Better Workers Move to Better Firms: A Simple Test to Identify Sorting*

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Abstract

Measuring assortative matching in the labor market has proved quantitatively difficult, specially because firms' and workers' types are generally unobserved. In this paper, we propose to use workers' mobility to identify the direction and strength of assortative matching. In the presence of positive (negative) assortative matching we should observe that good workers are more (less) likely to move to better firms than bad workers. As this test only requires that agents can be ranked according to their underlying types, cardinal measures of types are not necessary. We assume that agents' payoffs are monotone in their types, which allows us to use within-firm variation on wages to order workers and firm-level profits to rank firms. We then exploit a panel data set that combines Social Security earnings records for workers in the Veneto region of Italy with detailed balance sheet information for employers. We find robust evidence that positive assortative matching is a pervasive phenomenon in the labor market. Better workers are found to have higher probability of moving to better firms.

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1 Introduction

Are "good" workers matched to "good" firms? While in some specific markets, e.g., in the academic job market, there is anecdotal evidence of positive assortative matching - with good researchers having higher chances of being hired by good departments - it is not clear that this is a pervasive phenomenon in the labor market. Answering to this question has long remained elusive, mostly because a credible test has to be based on a correct observation of the underlying types of the firm and the worker, which is notoriously difficult. In fact, there is scarce empirical evidence of assortative matching (or sorting) between firms and workers, and there are no convincing measures to identify whether assortative matching is positive or negative, i.e. the issue of the sign of sorting. After the seminal contribution of Abowd, Kramarz and Margolis (1999), the negative correlation between the worker fixed effect and the firm fixed effect in a wage equation has been interpreted as evidence of negative assortative matching. However, Eeckhout and Kircher (2011) argue that these results may be misleading. They show that, using wage data alone, it is virtually impossible to identify the sign of sorting.

In this paper, we are interested in the measurement of assortative matching between firms and workers. In order to measure the sign and strength of sorting, we analyze mobility of workers across firms. The intuition is that in the absence of assortative matching we should observe that the probability that workers leave a firm to go to a firm of different quality is independent of the quality of the worker. In the presence of positive (negative) assortative matching we should observe that good workers are more (less) likely to move to better firms than bad workers. The strategy presented in this paper imposes minimum conditions on the data generating process and is fully compatible with most of the popular classes of mechanisms that generate sorting. We find ample evidence of positive assortative matching in the labor market, and the result is robust to wage non-monotonicity in the firm type, wage differentials driven by amenities and heterogeneous search intensity, which are the main criticisms to the existing measures of assortative matching.

It is controversial to empirically define the firm and worker types. In this context, types refer to productivity. Given the worker type, better firms should produce more and given the firm type, better workers should also produce more. Productivity is generally unobserved, and is driven by many characteristics that are also unobserved or hard to measure. The worker type is as a one-dimensional index that collapses information on the worker's cognitive skills (e.g Becker 1964) but also on non-cognitive skills, like the ability to communicate, the ability to work in teams, motivation, tenacity, and trustworthiness (e.g. Heckman and Rubistein 2001). The firm productivity is in general an unknown function that links a number of features related to technology, demand and market structure (Syverson, 2011).[1]

Our test does not require cardinal measures of the agent's types. In order to detect the direction and strength of sorting, it only requires local rankings of workers and firms according to their types. If agents' payoffs are monotone in their types (*ie:* given the type of the partner, the payoff of each agent is increasing in his/her own type), we can use within-firm variation in wages to order co-workers according to their types within the firm. Although there is a firm component in wages, this firm effect is held constant by exploiting variation in wages of co-workers. If profits per worker are monotone in the firm type, aggregated profits of multi-worker firms are also monotone in the firm type. Although there is worker component in the profit per worker, this effect is integrated out when we consider profit per firm in multi-worker firms.

The last essential condition for identification is that the equilibrium distribution of workers and firms implies some mismatches. If workers are always in their optimal firm type, identification of sorting may be complicated because both sources of heterogeneity contain the same information, and are then empirically indistinguishable. The test requires variation in types of co-workers, but also workers moving across firms of different types.

A simple search model with some limitation on firms to post new vacancies (e.g. Shimer and Smith, 2000), provides a natural starting point for thinking about sorting of worker and firms. The model also represents an appropriate laboratory to describe how the test works. It generates mismatches, and movements of workers across firms of different types. Moreover, the model produces payoffs that are increasing in the agent's type, but not necessarily monotone in the partner type. Our test is not specific to this model, but it is consistent if this model is the data generating process. In general, our test is valid whenever the payoffs are increasing in the agents' types, which is a condition consistent with most of the popular classes of labor market

[1]Examples of firms' productivity determinants include: market power and technology spillovers (e.g. Bloom, Schankerman, and Van Reenen 2007), human resources practices (e.g. Ichniowski and Shaw 2003), sunk costs (e.g. Collard-Wexler 2010), managerial talent and practices (e.g. Bloom and Van Reenen 2007) or organizational form (e.g. Garicano and Heaton 2010).

models in the literature.

Assortative matching between firms and workers generates two kinds of intrinsically related questions. The first question is positive and addresses the direction and strength of an association between worker and firm types. The second question is normative and is essentially related to the economic implications of sorting, such as assessing the size of the gains from matching workers to the appropriate firms. This kind of question, which is more relevant from a policy perspective, is hard to answer without a model, since it aims at producing policy recommendations and, therefore, needs to contemplate counterfactual scenarios. There are many modeling assumptions that shape the matching process in one direction or in the other, such as supermodular or submodular production function (Becker, 1964), type dependent or type independent value of the vacancy (Shimer and Smith, 2000), transferability of the utility function (Smith, 2006), search effort and search cost (Lentz, 2010). One of the purposes of the positive question is to provide insights on modeling the matching process. Therefore, it is prudent to use an empirical strategy that is as flexible as possible, and consistent with mechanisms able to generate different patterns of sorting. The approach presented in this paper is as agnostic as possible with regards to the labor market model that generates the data. We take no stance on the possible mechanisms that drive sorting. Our test only requires that agents' payoffs are monotone in their types, and that mismatches are occasionally observed in the labor market.

A better understanding of the equilibrium distribution of firms and workers is not only useful for model design. The strength of sorting is important to indirectly learn on the size of complementarity in production, as reflected by the magnitude of the cross partial derivative of the production function with respect to the worker and firm type. The direction of sorting is informative on the sign of that cross derivative. To know if good workers go to good firms is by itself relevant for policy. For example, low productivity firms have higher exit rates in the case of recessions (e.g. Caballero, 1994) or trade liberalization (e.g Melitz 2003). Under positive assortative matching, low skill workers are disproportionately affected by these displacements. Moreover, as this group is more credit constrained, the effect of a displacements is larger in terms of welfare.

We use a unique panel data set that combines Social Security earnings records for individual workers in the Veneto region of Italy with detailed balance sheet information for their employers.

This data set is especially valuable in our application because it contains not only the universe of incorporated business in this Italian region but also information on every single employee working in these firms.

We implement our test for the presence of sorting, finding strong evidence of positive assortative matching. Better workers are found to have higher probability to move to better firms. This result is remarkably robust and goes against previous findings in the literature (e.g. Abowd, Kramarz and Margolis (1999) find negative assortative matching). The evidence of positive assortative matching does not depend on the arrangements of workers and firms types. We find similar results if, instead of using the within-firm variation on wages, we use logwages or the worker quantiles in the within-firm distribution of wages. Positive assortative matching is also found if we order firms by their economic profits, accounting profits, or gross operating margin, using either profit per worker or profit per firm, and current profits or average profits across time. The significance of our results is also robust to the definition of movers: it is true for movers with an interim unemployment spell but also for job-to-job movers. This finding also holds when focusing on the subsample of workers who are exogenously forced to leave their firms due to a firm closure. Overall, sorting is found to be stronger for males than for females, and for workers in the manufacturing sector than for the service sector. Assortative matching is also stronger for medium-age and white-collar workers.

Using the same data, we finally perform the test proposed in Abowd, Kramarz and Margolis (1999). Not surprisingly, we find a statistically significant negative correlation between the firm fixed effect and the worker fixed effect, obtained from a standard log-wage regression. We discuss three potential mechanisms explaining the difference in conclusions that come out using the latter covariance or our measure of sorting. First, we provide evidence suggesting that wages are not always monotone in the firm type and, second, that amenities play an important role in explaining differences in the compensating strategies across jobs. Third, as argued by Bagger and Lentz (2011), the AKM test may be biased when sorting is generated by models with endogenous search effort. We then present results using slightly modified versions of our test, which are consistent with models with heterogeneous search intensity, which also suggest positive assortative matching.

The rest of the paper is organized as follows. Section 2 presents the related literature. The model and the empirical strategy are described in Section 3. Section 4 presents some relevant features of the institutional background and the data used. In Section 5, we show the results. In Section 6, we compare our results with results obtained using the AKM strategy and discuss the differences. Section 7 offers a short conclusion.

2 Related Literature

A large body of literature has analyzed whether assortative matching is positive or negative. The seminal paper of Becker (1973) studies the matching between heterogeneous agents in a frictionless market. Within a world with perfect competition, positive assortative matching (PAM) arises if the production function is supermodular. Shimer and Smith (2000) extend Becker's model to account for frictions, and prove the existence of an equilibrium steady-state in such a model. In an economy with frictions a supermodular production function is not enough to guarantee PAM. An interesting feature of introducing frictions is that the resulting strategies are based on matching sets rather than singletons, and therefore there are mismatches. Atakan (2006) explicitly models search costs and provides sufficient conditions that restore the classical result on PAM.

There have been many empirical attempts to obtain information on the association between workers types and firms types. The most influential one is Abowd, Kramarz and Margolis (1999; AKM henceforth) which uses mincer-type wage equations with worker and firm fixed effects, to recover a covariance between both sets of worker and firm specific coefficients. The latter correlation is used to make inferences on the direction and strength of assortative matching.

This strategy has two main limitations. First, the estimated covariance is biased due to correlated small-sample estimation noise in the worker and the firm fixed effects. Andrews, Gill, Schank and Upwarde (2008) and Abowd, Kramarz, Lengermann and Perez-Duarte (2003) find that, although the biases can be considerable, they are not sufficiently large to remove the negative correlation in datasets from Germany, France and the United States.

Second, as is pointed out in Lopes de Melo (2011) and Eeckhout and Kircher (2011), the AKM correlation may be biased due to non-monotonicities of wages in the firm type. The wage could be non-monotone in the firm type for a number of reasons, such as limitations in the capacity of the firms to post new vacancies (see Lopes de Melo (2011) or Eeckhout and Kircher (2011)) or between firm competition for workers (See Postel-Vinay and Robin (2002) or Cahuc Postel-Vinay and Robin (2006)).[2]

Given AKM's shortcomings, there have been a number of responses in the literature. Eeckhout and Kircher (2011) argue that, using wage data alone, it is virtually impossible to identify whether assortative matching between worker and firm types is positive or negative. They propose a method to measure the strength of sorting using information on the range of accepted wages of a given worker. The intuition behind this method is that if a worker is only willing to match with a small fraction of firms for a given level of frictions (which can also be identified from the data), the complementarities must be large. Their strategy is elegant but its empirical feasibility is questionable. To begin with, panel data with a long longitudinal dimension are needed in order to capture precisely an individual's range of wages. Moreover, the within-worker variation of wages depends not just on complementarities in the production function, but also on the primitive distribution of firm's types, productivity shocks, and friction patterns. Therefore, to backup the strength of sorting from information on individual wage-gaps one needs to make assumptions about these features of the model too. On top of these difficulties, one should note that the measure proposed by Eeckhout and Kircher (2011) is an indicator of the strength of sorting but not of its direction.

In a recent paper, Lopes de Melo (2011), proposes a different strategy to measure the degree of sorting, based on the correlation between a worker fixed effect and the average fixed effects of his coworkers. His estimates of both sets of fixed effects come from a log-wage equation in the spirit of AKM. He shows that in a simple search model with a supermodular production function and firm-type dependent values of the vacancies, the proposed measure works better than the AKM correlation.[3] Although this measure is relatively easy to obtain from the data, it shares one key limitation of Eeckhout and Kircher (2011): the worker-coworker measure of sorting cannot detect the sign of sorting. The approach presented in our paper complements the strategies presented

[2]In this class of models, workers can have a wage cut when moving to a better firm because they expect larger wage raises in firms with higher productivity.

[3]The AKM measure of sorting does not perform well because the model generates a wage function that is non-monotone in the firm type. Nevertheless, the wage function is monotone in the worker type, the firm profit function is monotone in the firm type, and there are mismatches due to frictions. Therefore, the measure of sorting propose in this paper would hold perfectly.

in Eeckhout and Kircher (2011) and Lopes de Melo (2011), in the sense that it is not only able to measure the strength of sorting but also the direction of assortative matching.

A different strategy to measure assortative matching is to assume that all the information concerning the worker type is contained in a set of observable characteristics, such as age and education. If this is true, a measure of the firm type can be obtained through production function panel data estimation: the firm-specific effect in the production function is informative about the firm type. This was proposed by Mendes, van den Berg and Lindeboom (2010). The latter paper, imposing a supermodular production function, finds evidence of positive assortative matching. Although this strategy is more natural, it has two main limitations. First, the estimation of production functions only using within-firm variation, in order to partial out the firm fixed effect, is not generally trouble-free.[4] Moreover, the estimation of the production function could be more problematic if it allows enough flexibility to be consistent with any sign of the cross derivative between firms and workers types. Second, only a small fraction of the workers wage variation is explained by observable characteristics. There is strong evidence suggesting that observable characteristics are not sufficient statistics of workers unobserved fixed heterogeneity in wage regressions.[5]

3 The Model

In this section, we use a search model to illustrate how movements of workers between firms can be used to uncover the sign and the strength of assortative matching. The model builds on Shimer and Smith (2000). Let us consider a continuous time, infinite horizon, stationary economy. This economy is populated by infinitely lived firms and workers. All agents are risk neutral and discount future income at the rate $\rho > 0$. Every firm is characterized by its productivity p. Let $\Psi(p)$ be the cumulative distribution function of p. Every firm has N jobs, but not every job is matched to a worker. Worker types are denoted by ϵ. The distribution of ϵ in the population of workers is $\gamma(\epsilon)$, with cumulative distribution function $\Gamma(\epsilon)$ and support $[\epsilon_{\min}, \epsilon_{\max}]$.

The output of the match (p, ϵ) is $f(p, \epsilon)$. We assume that there is no productive interaction

[4]The estimation of the relative productivity of different worker types is generally imprecise when only using within-firm variation, see for example Cahuc, Postel-Vinay and Robin (2006) or Hellerstein and Neumark (2004)

[5]See for example Lillard and Weiss (1979), Hause (1980) or Meghir and Pistaferri (2004).

between co-workers, therefore the output of a firm p is the sum of the output of its matched jobs. Moreover, for simplicity we assume that a worker contacts a job, but not a firm. Therefore, the output of the match (p, ϵ), and the outside options of the worker and the job, only depend on the type of the worker and the type of the firm, p and ϵ. A worker employed by a firm p receives a wage $w(p, \epsilon)$, and the firm receives $\pi(p, \epsilon)$. Because payoffs exhaust match output, $f(p, \epsilon) = w(p, \epsilon) + \pi(p, \epsilon)$. Unemployed workers and vacancies produce nothing when unmatched.

Employment relationships are exogenously destroyed at a constant rate $\delta > 0$, leaving the worker unemployed and the firm with one more vacancy. Workers and jobs meet with probability λ.[6] The match is only consummated if they are both unmatched and they both agree. The behavior of agents is described by their acceptance sets, which specify with whom they are willing to match. The value of the unemployment for a worker of type ϵ is:

$$\rho U(\epsilon) = \lambda \int_{M_w(\epsilon)} \left[W(p', \epsilon) - U(\epsilon)\right] v(p')dp',$$

where $v(p)$ is the density of vacancies, $M_w(\epsilon)$ is the set of acceptable firms for the worker ϵ, and $W(p, \epsilon)$ is the value of a job in a firm with productivity p for a worker of ability ϵ, and is defined by:

$$\rho W(p, \epsilon) = w(p, \epsilon) - \delta \left[W(p, \epsilon) - U(\epsilon)\right].$$

The value of a vacancy for a firm with productivity p, is:

$$\rho V(p) = \lambda \int_{M_f(p)} \left[J(p, \epsilon') - V(p)\right] u(\epsilon')d\epsilon',$$

where $u(\epsilon)$ is the density of unemployed workers, $M_f(p)$ is the set of acceptable workers for the firm p, and $J(p, \epsilon)$ is the value of a job employing a worker of ability ϵ, for a firm with productivity p, and is defined by:

$$\rho J(p, \epsilon) = \pi(p, \epsilon) - \delta \left[J(p, \epsilon) - V(p)\right].$$

The payoffs are determined by splitting the surplus of the match by the Generalized Nash

[6] Although there is not on-the-job search, the model features movements of workers between firms with an interim unemployment spell.

Bargaining Solution.[7] The surplus of the match between a firm p and a worker ϵ is sum of the differences between the value of the match and the outside option for each partner (*ie:* $S(p,\epsilon) = W(p,\epsilon) - U(\epsilon) + J(p,\epsilon) - V(p)$). If β is the bargaining power of the worker, the standard solution implies that the worker takes a fraction β of the surplus (*ie:* $W(p,\epsilon) - U(\epsilon) = \beta S(p,\epsilon)$) and the firm takes a fraction $(1-\beta)$ of the surplus (*ie:* $J(p,\epsilon) - V(p) = (1-\beta)S(p,\epsilon)$).

This model is equivalent to the model presented in Shimer and Smith (2000)[8], who provide a proof of the existence of an equilibrium. A steady-state search equilibrium implies that everyone maximizes his expected payoff, taking all other strategies as given; there are only matches providing (weakly) positive utility for both partners; and all unmatched rates are in steady-state.

The strategies of the agents consist of the acceptance sets. The match is created only if both partners agree, therefore if $S(p,\epsilon) > 0$ then $\epsilon \in M_f(p)$ and $p \in M_w(\epsilon)$. Shimer and Smith (2000) show that acceptance set convexity is logically necessary for assortative matching, hence acceptance sets can be characterized by their bounds. Therefore, $\epsilon \in M_f(p) \Leftrightarrow \epsilon_{min}(p) \leq \epsilon \leq \epsilon_{max}(p)$ where $\epsilon_{max}(p)$ is the highest type of worker contained in $M_f(p)$ and $\epsilon_{min}(p)$ is the lowest type of worker contained in $M_f(p)$. Equivalently, $p \in M_w(\epsilon) \Leftrightarrow p_{min}(\epsilon) \leq p \leq p_{max}(\epsilon)$, where $p_{max}(\epsilon)$ is the highest type of firm contained in $M_w(\epsilon)$ and $p_{min}(\epsilon)$ is the lowest type of firm contained in $M_w(\epsilon)$.

3.1 Identification of Sorting

This model provides an appropriate starting point for thinking about sorting of worker and firms, but also to describe how our test works. Although types are in general unobserved for the econometrician, payoffs of agents can be used to learn on the types of firms and workers.

Proposition 1 *Payoffs, are monotone (increasing) in the agents types.*

Proof: consider two workers, ϵ^- and ϵ^+ matched to the same firm p. ϵ^+ produces more, but not necessarily $S(p,\epsilon^+) > S(p,\epsilon^-)$ because $U(\epsilon^+) > U(\epsilon^-)$.[9]

[7]Search frictions create temporary bilateral rents, since an agreeable match now is generically strictly preferred to waiting for a better future match.

[8]Shimer and Smith (2000) study a problem with symmetric agents. To have symmetry we should assume that the primitive distribution of firms $\psi(p) = N\gamma(\epsilon)$.

[9]It is straightforward to show that the value of unemployment is increasing in the worker type, see Shimer and Smith (2000).

- If $S(p,\epsilon^+) > S(p,\epsilon^-)$, therefore $w(p,\epsilon^+) > w(p,\epsilon^-)$. Note that, if the surplus with ϵ^+ is larger than the surplus with ϵ^-, $W(p,\epsilon^+) - U(\epsilon^+) > W(p,\epsilon^-) - U(\epsilon^-)$. As the value of the being unmatched is higher for ϵ^+,[10] $W(p,\epsilon^+) > W(p,\epsilon^-)$. Given that the value of the job is higher for ϵ^+, we know that $w(p,\epsilon^+) - (\delta/2)S(p,\epsilon^+) > w(p,\epsilon^-) - (\delta/2)S(p,\epsilon^-) > w(p,\epsilon^-) - (\delta/2)S(p,\epsilon^+)$, therefore $w(p,\epsilon^+) > w(p,\epsilon^-)$.

- If $S(p,\epsilon^+) < S(p,\epsilon^-)$, therefore $w(p,\epsilon^+) > w(p,\epsilon^-)$. This is because the firm is worse-off with the best worker due to her higher value of the vacancy, $J(p,\epsilon^+) < J(p,\epsilon^-)$. Therefore, $\pi(p|\epsilon^+) + \delta V(p) < \pi(p,\epsilon^-) + \delta V(p)$, then as the value of the vacancy for the firm does not change, its payoff is lower with ϵ^+ than with ϵ^-, $\pi(p,\epsilon^+) < \pi(p,\epsilon^-)$. Now $f(p,\epsilon^+) - w(p,\epsilon^+) = \pi(p,\epsilon^+) < \pi(p,\epsilon^-) = f(p,\epsilon^-) - w(p,\epsilon^-)$, as $f(p,\epsilon^+) > f(p,\epsilon^-) \Rightarrow w(p,\epsilon^+) > w(p,\epsilon^-)$.

Therefore, $\partial \frac{w(p,\epsilon)}{\partial \epsilon}\Big|_p > 0$. The same is true for the payoff of the firm, $\partial \frac{\pi(p,\epsilon)}{\partial p}\Big|_\epsilon > 0$.[11] These monotonicity conditions do not directly provide a valid way to order workers and firms. This is because the payoffs also depend on the type of the partner, and due to frictions in the matching process, the partner's type is not deterministic. For example, there can be a bad worker receiving a higher wage than a good worker, simply because the latter found a firm less appropriate for his type.

Nevertheless, given that payoffs are increasing in the agent type, the better the type, the highest the expected payoff. Therefore, expected payoffs could be used to rank firms and workers. The expected payoff of firm p (*ie:* $\Pi(p)$) is $\int_{M_f(p)} \pi(p,\epsilon')u(\epsilon')d\epsilon'$, and the expected payoff of a worker ϵ is, $\int_{M_w(\epsilon)} w(p',\epsilon)v(p')dp'$. Although there is noise in the payoffs (which comes from a partner's type), in expected terms a better firm or worker must do better than a worse firm or worker. The intuition of this result is straightforward. An agent can always imitate the strategy (in terms of acceptance set and payoffs paid) of an agent with a lower type. The better agent produces more and pays the same, therefore the better agent receives more than the worse agent (with each partner of that acceptance set). This strategy is optimal for the low-type agent but can be suboptimal for the high-type agent. Then, if the high-type agent use her optimal strategy,

[10] See Shimer and Smith (2000).

[11] The proof is the mirror of the proof of proposition 1

she may obtain even more in terms of expected payoffs.[12]

Expected payoffs are unobserved, but they can be estimated by their sample counterparts. In many datasets, we observe firm's profits. Profits per firm are the sum of the profits per worker, for every worker employed in the firm. As long as there is a large number of workers per firm, a precise estimate of the expected payoff for every single firm can be recovered (in the dataset used in this paper, the average number of worker per firm is more than 209 workers, see Table 4.2). On the other hand, workers are generally matched with one firm per spell, and including the longitudinal dimension does not help (In our sample, on average workers are with 1.3 employers along the 7-year duration of our panel). Therefore, the average wage calculated in a sample of workers, can be as noisy as the wage, and not necessarily a good measure of the expected payoff of a worker. Moreover, as the difference between the average wage and the expected wage is produced by the type of firms to which the worker is matched, this noise is correlated with the firm types. Therefore, a correlation between the average wage and the average profit of the firm is not a good candidate to learn about sorting.

However, being able to rank firms allows us to use movements of workers between firms of different types, with an interim unemployment spell, to check whether there is positive or negative assortative matching. Shimer and Smith (2000) modify the definition of positive/negative assortative matching to be consistent with acceptance sets. In Shimer and Smith's definition, assortative matching is positive if for any firm types $p^+ > p^-$ and workers types $\epsilon^+ > \epsilon^-$, $p^+ \in M_w(\epsilon+)$ and $p^- \in M_w(\epsilon-)$, whenever $p^+ \in M_w(\epsilon-)$ and $p^- \in M_w(\epsilon+)$. One of the implication of this definition, is that there is PAM when bounds of the acceptance set are increasing in type and that there is negative assortative matching (NAM) when bounds are decreasing in type.

Proposition 2 *Consider two workers ϵ^+ and ϵ^-, with $\epsilon^+ > \epsilon^-$, whose matches with a firm p have ended. If there is positive (negative) assortative matching, ϵ^+ has higher (lower) chances than ϵ^-, of being re-hired by a firm better than p.*

[12] In the Appendix, we include a more formal proof of monotonicity of the expected value of payoffs.

Proof: This follows from the definition of PAM and NAM. The difference in probabilities of being re-hired by a firm better than p for the workers ϵ^+ and ϵ^- is:

$$\lambda\left[\int_{p}^{p_{max}(\epsilon^+)} v(p')dp' - \int_{p}^{p_{max}(\epsilon^-)} v(p')dp'\right]$$

If the bounds of the acceptance set are increasing in the worker type, there is PAM. Therefore if

$$\lambda\left[\int_{p}^{p_{max}(\epsilon^+)} v(p')dp' - \int_{p}^{p_{max}(\epsilon^-)} v(p')dp'\right] = \lambda\left[\int_{p_{max}(\epsilon^-)}^{p_{max}(\epsilon^+)} v(p')dp'\right] \geq 0$$

there is positive assortative matching. If the bounds of the acceptance set are decreasing in the worker type, then there is NAM. Therefore if:

$$\lambda\left[\int_{p}^{p_{max}(\epsilon^+)} v(p')dp' - \int_{p}^{p_{max}(\epsilon^-)} v(p')dp'\right] = -\lambda\left[\int_{p_{max}(\epsilon^+)}^{p_{max}(\epsilon^-)} v(p')dp'\right] \leq 0$$

there is negative assortative matching. Therefore, to identify whether there is PAM or NAM, we compare the probabilities of going up in the firm productivity ladder for two movers ϵ^+ and ϵ^-, with $\epsilon^+ > \epsilon^-$, who move from a firm p

$$Prob(\text{move UP}|p, \epsilon^+, move) > Prob(\text{move UP}|p, \epsilon^-, move),$$

where to *"move UP"* means being re-hired by a firm better than p (that is the same as being rehired by a firm p' with $\Pi(p') > \Pi(p)$). This test is not feasible, because ϵ^+ and ϵ^- are unobserved. But, if two workers are first observed in the same firm, we can use their previous wages to rank them. This follows from Proposition 1. If two workers are co-workers, the better worker must have a better wage. Therefore we can compare the probability of going up or down in the productivity ladder of firms' productivity, for two workers with different wages:

$$Prob(\text{move UP}|p, w(\epsilon^+, p), move) > Prob(\text{move UP}|p, w(\epsilon^-, p), move)$$

With some structure in the conditional probability model:

$$Prob(\text{move UP}|p, \epsilon, move) = w(\epsilon, p)'\gamma + \psi(p)$$

where $wage(\epsilon, p)$ is the wage of the worker ϵ in firm p and $\psi(p)$ is a firm p effect, in order to exploit only within-firm variation. Note that in the left-hand side, we have the probability that a worker moves to a better firm than p, conditional on a movement. The complementary event is that a worker still moves, but to a firm worse than p.

We make inference about the existence and the sign of assortative matching simply testing whether γ is different from zero. If $\gamma > 0 \Rightarrow PAM$, if $\gamma < 0 \Rightarrow NAM$ and if $\gamma = 0 \Rightarrow$ there is no evidence assortative matching.

Note that our test is not specific to the simple search model presented above. Indeed, the test produces correct measures of sorting when $\partial \frac{w(p,\epsilon)}{\partial \epsilon}\Big|_p > 0$ and $\partial \frac{\pi(p,\epsilon)}{\partial p}\Big|_\epsilon > 0$. Wages monotone in the worker type is a natural assumption, which is consistent with a family of models. There are only few exceptions, and most of them involve heterogeneity in offer arrival rates. Shimer (2005) and Eeckhout and Kircher (2010) propose two models with directed search and screening which deliver multiple equilibria and in some of the equilibria, wages could be non monotone in the worker type. The intuition is that a better worker may have a lower wage at a given firm but be compensated by a higher probability of getting hired. Lentz (2011) proposes an equilibrium search model with on-the-job search, strategic bargaining and endogenous search intensity, where low productivity firms pay wages which are not always monotone in the worker type. In Section 6, we present slightly modified versions of our test that are consistent with models with heterogeneous offer arrival rate.

4 Data, Definitions and Institutional Background

4.1 Institutional Background

Wage setting in Italy is governed by a "two-level" bargaining system.[13] Sectoral agreements (generally negotiated every two years) establish contractual minimum wages for different occupation classes (typically 7 or 8 sector-specific classes), that are automatically extended to all employees in the sector. Unions can also negotiate firm-specific contracts that provide wage premiums over and above the sectoral minimums. During the mid-1990s such firm-level bargains covered about 40% of private sector employees nationwide (ISTAT, 2000). In addition, individual employees receive premiums and bonuses that add to the minimum contractual wage for their job. In our estimation sample nearly all employees earn at least some premium: the 5th percentile of the percentage premium is 2.5%, while the median is 24%. The combination of sector and occupation minimum wages with individual-level wage premiums means that within-firm wage variability is quantitatively significant. In particular, according to Lazear and Shaw (2008), within-firm wage variability in Italy represents about two thirds of total wage variability, in line with the international evidence reported in their study.

4.2 Data

The data set used in the paper was obtained by Card, Devicienti and Maida (2010) by combining information from two different sources: individual labor market histories and earnings records, and firm balance sheet data. The job histories and earnings data were derived from the Veneto Workers History (VWH) dataset, constructed by a team leaded by Giuseppe Tattara at the University of Venice, using administrative records of the Italian Social Security System. The VWH contains information on private sector employees in the Veneto region of Italy over the period from 1975 to 2001 (see Tattara and Valentini, 2007).[14] Specifically, it includes register-based information for any job that lasts at least one day. On the employee side, the VWH includes total earnings during the calendar year for each job, the number of days worked during the year, the code of the

[13]This system was introduced in 1993, replacing an earlier system that included local and sectoral agreements and a national indexation formula. See Casadio (2003) and Dell'Aringa and Lucifora (1994). The Netherlands, Spain, and Portugal have similar two-level systems.

[14]The Veneto region has a population of about 4.6 million - approximately 8% of the total population of Italy.

appropriate collective national contract and level within that contract (i.e., a "job ladder" code), and the worker's gender, age, region (or country) of birth, and seniority with the firm. On the employer side the VWH includes industry (classified by 5-digit ATECO 91), the dates of "birth" and closure of the firm (if applicable), the firm's location, and the firm's national tax number (*codice fiscale*).

Firm-level balance sheet information was obtained from AIDA (*Analisi Informatizzata Delle Aziende*), a database distributed by Bureau Van Dijk, which includes information for incorporated non-financial firms in Italy with annual sales of at least 500,000 Euros.[15] AIDA contains the official balance sheet data for these firms, and is available starting in 1995. The AIDA data include sales, value added, total wage bill, capital, the total number of employees, industry (categorized by 5-digit code), and the firm's tax number.

Tax code identifiers are used to match job-year observations for employees in the VWH to employer information in AIDA for the period from 1995 to 2001. Additional checks of business names (*ragione sociale*) and firm location (firm address) in the two data sources were carried out to minimize false matches. As reported by Card et al. (2010), the match rate was relatively high: for about 95% of the AIDA firms it was possible to find a matching firm in the VWH.[16] The characteristics of our initial sample - potential matches between VWH and AIDA - are reported in column (1) of Table 1. Over the 1995-2001 period, the matched dataset contains about 850,000 individuals aged 16-64 who were observed in about 1 million job spells (about 3 million job*year observations) at over 23,000 firms.[17] On average 29% of workers in the sample are female, 20%

[15]See http://www.bvdep.com/en/aida.html. Only a tiny fraction of firms in AIDA are publicly traded. We exclude these firms and those with consolidated balance sheets (i.e., holding companies).

[16]The quality of the matches was further evaluated by comparing the total number of workers in the VWH who are recorded as having a job at a given firm (in October of a given year) with the total number of employees reported in AIDA (for the same year). In general the two counts agree very closely. After removing a small number of matches for which the absolute difference between the number of employees reported in the balance sheet and the number found in the VWH exceeded 100 (less than 1% of all firms), the correlation between the number of employees in the balance sheet and the number found in the VWH is 0.99. Total wages and salaries for the calendar year as reported in AIDA were compared with total wage payments reported for employees in the VWH. The two measures are highly correlated (correlation > 0.98), and the median ratio between them is close to 1.0.

[17]These represent about 10% of the total universe of firms contained in the VWH. The vast majority of the unmatched firms are non-incorporated, small family business (*societa' di persona*) that are not required by existing regulations to maintain balance sheets books, and are therefore outside the AIDA reference population. The average firm size for the matched sample of incorporated businesses (about 190 employees) is therefore substantially above the average for all firms (incorporated plus non-incorporated businesses) in the VWH (7.0 employees). Mean daily wages for the matched sample are also higher than in the entire VWH, while the fractions of female and younger workers are lower. See Card et al. (2010) for further details.

are white collars and a tiny minority, about 1%, are managers. The mean age is 35, mean tenure is 8.5 years and the mean daily wage was 69 Euros. While the median firm size is 69, the presence of a small number of relatively large firms raises the mean to 190 employees.

The bottom rows of Table 1 show the mean values of various indicators of firm profitability. We first compute a proxy for economic profits ($\pi_{j,t}$), as follows:

$$\Pi_{j,t} = Y_{j,t} - materials_{j,t} - w_{j,t}L_{j,t} - r_t K_{j,t}$$

where $Y_{j,t}$ denotes total sales of firm j in year t, $w_{j,t}L_{j,t}$ are firm labor costs, as reported in the firm's profit and loss report. To deduct capital costs, we compute $K_{j,t}$ as the sum of tangible fixed assets (land and buildings, plant and machinery, industrial and commercial equipments) plus immaterial fixed assets (intellectual property, R&D, goodwill).

The literature on capital investment in Italy suggests that during the mid-to-late 1990s a reasonable estimate of the user cost of capital (r_t) is in the range of $8 - 12\%$. Elston and Rondi (2006) report a distribution of estimates of the user cost of capital for publicly traded Italian firms in the 1995-2002 period, with a median of 11% (Elston and Rondi, 2006, Table A4). Arachi and Biagi (2005) calculate the user cost of capital, with special attention to the tax treatment of investment, for a panel of larger firms over the 1982-1998 period. Their estimates for 1995-1998 are in the range of $10 - 15\%$ with a value of 11% in 1998 (Arachi and Biagi, 2005, Figure 2).[18] We assume that r_t is at 10% in the estimation reported below. As we also show below, the results are not dependant on any particular definition of profit. Four additional profitability measures from the firm's profit and loss report are reported in Table 1: gross operating surplus (GOS):

$$GOS = sales - materials - LaborCosts - depreciation,$$

after-tax accounting profits (AP):

$$AP = sales - materials - LaborCosts - depreciation - DebtServices - tax$$

[18]Franzosi (2008) calculates the marginal user cost of capital taking into account the differential costs of debt and equity financing, and the effects of tax reforms in 1996 and 1997. Her calculations suggest that the marginal user cost of capital was about 7.5% pre-1996 for a firm with 60% debt financing, and fell to 6% after 1997.

as well as GOS per worker and AP per worker. Table 1 reports an average profit at about 3.6 million euros (in 2000 prices), and a profit per workers of around 14,900 euros. GOS are, on average, at 2.8 million, or 11,400 euros per worker. Mean AP are at 1,2 million and 4,100 per worker.

From the set of potential matches we made a series of exclusions to arrive at our estimation sample. First, we considered only those workers who - within the 1995-2001 period - switched from a firm in the dataset to another firm in the dataset at least once. Second, we eliminated apprentices and part-time employees. Third, we eliminated jobs at firms that had fewer than 10 employees. Finally, to minimize measurement error in wages we further restricted the sample to workers with a minimum of labor market attachment: workers that have worked a minimum of 26 days with the employer from which they separate and have earned wages not lower than the minimum of the "minimum wages" set by national contracts for the lowest category (this roughly corresponds to the bottom 1% of the wage distribution).[19] We also eliminated unusually high wages by dropping wages higher than the top 1% of the overall wage distribution.

Column (2) of Table 4.2 reports the characteristics of the of the workers and the firms, included in the sub-sample used for estimation. There are around 166,000 job switchers in the sample (or some 20% of the original sample), coming from 11,000 firms. As expected, job changers are on average younger than the overall sample (mean age in column (2) is 31), have lower tenure (less than 3 years) and earn comparatively less than the rest of the population (62 euro daily). The percentage of female workers, white collars workers and managers are also smaller in the job changer sample than in the overall sample of column (1). The table also reports the number of months that have elapsed from the separation from the former employer and the association with the new one. The median of this variable (labeled "lag" for short) is only 2 months. However, the mean lag is 7.7 months, which is consistent with the existence a relatively large fraction of long-term unemployed workers.

[19] Information about contractual minimum wages (inclusive of any cost-of-living allowance and other special allowances) were obtained from records of the national contracts. See Card et al. (2010) for details.

Table 1: Descriptive Statistics

	VWH - AIDA	
	Complete Sample	Movers sample
no. Job*year obs	3,088,113	214,588
no. Jobs	1,064,694	203,803
no. individuals	838,619	166,192
no. firms	23,448	11,030
mean age	35.2	31.1
% female	29.3	27.1
% white collar	29.6	25.4
% manager	1.1	0.3
mean tenure (months)	102.5	36.5
mean wage	69.4	61.7
mean log wage	4.12	4.05
mean lag (in months)	-	7.7
median lag	-	2.0
mean firm size	191	209
median firm size	69.0	67
mean profit*	3612.0	3871.9
mean profit p.w.*	14.9	13.9
mean GOS*	2781.9	2829.5
mean GOS p.w.*	11.4	9.8
mean account. profit*	1245.8	1091.3
mean acc. profit p.w. (after tax)*	4.1	1.6

Note: * 1000's of real euros

5 Results

The model is stylized, and hence it seems prudent to include a set of observable characteristics of the worker and the firm to control for other confounding mechanisms.[20] There are many worker characteristics that might affect wages and worker mobility, such as age, gender or migration status. Moreover, it is not clear to what extent the required monotonicity conditions for payoffs make sense when comparing co-workers in different occupations or firms in different sectors. Therefore, using a sample of movers we estimate the following conditional probability model:

$$Prob(\text{move UP}|p_j, \epsilon_i, x_{i,j}, move) = x_{i,j}'\beta + w(\epsilon_i, p_j)'\gamma + \psi_j \tag{1}$$

[20]Results from a simpler specification, only including log-wages and firms fixed effects as regressors, are presented in Table A1 in the Appendix. That specification is the direct empirical counterpart of equation (1). Results in Table A1 also give significant evidence of positive assortative matching.

where $Prob(\text{move UP}|p_j, \epsilon_i, x_{i,j}, move)$ is the conditional probability that an employee i who was working in a firm j, moves to a firm better than j. $wage_{\epsilon_i,p_j}$ is the wage that the worker received in the firm j. η_j is a firm j fixed effect, in order to partial out between firm variation. $x_{i,j}$ are characteristics of the worker i and her job in firm j. $x_{i,j}$ includes measures of the worker age, age squared, tenure, tenure squared, time dummies and indicators for females, migrants, blue collar, white collars and managerial occupations.

Table 2 shows results obtained when firm quality is defined in terms of economic profits. In column (1) the dependent variable is a indicator function that takes the value 1 when the new employer has a higher level of profit (measured at the time of hiring) than the old employer (measured at the time the worker has separated). Note that the previous measure of profits is firm and time specific. We think of the type as a fixed characteristic of the worker or the firm. Therefore, in the presence of transitory productivity shocks or measurement error, average profit across time can provide a more precise ordering of firms according to their type. In column (2), the indicator variable is therefore defined in terms of average profits, computed as:

$$AvProfit_j = \frac{\Sigma_{t=1}^{T_j} \pi_{j,t}}{T_j}$$

where T_j is the total number of periods where we observe the firm j in the sample. Workers may have been able to observe the evolution of profits over time and base their search and matching behavior on firms' time-averaged profits. Therefore columns (4) and (5) present results with past average profits, namely:

$$PastProfit_{j,t} = \frac{\Sigma_{\tau=1}^{t} \pi_{j,\tau}}{t}$$

Finally, columns (3) and (5) consider average profit and average profit per worker, respectively. The LOGIT estimates of columns (1)-(5) show that the log wage has a positive and significant impact on the probability that the worker moves to a firm with higher profits than his current firm, regardless of which definition of profit we use. This implies PAM: better workers are more likely to move to better firms.

The specifications where we use average profit and average profit per worker as a measure of

Table 2: Different definitions of Firm Quality

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1)	(2)	(3)	(4)	(5)
	Definition of firm quality ($\pi_{j,t}$)				
	Profits	Average Profit	Average Profit per worker	Past Average Profit	Past Av. Profit per worker
Log Wage	0.060	0.2076	0.2381	0.0960	0.1593
	(0.025)	(0.0280)	(0.0275)	(0.0266)	(0.0267)
age	−0.022	0.1303	0.1296	−0.0335	0.0053
	(0.004)	(0.0051)	(0.0050)	(0.0046)	(0.0046)
age^2	0.0002	-0.0019	-0.0019	−0.0003	−0.00018
	(0.0001)	(0.0001)	(0.0001)	(0.00006)	(0.00006)
Female	0.0414	−0.0838	−0.2039	−0.0501	−0.1099
	(0.0157)	(0.0177)	(0.0174)	(0.0164)	(0.0165)
Migrant	−0.077	−0.2056	−0.1284	−0.0756	−0.0725
	(0.022)	(0.0237)	(0.0237)	(0.0227)	(0.0229)
Tenure	0.0011	−0.0016	−0.0001	0.0008	0.0022
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.00033)
Tenure^2	-1.84e^{-6}	8.41e^{-7}	-3.40e^{-6}	-1.37e^{-6}	-7.47e^{-6}
	(1.44e^{-6})	(1.57e^{-6})	(1.49e^{-6})	(1.46e^{-6})	(1.45e^{-6})
firm effects	yes	yes	yes	yes	yes
Observations	177,707	175,003	171,738	175,657	174,470
Pseudo R^2	0.1875	0.2841	0.2729	0.2317	23.44

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single logistic regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

firm quality fit the data significantly better than the alternative specifications. This pattern is observed in most of the robustness checks performed along the paper. One potential mechanism that explains this regularity is the existence of idiosyncratic shocks to productivity. In the presence of shocks to productivity, the average profit is a more stable function of the time-invariant firm type. [21]

Note that there appears to be some heterogeneity in the conditional probability of moving to a better firm for workers belonging to various sub-groups, although in many cases the impact of worker characteristics is not clear-cut and is not always precisely estimated. After conditioning for wages, female and migrant workers seem to be less likely than the rest of workers to move to better firms. The effect of age and tenure is instead more dubious, with only very weak evidence that more mature workers and those with a longer tenure are more likely to improve the quality of their employers.

[21] This is because the variance of the average shock is of order $1/T_j^2$, as opposed to the variance of the idiosyncratic shocks, where T_j is the number of periods where the firm j is observed.

In the Appendix we show that evidence in favor of the PAM result is robust and pervasive across various population subgroups. Re-estimating our models on the sub-sample of males confirms the results shown above for any profit definition. PAM is also found if we re-estimate our models separately on the sub-sample of blue collar workers and on the sub-sample of white collar workers (including the small number of managers). PAM is broadly confirmed for workers aged 30 or less, and is somewhat less statistically significant (but still positive) for workers aged 45 or more. Finally, separate estimation by sector confirm that, for any profit definitions, PAM is found in both the manufacturing and the service sector, with some evidence of a stronger PAM in the former sector.

5.1 Different Specifications of the Conditional Probability Model

In Table 3 firm's quality is defined in terms of current profit per worker, but different specifications of the conditional probability model are compared. Wages are only an ordinal measure of the worker type. Any monotone transformation of wages is also a valid candidate to include in the regressions. Some transformations might imply a better fit of the data than others. Entering the wage in levels (as opposed to in logs) does not affect our main result: the coefficient remains positive and statistically significant (column 1).[22] Columns (2) and (3) compare PROBIT and LOGIT estimates, showing that the PAM result is robust to these alternative distributional assumptions. We next take on board a linear probability model, which allows us to show that the results are insensitive to partialling out wages at the firm level (i.e. inserting in the model firm fixed effect; column 4) as opposed at the firm *and* year level (i.e. using unrestricted firm*year fixed effects, as in column 5). Note that, since the combination of firm and year effect is very large (14,723), the average number of observations per firm-year cell is only 8.84. Therefore LOGIT or PROBIT would generate biased estimated due to the presence of incidental parameters; however, it is still possible to differentiate them out using the linear probability model.

[22]Most of the specifications have been replicated using wages as opposed to log-wages without significant changes in results.

Table 3: Different Specifications of the Probability Model

$y = 1(\text{next } \Pi > \text{current } \Pi)$	(1)	(2)	(3)	(4)	(5)
	Conditional Probability Model				
	LOGIT	LOGIT	PROBIT	Linear Probability Model	Linear Probability Model
Wage	0.0011				
	(0.0003)				
Log Wage		0.1155	0.0668	0.0223	0.0343
		(0.0253)	(0.0152)	(0.0050)	(0.0062)
age	0.0023	0.0015	0.0010	0.0003	−0.0011
	(0.0042)	(0.0043)	(0.0025)	(0.0008)	(0.0010)
age^2	−.0001	−0.0001	−0.0001	−0.0001	$3.88e^{-6}$
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	$(1.43e^{-5})$
Female	0.0623	−0.0584	−0.0346	−0.0113	−0.0134
	(0.0155)	(0.0155)	(0.0093)	(0.0031)	(0.0036)
Migrant	−0.0542	−0.0514	−0.0313	−0.0101	−0.0041
	(0.0218)	(0.0218)	(0.0131)	(0.0043)	(0.0052)
Tenure	0.0020	0.0019	0.0011	0.0004	0.0003
	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Tenure^2	$-6.41e^{-6}$	$-6.06e^{-6}$	$-3.66e^{-6}$	$-1.16e^{-6}$	$-1.19e^{-6}$
	$(1.40e^{-6})$	$(1.41e^{-6})$	$(8.47e^{-7})$	$(2.79e^{-7})$	$(3.40e^{-7})$
firm effects	yes	yes	yes	yes	yes
firm by year effect	no	no	no	no	yes
Observations	178,094	178,094	90,614	178,094	130,212
Number of firms	7,746	7,746	7,746	7,746	14,723
Av. Movers per firm	22.99	22.99	22.99	22.99	8.84
Pseudo R^2	0.1732	0.1732	0.2033	0.1798	0.2984

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$ over the number of workers. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses. Number of firms in Column (5), represents number of firms-years groups. Average number of movers in Column (5) represents the average number of movers by firm-year.

5.2 Different Definitions of Profits

With the next set of estimates, we further investigate the robustness of the results to different definitions of profits. In Table 4, firm quality is alternatively defined in terms of gross operating surplus (GOS), GOS per worker. Average GOS and average GOS per worker are also considered, using either the whole sequence of observed GOS or only GOS up to the time of the worker separation (see section 4 for details). The same set of estimates are reported in Table 5 but with reference to accounting profit measures (AP). In the appendix (Table A.2) we show that all these different measures of firm quality are positively correlated; however the range of the correlation coefficients (as low as 0.3 for some measures) suggests that they may convey non-redundant information. It is reassuring that in all these cases we find robust evidence of PAM.

Table 4: Different definitions of Profits

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Gross Operating Surplus	GOS per worker	Average GOS	Average GOS per worker	Past Av. GOS	Past Av. GOS per worker
Log-wage	0.154	0.102	0.231	0.184	0.236	0.186
	(0.03)	(0.029)	(0.032)	(0.031)	(0.031)	(0.03)
Age	0.014	0.0007	0.027	0.005	0.011	-.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age^2	-.0003	-.0001	-.0005	-.0002	-.0003	-.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.038	-.075	0.022	-.084	0.048	-.103
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
Migrant	-.152	-.051	-.162	-.046	-.147	-.069
	(0.03)	(0.03)	(0.032)	(0.032)	(0.031)	(0.031)
Tenure	0.0004	0.002	0.0005	0.002	0.0009	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-1.07e-06	-6.37e-06	-4.26e-06	-7.10e-06	-4.20e-06	-7.42e-06
	(1.83e-06)	(1.78e-06)	(1.98e-06)	(1.91e-06)	(1.92e-06)	(1.85e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	103,214	102,441	98,131	95,594	100,435	99,109
Number of firms	6,431	6,460	6,080	5,771	6,186	6,026
Movers/firm	16.05	15.86	16.14	16.56	16.24	16.45
Pseudo R^2	0.2303	0.1976	0.2646	0.2525	0.2591	0.2358

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Gross Operating Surplus is defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t}$. Each column represents a single logistic regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

5.3 Within-Firm Regressions

The test requires that wages are monotone in the worker type. This condition implies that within the firm, worker types can be indexed by their wages. In previous specification we have included a firm fixed effect in the conditional probability model in order to have wages relatives to the mean wage in each firm. It could be the case that other moments of the within-firm distributions of wages are firm-specific. For example in models with between-firms Bertrand competition and two-sided heterogeneity, such as Cahuc, Postel-Vinay and Robin (2006), the within-firm variance and skewness are associated with the firm type. If this is the case, the effect of wages on the probability of a transition could be heterogeneous across firms. In Table 6 we show results obtained with within-firm regressions. In particular, we run linear probability models or LOGIT models firm-by-firm. In these specification every moment of the within-firm distribution of wages is allowed to be firm-type dependent. Estimation requires that we restrict ourselves to the subsample of relatively large firms where a minimum number of job changers can be observed (30 in our case).

Table 5: Different definitions of Profits

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
	Accounting Profits	Accounting Profits per worker	Average AP	Average AP per worker	Past Av. AP	Past Av. AP per worker
Log-wage	0.156	0.126	0.063	0.058	0.124	0.097
	(0.029)	(0.028)	(0.032)	(0.031)	(0.031)	(0.03)
Age	0.0009	-.007	0.015	0.011	0.001	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age^2	-.0001	-1.00e-05	-.0004	-.0003	-.0001	-.0002
	(0.00009)	(0.00009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.016	-.030	0.004	-.051	0.019	-.048
	(0.021)	(0.02)	(0.023)	(0.022)	(0.022)	(0.021)
Migrant	-.112	-.062	-.108	-.089	-.097	-.099
	(0.03)	(0.03)	(0.032)	(0.032)	(0.031)	(0.031)
Tenure	0.0007	0.001	0.0003	0.002	0.001	0.002
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-2.00e-06	-4.62e-06	-1.18e-06	-4.67e-06	-2.47e-06	-7.32e-06
	(1.80e-06)	(1.74e-06)	(2.02e-06)	(1.89e-06)	(1.91e-06)	(1.81e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	104,733	103,198	98,533	95,929	101,379	98,874
Number of firms	6,744	6,517	6,280	5,767	6,376	6,038
Movers/firm	15.53	15.84	15.69	16.63	15.90	16.38
Pseudo R^2	0.2143	0.1854	0.2830	0.2477	0.2602	0.2246

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Accounting profits are defined as value of sales minus cost of materials, wages, depreciation of capital and debt services. Each column represents a single logistic regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

The estimated coefficients for each firm were then averaged across firms and reported in the table, along with the standard deviation of the average. Albeit we loose some precision in this exercise, the results are once more suggestive of PAM.

5.4 Within-Firm Wage Quantiles

Assuming that wages are monotone in the worker type allows us to use within-firm variation on wages to order workers relative to their co-workers. Wages are not a cardinal measure of worker types. A different possibility that comes out of the same ordinal variable is to include in the regressions the quantile in the within-firm distribution of wages. Including the wage-quantile instead of the wage in the regression gives a closer connection with the ordering intuition exploited in this paper. The quantile of the within-firm distribution of wages only tells us which worker is better without any information on the size of that difference.

Results are presented in Table 7. We observe that if we do not include the worker's wage

Table 6: Within-Firm Regressions

	(1)	(2)	(3)	(4)
	Profit per Worker			
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Linear Probability Model	LOGIT	Linear Probability Model	LOGIT
Log-Wage	0.058	4.125	0.060	0.651
	(0.022)	(2.550)	(0.015)	(0.170)
Age	0.003	-6.205	0.003	-0.637
	(0.003)	(1.951)	(0.002)	(0.189)
Age^2	-6.20e-5	0.087	-5.57e-5	0.009
	(5.17e-5)	(0.028)	(3.52e-5)	(0.003)
Female	-0.009	0.138	0.001	-0.039
	(0.011)	(0.113)	(0.008)	(0.052)
Migrant	-0.029	-0.018	-0.017	-0.125
	(0.011)	(0.081)	(0.008)	(0.048)
Tenure	0.0003	-0.167	0.001	-0.014
	(0.0004)	(0.067)	(0.0003)	(0.007)
Tenure^2	3.98e-6	0.003	-9.04e-6	0.001
	(1.03e-5)	(0.001)	(8.96e-6)	(0.0002)
Observations	47,459	47,459	107,110	107,110
Number of firms	713	713	1325	1325
Av. Movers per firm	66.56	66.56	80.84	80.84

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - 0.1 \times K_{j,t}$. Each column presents the mean and the standard deviation of the mean of coefficients estimated in individual regressions at the firm level.

but its quantile on the within-firm distribution of wages, we still obtain evidence of PAM. The coefficient of the wage quantile is significantly positive in every specification, with the exception of Column (1) which uses aggregated economic profit as a measure of the firm quality. As noted before, when we use average profits or average profits per worker as a measure of firm quality, we generally get a better fit of the data and more stable results.

5.5 Different Definitions of Movers

In the model presented in Section 3 there is no on-the-job search. Hence, it describes movements of workers between firms with an interim unemployment spell. In the previous tables we have considered every mover, independently of the duration of the interim unemployment spell. In order to guarantee that every mover considered in the analysis is a worker that comes from a match destruction, we restrict our sample in terms of the duration of the *interim* unemployment spell. Moreover, we ask how our results change if instead of movers that comes from a match

Table 7: Within-Firm Wage Quantiles

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Wage Quantile	0.008	0.091	0.153	0.216	0.052	0.152
	(0.023)	(0.023)	(0.025)	(0.025)	(0.024)	(0.024)
Age	-.021	0.001	0.131	0.129	-.033	0.005
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Age^2	0.0002	-.00009	-.002	-.002	0.0004	-.0002
	(0.00006)	(0.00006)	(0.00007)	(0.00007)	(0.00006)	(0.00007)
Female	0.034	-.063	-.092	-.208	0.043	-.113
	(0.016)	(0.015)	(0.018)	(0.017)	(0.016)	(0.016)
Foreign	-.081	-.052	-.206	-.125	-.078	-.070
	(0.022)	(0.022)	(0.024)	(0.024)	(0.023)	(0.023)
Tenure	0.001	0.002	-.002	-.0003	0.0009	0.002
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Tenure^2	-2.20e-06	-5.92e-06	8.55e-07	-2.94e-06	-1.52e-06	-7.00e-06
	(1.45e-06)	(1.42e-06)	(1.58e-06)	(1.50e-06)	(1.50e-06)	(1.46e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	177,740	178,144	175,040	171,782	175,695	174,517
Number of firms	7,656	7,750	7,597	7,409	7,409	7,345
Av. Movers per firm	23.21	22.98	23.04	23.18	23.71	23.75
Pseudo R^2	0.18	0.17	0.28	0.27	0.25	0.23

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

destruction, we consider job-to-job movers.

We cannot directly identify job-to-job transitions. However, given that we observe the number of months between the worker's separation from the current employer and the association to a new employer, we can define job-to-job movers as those with no more than 1 month between the two jobs.[23] The results for the subsample excluding job-to-job movers are shown in column (1) of Table 8. For robustness, column (2) adopts a more stringent requirement to identify workers whose job are destroyed: all these workers have spent at least 3 months in unemployment before getting a job with a new employer. The results for the sub-sample of only job-to-job movers are shown in column (3) of Table 8. The remaining columns consider alternative definitions of movers, as detailed in the last row of the table: those with an intervening spell of up to three months (column 3) and those with a spell up to six months (column 4). As before wages significantly increase the probability of moving to a firm with higher profit per worker, and are therefore

[23] Royalty (1998) and Nagypal (2004) define job-to-job transitions equivalently.

consistent with PAM. There are no major differences in the various definitions of movers.

Table 8: Different Definitions of Movers

LOGIT	(1)	(2)	(3)	(4)	(5)
	Definition of firm quality ($\Pi_{j,t}$)				
$y = 1(\text{next }\Pi > \text{current }\Pi)$	Current profits per worker	Current Profit per worker	Current Profit per worker	Current Profit per worker	Current Profit per worker
Log Wage	0.1126	0.1036	0.1295	0.1278	0.1265
	(0.0296)	(0.0465)	(0.0376)	(0.0347)	(0.0329)
age	0.0017	0.007	0.0029	0.0054	0.0035
	(0.0048)	(0.0048)	(0.0080)	(0.0073)	(0.0068)
age^2	$-.0001$	$-.0002$	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	-0.0414	-0.0288	-0.1110	-0.1224	-0.1220
	(0.0177)	(0.0026)	(0.0256)	(0.0231)	(0.0215)
Migrant	-0.0549	-0.0423	-0.0021	-0.0679	-0.0455
	(0.0248)	(0.0341)	(0.0379)	(0.0332)	(0.0301)
Tenure	0.0016	0.0060	0.0011	-0.0013	0.0017
	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-4.95e^{-6}	-1.19e^{-6}	-3.54e^{-6}	-4.26e^{-6}	$-7.15e^{-7}$
	(1.70e^{-6})	(2.68e^{-6})	(2.02e^{-6})	(1.88e^{-6})	(1.79e^{-6})
firm effects	yes	yes	yes	yes	yes
Observations	133,711	98,820	76,800	90,614	102,256
Number of firms	6,945	6,021	5,616	6090	6,397
Av. Movers per firm	19.25	16.41	13.68	14.88	15.98
Pseudo R^2	0.1717	0.1907	0.2038	0.2033	0.2317
Duration of the unemployment spell	$[1,\infty]$	$[3,\infty]$	$[0,1]$	$[0,3]$	$[0,6]$

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single logistic regression. Duration of the unemployment spell is the number of months between two consecutive job spells. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

5.6 Exogenous Match Destruction

Involuntary worker separations identified as in Table 8 are likely to provide reasonably good empirical counterparts of the exogenous job destructions described by the model in Section 3. One concern is that, although separations with one month or even up to three months of intervening unemployment are involuntary for the worker, they may not be independent from the worker type. One may suspect that the firm selects which worker to fire according to their underlying characteristics, and therefore the workers that separate from a firm represent a non-random sample from a firm's workforce.

It is possible to obtain estimates of the strength and direction of sorting that are unaffected by such a concern by limiting the sample to workers who separate because of a firm closure.[24] In this case, all workers are forced to leave the firm, irrespective of their characteristics. With our data, it is possible to identify 710 firms which closed their business during the 1995-2001 time period, involving about 12,000 workers. Despite this dramatic reduction in sample size, the results from this additional sets of estimates, collected in Table 9, are once again indicative of PAM. Column (1) shows the results from a logit regression with firm fixed effects, while column (2) show the results from a linear probability model with firm*year fixed effects. In both cases, the wage coefficient is positive, statistically significant and similar in magnitude to the estimates reported earlier.

The results presented in column (1) and (2) are obtained using our test, but only using data on movers who come from a firm closure. With this test, we make inference on assortative matching analysing how the probability of moving up in the firm productivity ladder differs for co-workers of different types. We order firms by their types using profits. Even though we are using average profit (instead of current profit) for this exercise, it is still possible that the estimates may be contaminated by the low profitability of firms that are closing down. For this reason, in columns (3) and (4), we slightly modify our test in a way that does not depend on the profit of the separating (closing) firm. Specifically, in columns (3) and (4) we run linear regression models where the dependent variable is the quantile in the distribution of firm profit of the worker's new employer. We use the same set of controls than before (including firm, or firm and year, fixed effects, respectively). Note that, in analogy with the ordinal nature of the dependent variable, the quality of the worker is represented by the worker's rank in the wage distribution of the separating firm. The results are once more supportive of PAM. After a firm closure, workers with higher wages than their former co-workers move to better firms than those co-workers do.

[24]Cingano and Rosolia (forthcoming) use a similar strategy to identify the strength of information spillovers on workers' unemployment duration.

Table 9: Exogenous Match Destruction

	(1)	(2)	(3)	(4)
	$y = 1(\text{next } \Pi > \text{current } \Pi)$		$y = \text{current } \Pi$	
	LOGIT	Linear Probability Model	Linear Regression	Linear Regression
Log wage	0.233	0.036		
	(0.114)	(0.015)		
Wage quantile			0.019	0.029
			(0.01)	(0.011)
age	0.043	0.003	0.004	0.003
	(0.021)	(0.003)	(0.002)	(0.002)
Age^2	-.0007	-.00006	-.00008	-.00007
	(0.0003)	(0.00004)	(0.00003)	(0.00003)
Female	-.237	-.030	-.028	-.024
	(0.068)	(0.009)	(0.007)	(0.007)
Migrant	0.016	0.009	-.026	-.025
	(0.098)	(0.014)	(0.01)	(0.01)
Tenure	0.002	0.00009	-.00003	-.00005
	(0.001)	(0.0002)	(0.0001)	(0.0001)
Tenure^2	-9.16e-06	-8.77e-07	5.12e-07	5.86e-07
	(5.20e-06)	(7.34e-07)	(5.34e-07)	(5.60e-07)
firm effects	yes		yes	
firm*year effects		yes		yes
Obs.	10049	12068	10680	10680
$(pseudo)R^2$	0.270	0.532	0.183	0.281

In col. (1) and (2) the dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. In col. 3 and 4 the dependent variable is the percentile in the profit distribution of the worker's new employer. In col (5) the dependent variable is the log of the new employer's profit. Profit is defined as average profit per worker. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

6 Discussion

6.1 Firm Fixed Effects and Worker Fixed Effects in Wage Equations

In order to compare our results with the ones obtained using the approach presented in Abowd, Kramarz and Margolis (1999), we estimate the following equation:

$$w_{i,j,t} = x'_{i,j,t}\beta + \eta_i + \xi_j + u_{i,j,t}, \tag{2}$$

where $x_{i,j,t}$ are observable, time varying, characteristics of the worker and the firm, η_i is the worker i fixed effect and ξ_j is the firm j fixed effect.

The results are presented in Table 10. We find the standard result of a negative and significant correlation between the worker fixed effects and the firm fixed effects. It is striking that using our

Table 10: OLS estimates of equation(2)

AKM Approach

Log-Wages	Coefficient	Std-Dev.
Age	0.0486	(0.00018)
Age^2	-0.0004	(2.34E-06)
Tenure	0.0006	(0.000013)
Tenure^2	-1.43E-06	(5.90E-08)
White-Collard	0.0510	(0.000734)
Manager	0.2879	(0.003016)
Firm Fixed Effects η_j	11,985	
Worker Fixed Effects η_i	778,388	
Observations	2,672,812	
$Correlation(\xi_j, \eta_i) = -0.0216$ with $p - value < 0.0001$		

approach we find significant evidence of PAM and using the AKM approach we find significant evidence of NAM. In the rest of this section we provides some insights into the potential mechanism that generates this difference.

6.2 Wages non-monotone in the firm type

One of the potential explanations of the divergence in results is the mechanism presented in Eeckhout and Kircher (2011) and in Lopes de Melo (2011). They argue that if the value of a vacancy depends on the firm type, it is not always the case that a better firm pays a higher wage. A type-dependent value of vacancies is consistent with firms investing to acquire their type; there could be ex-ante free entry, but after investment in their type the value of the vacancy depends on the firm's productivity. If wages are non-monotone in the firm type, equation (2) is mis-specified. In this subsection, we show evidence suggesting that wages are not always monotone in the firm type. In particular, we analyze whether workers that move to better (or worse) firms according to our metric of firm quality receive higher (or lower) wages. Note that by tracking the same worker we keep the worker effect constant. Results are presented in Table 11.

Considering that our measure to orders firms by their quality is correct, we find strong evidence of non-monotonicity of wages in the firm type. There is an association between positive changes in firm type and positive changes in wages. But we observe a large number of workers moving to worse firms where they receive better wages and workers that end up in a better firm receiving

Table 11: Number of Movers According to their Changes in Wages and Changes in Firm Quality

Profits per Worker												
	Any Movers				Job-to-Job Movers				Job-to-Job Movers & Stable Jobs			
	Worse Wage		Better Wage		Worse Wage		Better Wage		Worse Wage		Better Wage	
Worse Quality	49,381	(47.1%)	55,467	(52.9%)	19,981	(43.2%)	26,257	(56.8%)	7,752	(39.2%)	12,032	(60.8%)
	(50.9%)		(43.9%)		(48.5%)		(43.1%)		(46.0%)		(43.1%)	
Better Quality	47,680	(40.2%)	70,905	(59.8%)	21,186	(38.0%)	34,633	(62.0%)	9,086	(36.4%)	15,854	(63.6%)
	(49.1%)		(56.1%)		(51.5%)		(56.9%)		(54.0%)		(56.9%)	
Profits												
	Any Movers				Job-to-Job Movers				Job-to-Job Movers & Stable Jobs			
	Worse Wage		Better Wage		Worse Wage		Better Wage		Worse Wage		Better Wage	
Worse Quality	50,105	(47.1%)	56,338	(52.9%)	20,760	(42.8%)	27,713	(57.2%)	8,260	(38.8%)	13,040	(61.2%)
	(51.6%)		(44.6%)		(50.4%)		(45.5%)		(49.1%)		(46.8%)	
Better Quality	46,956	(40.1%)	70,034	(59.9%)	20,407	(38.1%)	33,177	(61.9%)	8,578	(36.6%)	14,846	(63.4%)
	(48.4%)		(55.4%)		(49.6%)		(54.5%)		(50.9%)		(53.2%)	

Note: Change in wages is calculated as the difference between the average daily wages in two consecutive spells. Job-to-Job movers are defined as movements between two consecutive spells with less than 1 month of unemployment in between. Stable jobs are defined as spells that last at least one year.

lower wages. If we consider only job-to-job movers with stable jobs,[25] 36 percent of movers going to a better firm end up receiving a wage decrease and 60 percent of movers going to worse firm get a wage increase.

6.3 Amenities

In the tabulations presented in Table 11, there is a surprisingly large number of workers moving to jobs with lower wages. When only considering job-to-job movements, this proportion is significantly lower, but still large. Amenities are the first candidates to explain this pattern. The dataset used in this paper does not contain information on amenities. Nevertheless, as long as the level of amenities is constant within the firm, our measure of sorting is not affected by the presence of workers moving to firms that offer them lower wages but higher compensating differentials. This is because we only use wages to order workers within the firm.

However, amenities might affect the AKM measure of sorting. This is due to the fact that firm quality is inferred from mean wages paid by the firm. To illustrate this point, consider to identical firms with different compensations strategies. One pays higher wages and lower level of amenities and the other one pays lower wages with higher level of amenities. The AKM approach would wrongly conclude that the first firm is better than the last one. Moreover, amenities might not simply mean different compensating strategies: good working conditions may have a positive impact on firm-level productivity (see Daniel and Sofer (1998) for a discussion).

6.4 Endogenous Search Intensity

The model presented in Section 3, as Eeckhout and Kircher (2011) and Lopes de Melo (2011) emphasize the role of the limitations on firms to post new vacancies as the mechanism that generates sorting in the labor market. Alternatively, sorting can be generated by allowing endogenous search intensity in standard equilibrium search models. In this case the firm is totally passive and sorting is a result of differential search intensities rather than matching-set variation. This model

[25] This sample selection aims to reduce noise, but the same pattern are true for different groups of movers (see Table 11). Job-to-Job movements are defined as movements between two consecutive employment spells with less than 1 month of unemployment in between. Stable jobs are defined as employment spells that last at least one year.

is fundamentally asymmetric in that sorting is driven by worker behavior only. This mechanism is proposed in Lentz (2010).

The environment described in Lentz (2010) implies that every worker, independently of her type, prefers to have a job in a better firm. This implication seems dubious in light of the evidence presented in Table 11, where more than 40% of job-to-job movers end up in a worse firm than before, and a large portion of them with a higher wage. Nevertheless, as it has been discussed in section 5, it could be the case that not all of these movements are necessarily job-to-job.[26] Moreover, some of these movements can be driven by non-economic reasons. Therefore, we are concerned about the performance of our test if sorting is generated purely by search intensity.

Sorting by search intensity may also generate biased measures of sorting using the AKM strategy, because wages might be non-monotone in the firm type but also non-monotone in the worker type (Bagger and Lentz, 2011). In this subsection we show that a slightly modified version of our test, one consistent with the environment described in Lentz (2010), also gives significant evidence of positive assortative matching. One of the critical conditions required for consistency of our measure of sorting is partial monotonicity of wages on the worker type. As it is pointed out in Bagger and Lentz (2011), to endogenize search intensity generates wages that are not always increasing in the worker type, even after conditioning on the firm type. In the case of a supermodular production function, search intensity is increasing in the worker type. Bagger and Lentz (2011) show that, if the production function is supermodular, since the present values of future outcomes is more valuable for a high skilled worker than for a low skilled worker, at low-productivity firms the difference in wage growth expectations may result in lower wages for the high skilled worker. This is because the firm extracts part of the rent generated by the higher present value of future offers.

Although in this case wages are not always monotone in the worker type, we can select the sample to have only observations where this condition holds. In the model presented in Lentz (2011), there is on-the-job search and strategic bargaining that generates Bertrand competition between the incumbent firm and a rival "poaching" firm.[27] When one worker meets a potential

[26]We are unable to distinguish between voluntary and involuntary separations in our data. As it has been pointed out in section 5, we define job-to-job changers equivalently to Royalty (1998) and Nagypal (2004), as these unemployment spells with no more than 1 month of unemployment in between.

[27]This wage setting scenario has been proposed in Postel-Vinay and Robin (2002). An extension where the

Table 12: Endogenous Search Intensity

$y = 1(\text{next } \Pi > \text{current } \Pi)$	(1) Similar firms defined in terms of 10 percentiles	(2) Similar firms defined in terms of 5 percentiles	(3) Top firms defined in terms of 10 percentiles	(4) Top firms defined in terms of 5 percentiles
Wage×similar-firm	0.064	0.093	-	-
	(0.024)	(0.033)	-	-
Wage×(1-similar-firm)	0.017	0.018	-	-
	(0.013)	(0.013)	-	-
similar-firm	-.272	-.392	-	-
	(0.135)	(0.186)	-	-
Wage	-	-	0.0510	0.0407
	-	-	(0.0096)	(0.011)
Age	0.007	0.007	-0.0004	0.0014
	(0.003)	(0.003)	(0.0027)	(0.0033)
Age^2	-.0001	-.0001	-9.83e-06	-.0001
	(0.00004)	(0.00004)	(0.00003)	(0.00005)
Female	-.032	-.032	0.0270	0.0231
	(0.009)	(0.009)	(0.0073)	(0.0081)
Foreign	-.024	-.024	-0.0083	0.0359
	(0.011)	(0.011)	(0.0144)	(0.0168)
Tenure	0.0002	0.0002	0.0002	0.0001
	(0.0006)	(0.0006)	(0.002)	(0.0002)
Tenure^2	9.95e-06	1.00e-05	-1.07e-06	-4.14e-07
	(1.00e-05)	(1.00e-05)	(6.03e-07)	(6.94e-07)
Observations	27,956	27,956	8,281	4,080
R^2	0.267	0.267	0.094	0.061

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Firms are ordered in terms of economic profit per worker. Each column represents a single linear probability model with firm dummies. Year and occupation dummies are included in all regressions. Standard errors in parentheses. Column (1) and Column (2) consider workers who switch at least three times. Similar-firm is an indicator that takes the value one if the worker comes from a firm in the same group than the current firm. Column (3) and Column (4) present results only for the right tail of the distribution of firms types.

employer, the current firm and the poaching firm compete for the worker, and the most productive firm wins. In this model, when the poaching firm is identical to the current firm, the worker extract the full rent, and the wage is equal to the match productivity. This last implication can be used to order workers by their types. If the worker's previous firm is close enough to the current firm, wages are almost identical to the match productivity. Therefore, we use wages to order co-workers that come from a similar firm than the current firm in which they are working. We perform the same test as before but only allowing a different effect of wages on the probability of moving to a better firm for co-workers who firstly moved between two similar firms.

Results are presented in Table 12. In Column (1) of Table 12, we define approximately

worker bargaining power is allowed to be different from zero was presented in Flinn and Dey (2005) and Cahuc, Postel-Vinay and Robin (2006) homogeneous groups of employers as firms in the same decile of the distribution of profit per worker (ten groups). In Column (2) of Table 12, homogeneous groups are defined in terms of five percentiles of the distribution of average profit per worker (20 groups). The coefficient of wages, for the workers whose previous employer was a firm similar to the current one, is significantly positive in both specifications. Moreover, the effect is stronger for this group of workers than for workers who have not firstly moved between two similar firms.[28]

Note that this last modification of the test is valid whenever there is between firms Bertrand competition. In a similar model with endogenous search intensity but without strategic bargaining we might also have non-monotone wages. Extending the model presented in Bartolucci (2011), where workers can choose their search intensity in the spirit of Lentz (2010), there might be wages which are non-monotone in the worker type in the case of NAM. As in Lentz (2010), in the presence of NAM there are more incentives for low skilled workers to increase their search intensity. Since wages are increasing in the on-the-job offer arrival rate[29], in some firms, the higher offer-arrival rate of low-type workers can compensate for their lower productivity. Equivalently to the case with Bertrand competition, we can select a subsample of firms where this effect is negligible. Note that, as in the model presented in Lentz (2010), in this case every worker prefers to go to a better firm; therefore, in the best firm of the market any worker continues searching. This means that for firms in the extreme right tail of the distribution of firm types the search intensity effect is negligible, which allows us to use wages to order workers by their type.[30] In this case we perform our test but only including firms in the right tail of the distribution of firm's profit. Results are presented in Table 12. In Column (3) of Table 12, we present results with the sample of firms in the top 10% of the distribution of average profit per worker, and in Column (4) of Table 12, we present results only using a sample of firms in the top 5% of the distribution of average profit per worker. In both sub-samples, wages are posively and significantly correlated

[28]Note that this exercise is very demanding in terms of data, because we select workers who move at least three times. To order workers by their wages in this context, we need to identify those workers who come from a firm similar to the current one. For that purpose, we need to track workers in two consecutive spells. Finally, we require a third spell, to see which worker is moving to a better firm and which worker is moving to a worse firm. This sample trimming significantly reduces the number of valid observations per firm. A maximum likelihood estimation of the conditional probability model with firm dummies may generate biased results due to the presence incidental parameters. Therefore, we only present results for a linear probability model.

[29]See Figure 1 in Bartolucci (2011).

[30]A similar test is proposed in a different context by Bagger and Lentz (2011).

with the probability of moving to a better firm.

6.5 Heterogenity in search frictions

Both sets of results presented in Table 12 confirm the robustness of the evidence for positive assortative matching. These last tests were primarily to show that the result of PAM is robust to sorting generated by endogenous search intensity, where wages are not always monotone in the worker type. Nevertheless, results presented in Table 12 are also informative on the empirical relevance of an alternative mechanism to generate sorting. Mendes, van den Berg and Lindeboom (2010) argue that heterogeneity in search frictions is another potential mechanism driving the observed PAM. Their intuition is that without complementarity in production, PAM may arise because more productive workers might also be more efficient searchers. If this is the case, better workers climb the productivity ladder more quickly. This kind of sorting is similar to the sorting generated by search intensity discussed in Lentz (2010). In such a situation every worker wants to work in the best firm. This is not consistent with some of the evidence presented in Table 11, where an important fraction of job-to-job movements were toward lower-quality firms, and most of those without a wage cut. Moreover, in Table 12, we show that PAM is persistent when considering only the top firms of the market. In that case, not only are workers moving to worse firms, but also the probability of that event is negatively correlated with the worker's type.

If our results of PAM are driven by heterogeneity in search frictions, we should not find an effect of wages on the probability of moving up in the firm productivity ladder, once we control for that source of heterogeneity. To check for this, we re-estimate our measure of PAM, comparing co-workers who are as similar as possible in terms of labor market frictions.

For that purpose, we exploit the full length of the VWH data. Specifically, we focus on the sub-sample of 1995-2001 movers who have been active in the labor market prior to 1995. For these workers we are actually able to reconstruct their labor market history going back to 1975. Hence, we re-run our main test (as in Table 2), including a full set of controls for worker's past labor market histories. These controls are the worker's number of past employment spells, the number of past unemployment spells, the average duration of past employment spells and the average duration of past unemployment spells. To make our case more compelling, we avoid gender differences in search behavior by focusing on men only. The results appear in Table 13. Individuals with a larger number of past employment spells, a lower number of unemployment spells, and a shorter duration in past unemployment are found to be more likely to switch to better employers. However, after controlling for this additional source of heterogeneity, the effect of a worker's wage remains positive and statistically significant. Moreover, the estimated coefficient is not significantly different from the one in comparable specifications of previous tables, suggesting that heterogeneity in search intensity is unlikely to play a major role in driving our PAM result.

As stated in the introduction, the presence of complementarities in production is important for policies that aim to achieve the optimal allocation of resources. In this paper, we do not provide direct evidence of such complementarities, but find strong evidence of positive assortative matching, which is consistent with complementarities. In addition, we do not find evidence in favor of PAM driven by a correlation between the worker types and heterogeneity in search efficiency.

7 Conclusions

In this paper we propose a test to measure the strength and the direction of assortative matching between firms and workers. We analyze the mobility of workers across firms, exploiting the fact that in the absence of assortative matching we should observe that the probability that workers leave one firm to go to another firm of different quality is independent of the worker quality. In the presence of positive (negative) assortative matching we should observe that good workers are more (less) likely to move to better firms than bad workers. The strategy presented in this paper imposes minimum conditions on the data generating process. Also, our measures of sorting are robust to wages non-monotone in the firm type, which is the main criticism to the existing measures.

Our test does not require cardinal measures of the quality of workers and firms. The test only requires a general monotonicity condition: that the payoffs of the agents are monotone in the agents types, conditional on the partner type. If, given the firm type, wages are monotone in the worker type, we can use within-firm variation on wages, which by definition partials out the firm effect, to order workers within the firm by their types. Meanwhile, if profits per worker are

Table 13: Heterogeneity Search Frictions

LOGIT	(1)	(2)	(3)	(4)
	Definition of firm quality ($\Pi_{j,t}$)			
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit per worker
Log wage	0.162	0.15	0.2	0.214
	(0.034)	(0.037)	(0.036)	(0.035)
Age	0.006	0.122	0.125	0.015
	(0.006)	(0.007)	(0.007)	(0.007)
Age^2	-.0001	-.002	-.002	-.0003
	(0.00008)	(0.0001)	(0.0001)	(0.00009)
Migrant	-.107	-.251	-.146	-.158
	(0.03)	(0.033)	(0.033)	(0.032)
Tenure	0.002	-.001	0.0004	0.002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Tenure^2	-5.99e-06	1.65e-06	-4.44e-06	-8.97e-06
	(2.60e-06)	(2.83e-06)	(2.77e-06)	(2.73e-06)
Past tenure /100	0.006	0.018	0.053	0.023
	(0.035)	(0.038)	(0.038)	(0.037)
Past unemployment /100	-0.114	-0.148	-0.180	-0.127
	(0.046)	(0.050)	(0.051)	(0.049)
No. past spells	0.006	0.027	0.041	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
No. un. spells	-.018	-.039	-.050	-.021
	(0.008)	(0.008)	(0.008)	(0.008)
Obs.	103817	101858	99195	100930
pseudoR^2	0.171	0.262	0.254	0.230

The dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single logistic regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses. Past tenure is the average tenure in past employment spells. Past unemployment is average duration in past unemployment spells. No. past spells is the number of past employment spells. No. un. spells is the number of past unemployment spells. Male workers only. Subsample of 1995-2001 movers who where active in the labor market prior to 1995.

monotone in the firm type, we can use firm-level (observed) profits to estimate the firm's expected profits, and hence order firms by type.

We use a matched data set that combines administrative earnings records for individual workers in the Veneto region of Italy with detailed balance sheet information for their employers. Our test for the presence of assortative matching finds strong evidence of positive assortative matching: better workers are found to have a higher probability of moving to better firms. We find similar results if instead of using the within-firm variation on wages, we use logwages or the worker quantiles in the within-firm distribution of wages. Positive assortative matching is also found if firms are indexed by their economic profit, accounting profits or gross operating margin, profit per worker or profit per firm, and current profits or average profits. The evidence of PAM is also robust to the definition of movers; it is true for movers with an interim unemployment spell but also for job-to-job movers. Moreover, our main findings are also confirmed by workers' mobility generated by exogenous firm closures. Our test is also used to compare the strength of sorting in different markets. Sorting is stronger for males than for females, and stronger for workers in the manufacturing sector than for workers in the service sector. We also find that positive assortative matching is stronger for medium age and white collar workers.

Finally, we replicate the AKM strategy in our data, and find the standard result of a significantly negative correlation between firm's and worker's fixed effects from a log-wage equation. There are a number of reasons that can explain the divergence in results between both tests. We observe that a significant number of workers are moving to worse firms with wage gains or to better firms with wage losses. This evidence suggest that wages are non-monotone in the firm type, as described in Eeckhout and Kircher (2011) and Lopes de Melo (2011). There is also a large proportion of workers with job-to-job movements implying wage losses, which suggests that there are non-monetary payoffs for workers. Amenities or compensating differentials can affect the AKM measure but not our test if they are constant within the firm. Heterogeneity in search intensity has also been mentioned as a possible cause of misspecification in the AKM approach. Heterogeneous contact rates might generate wages that are not necessarily monotone in the worker type. We present evidence of PAM using two slightly modified versions of our test that are consistent with worker heterogeneity in job-offer arrival rates. Our results also lend little support to the hypothesis that the observed PAM is driven by a correlation between the worker types and heterogeneity in search efficiency. Although our paper does not provide direct evidence of complementarities in production, the finding of pervasive positive assortative matching does suggest the existence of such complementarities.

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A Appendix

A.1 Additional Proofs

In this subsection we show that the expected payoffs are monotone in the agent's type. We focus the discussion in the case of a firm, but the same is true for the worker. The expected profit of a firm with productivity p is:

$$\Pi(p) = \int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p,\epsilon) - w(p,\epsilon)\right] d\Gamma(\epsilon|p) \tag{3}$$

By the Leibniz integral rule:

$$\frac{\partial \Pi(p)}{\partial p} = \int_{\epsilon_{min}}^{\epsilon_{max}} \partial \frac{\{[f(p,\epsilon) - w(p,\epsilon)]\, \gamma(\epsilon|p)\}}{\partial p} d\epsilon \tag{4}$$

As $\partial \frac{\pi(p,\epsilon)}{\partial p}\Big|_{\epsilon} > 0$, it is straightforward to show that (4) is higher than zero rewriting (4) as

$$\frac{\partial \Pi(p)}{\partial p} = \int_{\epsilon_{min}}^{\epsilon_{max}} \partial \frac{[\pi(p,\epsilon)]}{\partial p} \gamma(\epsilon|p) d\epsilon + \int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p,\epsilon)] \partial \frac{\gamma(\epsilon|p)}{\partial p} d\epsilon \tag{5}$$

The first term on the right hand side of (5) is positive (see Section 3). This means that for every worker ϵ working in a firm p (*ie:* $\gamma(\epsilon|p) \neq 0$), the derivative of the profit function with respect to p is positive.

The second term in the right hand side of (5) can be shown to be also positive. Compare two firms, p and p^+, where $p < p^+$. The output that a worker ϵ produces in firm p^+ is higher than the output than the same worker produces in p. We know that if a worker of type ϵ was feasible for p, meaning that he produces enough to generate a positive surplus (therefore, $\Gamma(\epsilon|p) \neq 0$), the same worker is going to be attainable for p^+, in the sense that if the firm p^+ offers the same wage to the worker, the firm p^+ is obtaining more than the firm p, and the worker is as happy as it is with p. It may be the case that for the firm p^+, it is not profitable to have that worker, due to its different value of a vacancy, but if the firm p^+ does not hire the worker it is in its own interest. On the other hand, if a worker was working in p^+, it is not necessarily true that he is attainable for p, because as $f(p,\epsilon) < f(p^+,\epsilon)$, we cannot guarantee that p is able to pay $w(p^+,\epsilon)$.

Therefore there might be some workers which are happy to work in p^+, but not in p. Formally, as $f(p^+, \epsilon) - w(p^+, \epsilon) > 0$ for every ϵ with $\Gamma(\epsilon|p^+) > 0$:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+, \epsilon) - w(p^+, \epsilon)\right] d\Gamma(\epsilon|p^+) > \int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+, \epsilon) - w(p^+, \epsilon)\right] d\Gamma(\epsilon|p) \tag{6}$$

Which is the same as:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} \left[\pi(p^+, \epsilon)\right] \gamma(\epsilon|p^+) d\epsilon > \int_{\epsilon_{min}}^{\epsilon_{max}} \left[\pi(p^+, \epsilon)\right] \gamma(\epsilon|p) d\epsilon \tag{7}$$

When p^+ converges to p:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p^+, \epsilon)] \partial \frac{\gamma(\epsilon|p)}{\partial p} d\epsilon > 0 \tag{8}$$

A.2 Additional Tables

Table A1: Without Covariates

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.082	0.188	0.276	0.36	0.104	0.257
	(0.021)	(0.021)	(0.023)	(0.022)	(0.022)	(0.022)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	177,740	178,144	175,040	171,782	175,695	174,517

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Standard errors in parentheses.

Table A2: Only Male workers

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1) Profit	(2) Profit per worker	(3) Average Profit	(4) Average Profit per worker	(5) Past Av. Profit	(7) Past Av. Profit per worker
	Definition of firm Profit					
Log-wage	0.059	0.156	0.152	0.208	0.127	0.205
	(0.03)	(0.03)	(0.032)	(0.032)	(0.031)	(0.031)
Age	-.029	0.006	0.157	0.167	-.043	0.015
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Age^2	0.0003	-.0002	-.002	-.002	0.0005	-.0003
	(0.00007)	(0.00007)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Foreign	-.090	-.069	-.243	-.153	-.094	-.096
	(0.025)	(0.025)	(0.026)	(0.027)	(0.026)	(0.026)
Tenure	0.001	0.002	-.001	-.00008	0.0009	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-1.43e-06	-5.12e-06	6.08e-07	-3.57e-06	-1.33e-06	-7.05e-06
	(1.71e-06)	(1.67e-06)	(1.85e-06)	(1.76e-06)	(1.77e-06)	(1.73e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	130,668	130,671	128,442	125,550	128,892	127,523

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A3: White-Collar Workers

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1) Profit	(2) Profit per worker	(3) Average Profit	(4) Average Profit per worker	(5) Past Av. Profit	(7) Past Av. Profit per worker
	Definition of firm Profit					
Log-wage	0.193	0.183	0.5	0.361	0.267	0.303
	(0.046)	(0.045)	(0.051)	(0.049)	(0.048)	(0.048)
Age	-.019	0.009	0.058	0.069	-.027	0.011
	(0.012)	(0.012)	(0.014)	(0.013)	(0.013)	(0.013)
Age^2	0.00006	-.0003	-.001	-.001	0.0001	-.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Female	-.069	-.018	-.046	-.049	0.004	-.021
	(0.03)	(0.03)	(0.033)	(0.033)	(0.031)	(0.031)
Foreign	0.186	0.101	0.167	0.016	0.246	0.132
	(0.087)	(0.086)	(0.096)	(0.096)	(0.09)	(0.09)
Tenure	-.002	-.0004	-.004	-.002	-.002	0.0007
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
Tenure^2	5.03e-06	-1.61e-07	6.17e-06	-2.53e-07	2.46e-06	-6.15e-06
	(3.01e-06)	(2.88e-06)	(3.35e-06)	(3.08e-06)	(3.14e-06)	(2.98e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	39,560	39,657	37,544	37,128	38,091	38,202

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A4: Blue Collar Workers

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	-.038	0.131	0.022	0.253	-.020	0.154
	(0.036)	(0.036)	(0.04)	(0.039)	(0.037)	(0.037)
Age	-.028	-.003	0.141	0.139	-.040	0.001
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Age^2	0.0003	-1.00e-05	-.002	-.002	0.0005	-.0001
	(0.00007)	(0.00007)	(0.00008)	(0.00008)	(0.00007)	(0.00007)
Female	0.078	-.101	-.097	-.296	0.068	-.175
	(0.02)	(0.02)	(0.023)	(0.022)	(0.021)	(0.021)
Foreign	-.087	-.067	-.255	-.152	-.089	-.090
	(0.024)	(0.023)	(0.025)	(0.025)	(0.024)	(0.025)
Tenure	0.002	0.003	-.0002	0.0004	0.002	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-3.70e-06	-7.59e-06	-1.89e-06	-3.82e-06	-2.57e-06	-6.53e-06
	(1.76e-06)	(1.72e-06)	(1.91e-06)	(1.81e-06)	(1.81e-06)	(1.76e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	130,847	130,848	127,711	126,370	128,736	127,813

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A5: Young Workers (20-35 Years Old)

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.073	0.149	0.209	0.223	0.13	0.178
	(0.043)	(0.042)	(0.047)	(0.046)	(0.044)	(0.045)
Age	-.015	-.003	0.058	0.063	-.025	0.0006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.021	-.058	0.001	-.117	0.026	-.099
	(0.021)	(0.021)	(0.024)	(0.023)	(0.022)	(0.022)
Foreign	-.113	-.052	-.222	-.169	-.127	-.083
	(0.035)	(0.034)	(0.037)	(0.037)	(0.036)	(0.036)
Tenure	0.0003	0.003	-.002	0.002	-.0001	0.004
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Tenure^2	3.39e-06	-.00002	-6.43e-06	-.00004	4.54e-06	-.00003
	(7.63e-06)	(7.54e-06)	(8.10e-06)	(8.00e-06)	(7.84e-06)	(7.80e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	93,654	93,451	91,627	89,430	92,411	90,993

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A6: Mid-Career Workers (35-50 Years Old)

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.156	0.176	0.351	0.341	0.189	0.228
	(0.043)	(0.042)	(0.047)	(0.046)	(0.044)	(0.044)
Age	-.009	-.008	-.017	-.014	-.008	-.011
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.052	-.107	-.193	-.347	0.081	-.165
	(0.03)	(0.029)	(0.033)	(0.033)	(0.031)	(0.031)
Foreign	-.096	-.089	-.231	-.148	-.069	-.106
	(0.034)	(0.033)	(0.037)	(0.036)	(0.035)	(0.035)
Tenure	0.002	0.002	-.0006	0.0004	0.002	0.003
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Tenure^2	-5.99e-06	-6.57e-06	-3.19e-06	-4.79e-06	-6.98e-06	-9.82e-06
	(2.34e-06)	(2.31e-06)	(2.54e-06)	(2.42e-06)	(2.43e-06)	(2.36e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	59,189	59,322	56,016	56,157	57,290	56,600

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A7: Older Workers (50-65 Years Old)

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.059	0.155	0.094	0.386	-.034	0.18
	(0.108)	(0.106)	(0.128)	(0.119)	(0.116)	(0.113)
Age	-.005	-.014	-.054	-.050	-.005	-.011
	(0.006)	(0.006)	(0.009)	(0.008)	(0.007)	(0.007)
Female	0.141	0.054	-.304	-.330	0.08	-.107
	(0.078)	(0.077)	(0.106)	(0.1)	(0.091)	(0.088)
Foreign	0.139	0.0004	-.328	-.156	0.05	-.108
	(0.125)	(0.126)	(0.146)	(0.145)	(0.134)	(0.137)
Tenure	0.002	0.002	-.004	-.002	-.0007	-.0003
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Tenure^2	-2.00e-06	-6.14e-06	1.00e-05	3.36e-06	6.43e-06	4.10e-06
	(4.71e-06)	(4.61e-06)	(5.46e-06)	(4.99e-06)	(4.92e-06)	(4.69e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	9,895	10,111	7,906	8,962	8,874	9,047

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A8: Manufacturing

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.092	0.129	0.224	0.205	0.147	0.176
	(0.033)	(0.032)	(0.036)	(0.035)	(0.034)	(0.034)
Age	-.029	-.006	0.15	0.145	-.045	0.002
	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)
Age^2	0.0003	0.00003	-.002	-.002	0.0005	-.0001
	(0.00008)	(0.00008)	(0.0001)	(0.00009)	(0.00008)	(0.00008)
Female	0.052	-.070	-.056	-.231	0.06	-.133
	(0.02)	(0.019)	(0.023)	(0.022)	(0.021)	(0.021)
Foreign	-.114	-.084	-.257	-.164	-.124	-.074
	(0.027)	(0.026)	(0.029)	(0.028)	(0.028)	(0.027)
Tenure	0.001	0.002	-.001	0.0005	0.0005	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-1.70e-06	-7.84e-06	-4.21e-07	-5.69e-06	-5.55e-07	-7.49e-06
	(1.72e-06)	(1.66e-06)	(1.88e-06)	(1.74e-06)	(1.78e-06)	(1.69e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	115,331	115,782	114,265	112,102	114,511	113,697

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A9: Services

LOGIT $y = 1(\text{next } \Pi > \text{current } \Pi)$	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Log-wage	0.047	0.105	0.201	0.295	0.053	0.157
	(0.043)	(0.043)	(0.047)	(0.047)	(0.045)	(0.046)
Age	-.013	0.013	0.104	0.109	-.018	0.008
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Age^2	0.0001	-.0003	-.002	-.002	0.0001	-.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.017	-.039	-.128	-.153	0.025	-.075
	(0.026)	(0.026)	(0.029)	(0.029)	(0.027)	(0.028)
Foreign	0.002	0.017	-.107	-.059	0.035	-.075
	(0.039)	(0.04)	(0.041)	(0.043)	(0.041)	(0.042)
Tenure	0.001	0.001	-.003	-.002	0.001	0.002
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Tenure^2	2.24e-07	-6.00e-07	6.56e-06	4.16e-06	-9.44e-07	-6.73e-06
	(2.71e-06)	(2.73e-06)	(2.96e-06)	(2.95e-06)	(2.79e-06)	(2.87e-06)
firm effects	yes	yes	yes	yes	yes	yes
Obs.	62,174	62,038	60,578	59,471	60,974	60,563

Dependent variable is a dummy that takes the value one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - materials_{j,t} - L'_{j,t}w_{j,t} - K'_{j,t}r_t$. Each column represents a single regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

Table A10: Correlations between Different Measures of Profits

profits	1.00																	
profits/W	0.55	1.00																
Av. profits	0.62	0.35	1.00															
Av. Profits/W	0.32	0.52	0.54	1.00														
Av. Past Porfits	0.78	0.45	0.69	0.33	1.00													
APP/w	0.45	0.70	0.37	0.66	0.52	1.00												
GOS	0.82	0.51	0.56	0.30	0.68	0.41	1.00											
GOS/w	0.49	0.79	0.31	0.46	0.39	0.61	0.58	1.00										
Av.GOS	0.58	0.34	0.87	0.53	0.62	0.36	0.59	0.35	1.00									
Av. GOS/w	0.28	0.48	0.49	0.83	0.29	0.56	0.32	0.50	0.55	1.00								
Av. past GOS	0.72	0.43	0.63	0.32	0.84	0.49	0.75	0.46	0.68	0.34	1.00							
APGOS/w	0.40	0.63	0.33	0.57	0.45	0.79	0.45	0.69	0.38	0.65	0.53	1.00						
Accounting P.	0.55	0.44	0.43	0.30	0.47	0.36	0.57	0.44	0.43	0.30	0.49	0.37	1.00					
AP/W	0.40	0.54	0.31	0.37	0.34	0.44	0.43	0.56	0.32	0.37	0.36	0.45	0.76	1.00				
AV. AP.	0.43	0.33	0.66	0.51	0.45	0.34	0.43	0.32	0.68	0.51	0.46	0.34	0.53	0.43	1.00			
AV. AP/w	0.29	0.38	0.49	0.63	0.29	0.42	0.29	0.37	0.51	0.65	0.31	0.43	0.42	0.48	0.73	1.00		
AV. past AP.	0.53	0.38	0.50	0.33	0.58	0.42	0.52	0.38	0.50	0.33	0.60	0.43	0.69	0.56	0.66	0.49	1.00	
APAP/w	0.37	0.46	0.35	0.44	0.40	0.55	0.37	0.46	0.37	0.45	0.43	0.57	0.55	0.66	0.51	0.64	0.72	1.00