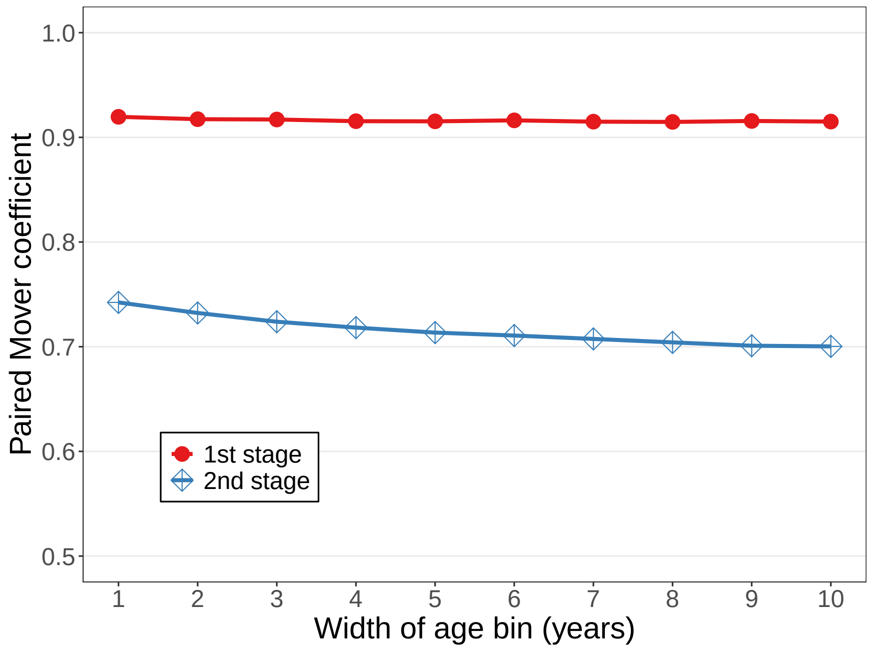
Table A13: Forward and Backward Paired Mover Test

A. "Forward"								
Dependent Var.:	Gap in Destination, $t=1$		Gap in Destination, $t=2$		Gap in Destination, $t=1$		Gap in Destination, $t=2$	
	Baseline	Excl. $t=0$	Excl. $t=1$	"Donut"	Baseline	Excl. $t=0$	Excl. $t=1$	"Donut"
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A1. 2nd Stage								
Gap in Origin, $t=0$	0.699		0.709		0.714		0.720	
	(0.001)		(0.001)		(0.001)		(0.001)	
Gap in Origin, $t=-1$		0.706		0.718		0.709		0.718
		(0.001)		(0.001)		(0.001)		(0.001)
Observations	1,981,191	1,334,963	1,365,703	924,365	924,365	924,365	924,365	924,365
A2. 1st Stage								
Gap in Origin, $t=-1$	0.925		0.931		0.935		0.935	
	(0.0005)		(0.0006)		(0.0007)		(0.0007)	
Gap in Origin, $t=-2$		0.728		0.720		0.720		0.720
		(0.0005)		(0.0005)		(0.0005)		(0.0005)
F-statistic	3,133,829.8	2,602,755.8	2,134,709.8	1,769,423.0	1,649,703.4	1,769,423.0	1,649,703.4	1,769,423.0

B. "Backward"								
Dependent Var.:	Gap in Origin, $t=0$		Gap in Origin, $t=-1$		Gap in Origin, $t=0$		Gap in Origin, $t=-1$	
	Baseline	Excl. $t=0$	Excl. $t=1$	"Donut"	Baseline	Excl. $t=0$	Excl. $t=1$	"Donut"
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
B1. 2nd Stage								
Gap in Destination, $t=1$	0.824		0.792		0.826		0.797	
	(0.001)		(0.001)		(0.001)		(0.001)	
Gap in Destination, $t=2$		0.653		0.629		0.653		0.629
		(0.001)		(0.001)		(0.001)		(0.001)
Observations	1,365,703	987,194	1,365,703	987,194	987,194	987,194	987,194	987,194
B2. 1st Stage								
Gap in Destination, $t=2$	0.600		0.600		0.627		0.627	
	(0.0005)		(0.0005)		(0.0006)		(0.0006)	
Gap in Destination, $t=3$		0.681		0.681		0.681		0.681
		(0.0005)		(0.0005)		(0.0005)		(0.0005)
F-statistic	1,329,354.4	1,138,148.6	1,329,354.4	1,138,148.6	1,054,409.5	1,138,148.6	1,054,409.5	1,138,148.6

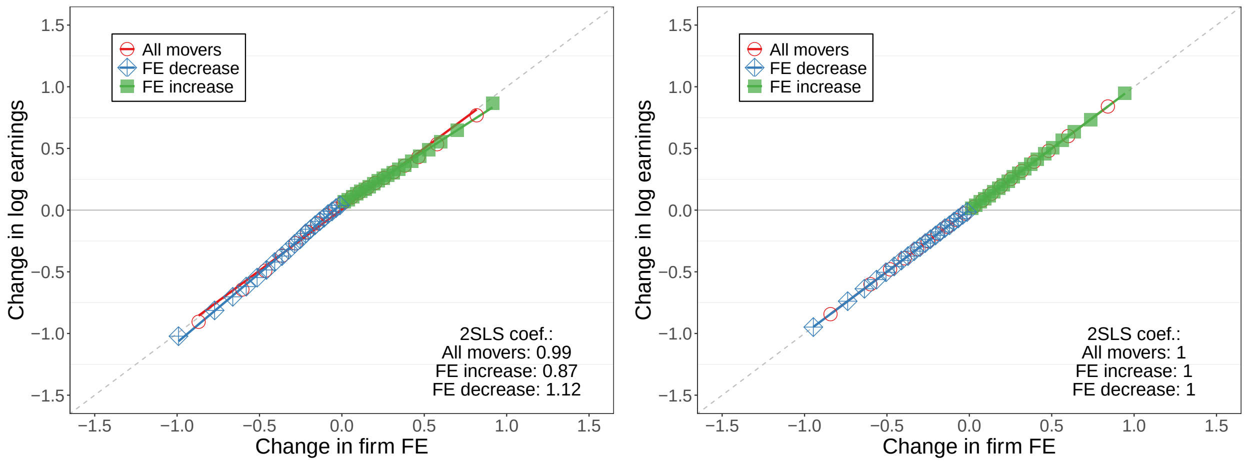
This table shows results from the forward (baseline) and backward versions of the paired movers test. Panel A shows results from the forward version, where we regress the gap in earnings at the destination firm on the gap in earnings at the origin firm. Panel B shows results from the backward version, where we regress the gap in earnings at the origin firm on the gap in earnings at the destination firm. In both panels, the first stage results are shown in the lower half and the second stage results are shown in the upper half. Columns 1 and 5 show baseline results using the gap in earnings at $t=0$ (Panel A) or $t=1$ (Panel B) as regressor. Columns 2 and 6 exclude the contemporaneous period from the regression, i.e., they use only the lagged gap in earnings at the origin (Panel A) or destination (Panel B) as regressor. Columns 3 and 7 exclude one period after/before the move from the regression, i.e., they use only the gap in earnings at $t=2$ (Panel A) or $t=-1$ (Panel B) as regressor. Finally, Columns 4 and 8 implement a "donut" version of the paired movers test, where both the contemporaneous period and one period after/before the move are excluded from the regression.

Figure A1: Paired Movers Test, sensitivity to age bin width



This figure shows the paired mover coefficient using an alternative estimation approach compared to the baseline. Rather than residualizing earnings for covariates, we match workers on gender and age bins. The figure shows how our estimates vary with the size of the age bins.

Figure A2: Event Study Test in the Model: Endogenous vs Exogenous Mobility

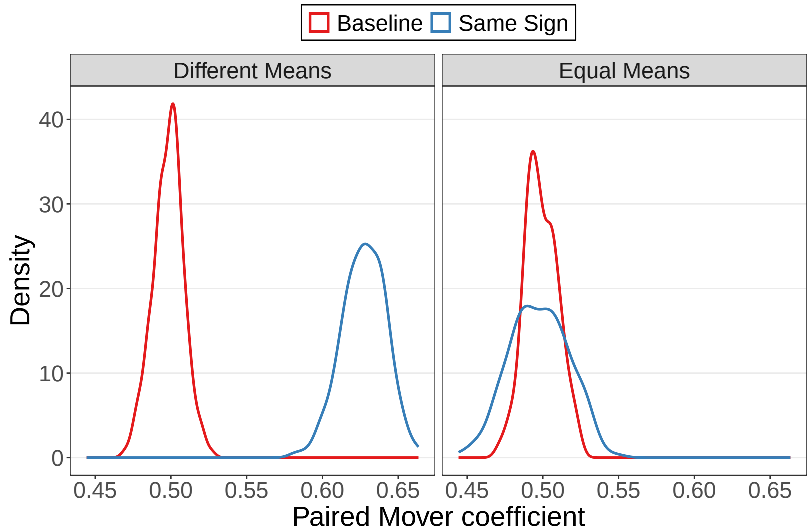


(a) Endogenous Mobility

(b) Exogenous Mobility

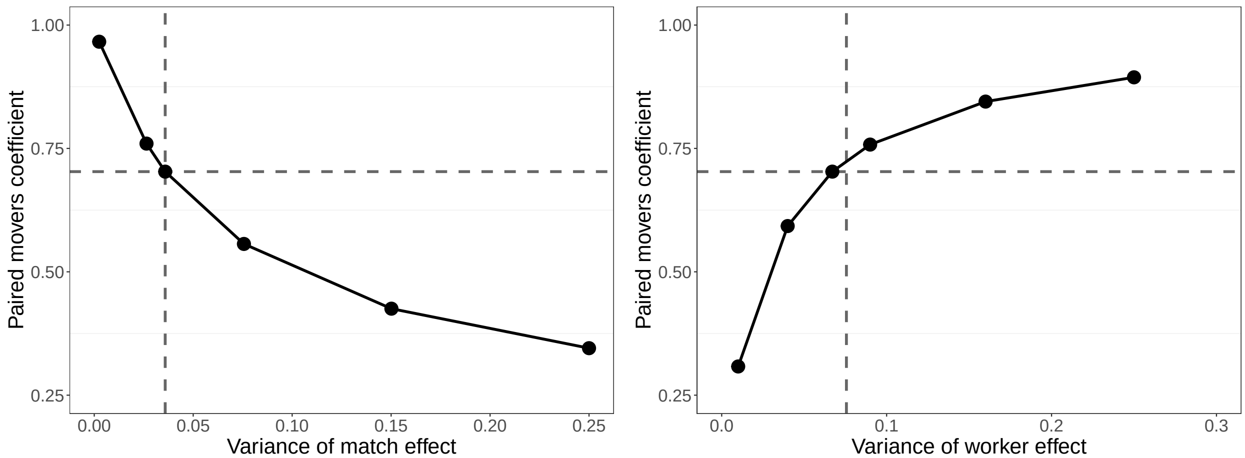
This figure shows the event study test in model simulated data under endogenous and exogenous mobility. Panel A shows the event study test results when workers choose their destination firms according to the model's mobility process (endogenous mobility). Panel B shows the event study test results when workers accept all offers (exogenous mobility). In both panels, we estimate firm effects in two randomly split samples of the data and run a 2SLS regression as in Appendix Table A9. We plot the reduced form scatterplot and the 2SLS estimates with for all movers, moves with firm FE increases, and moves with firm FE decreases.

Figure A3: Bias in Same Sign Paired Movers Test: Monte Carlo Simulations



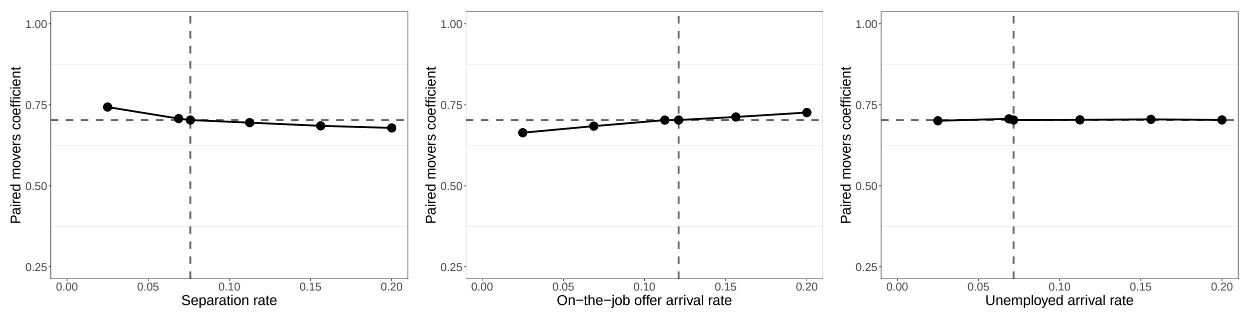
This figure shows the results of Monte Carlo simulations to assess bias in the same sign paired movers test. We simulate the income process of two workers by drawing two correlated random variables, one for the origin firm and one for the destination firm. We add an independent mean-zero shock to each. We create a lagged variable for the origin firm using an AR(1) process. We either leave the order of workers random, or sort them so that the gap in earnings at the origin firm is positive. We compute the paired movers coefficient using the same IV regression as in the baseline. We repeat this exercise 1,000 times.

Figure A4: Paired Movers coefficient and model parameters



(a) Match Effects ($Var(\mu_{ij})$)

(b) Worker Effects ($Var(h_i)$)



(c) Separation Rate (δ)

(d) On-the-job arrival rate (λ_1)

(e) Unemployed arrival rate (λ_0)

This figure shows heuristic identification plots. In each panel we start with the estimated parameter (shown in the vertical dashed line). We then vary that estimated parameter (holding all other model parameters constant) and show how changing that parameter affects the paired movers coefficient.