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

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Abstract

We propose a test that uses information on workers' mobility, wages and firms' profits to identify the sign and strength of assortative matching. The basic intuition underlying our empirical strategy is that, in the presence of positive (negative) assortative matching, good workers are more (less) likely to move to better firms than bad workers. Assuming that agents' payoffs are increasing in their own types allows us to use within-firm variation on wages to rank workers by their types and firm profits to rank firms. We 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. This result is in contrast with what we find from correlating the worker and firm fixed effects in standard Mincerian wage equations.

KEYWORDS: Assortative matching, workers' mobility, matched employer-employee data.
JEL CLASSIFICATION CODES: J6, J31, L2.

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1 Introduction

Are better workers matched to better firms? In some job markets, like academia, there is anecdotal evidence of positive assortative matching, with better researchers being more likely to be hired by better departments. However, whether positive assortative matching is a pervasive phenomenon in the labor market is a question that remains elusive. This is because a direct test of assortative matching requires knowledge of the underlying types of the firm and the worker, and this is notoriously difficult to obtain. In this paper, we propose a novel test of the sign and strength of assortative matching that tackles this identification challenge by combining information on workers' mobility, wages and firms'profits.

Uncovering the actual patterns of assortative matching is key for a better understanding of the functioning of the labor market. In particular, the sign and strength of assortative matching contain policy-relevant information about the sign and size of complementarities in production between workers and firms. For instance, a subsidy to education would (not) be justified in case of positive (negative) complementarity in the production function. This is because an increase in the worker's productivity has a positive (negative) externality on the firm's marginal productivity. Moreover, knowing the direction of sorting is important to shed light on the transmission of shocks. For example, macro shocks such as recessions and trade liberalization push low-productivity firms out of the market (e.g. Caballero, 1994 and Melitz, 2003). Under positive assortative matching, low skill workers are disproportionately affected by these displacements and, to the extent that this group is more credit constrained (e.g. Sullivan, 2008), the welfare effect of their displacements is larger. Furthermore, whether sorting is positive or negative is helpful for testing different economic models that exhibit distinct matching patterns in equilibrium.[1]

Ideally, to measure assortative matching one would need to observe worker and firm types. Although the worker and firm types are straightforward to define theoretically, it is hard to agree on their empirical counterparts. Types refer to productivity, or more broadly to the value of productivity. Given the worker type, better firms should produce more; 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 difficult to measure. The

[1]For example, there are models predicting positive assortative matching (PAM) as in Shimer (2005) or Lise et al. (2008), negative assortative matching (NAM) as in Woodcock (2010), or random allocation of workers to firms as in Postel-Vinay and Robin (2002).

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 Rubinstein 2001). The firm productivity is in general an unknown function that conflates a number of features related to technology, demand and market structure (Syverson, 2011).[2]

Following the seminal contribution of Abowd, Kramarz and Margolis (1999) - henceforth, AKM - recent papers have presented the correlation between the worker fixed effect and the firm fixed effect estimated from wage equations as an attempt to measure the direction and strength of sorting. The common finding is that this correlation is insignificant or even negative, implying that positive assortative matching plays little role in the labor market. However, Eeckhout and Kircher (2011) and Lopes de Melo (2008) have shown that these results may be misleading, as the worker and firm fixed effects estimated from wage equations do not necessarily reflect the agents' underlying types.[3] Furthermore, Eeckhout and Kircher (2011) show that it is virtually impossible to identify the sign of sorting using wage data alone.

In this paper, we show how to use information on workers' mobility, wages and firms' profits to learn about the sign and strength of assortative matching. The basic intuition underlying our empirical strategy is that, in the absence of assortative matching, the probability that a worker leaves a firm to go to another one 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. Our test does not require cardinal measures of the agent's types. In order to detect the sign and strength of sorting, this test only requires local rankings of workers and firms according to their types. If agents' payoffs are increasing in their own types, we can exploit within-firm variation in wages to order co-workers according to their types. Although there is a firm component in wages, this firm effect is held constant by exploiting variation in wages of co-workers. If match profits are increasing 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 of

[2]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).

[3]In models where firms are constrained in their capacity to generate new vacancies, wages are not always monotone in the firm type.

each match, this effect is integrated out when we consider firm-level profits. The latter can be observed and used to rank firms according to their types.

To provide a natural starting point for thinking about sorting of worker and firms, we sketch below a simple search model with two-sided heterogeneity and job scarcity - i.e., we introduce some limitation on firms to post new vacancies. Our model is a slightly modified version of the one presented in Shimer and Smith (2000), to make it consistent with multi-worker firms. This simple model represents an appropriate laboratory to describe how our test of sorting works in practice. The model generates mismatches between workers and firms, movements of workers across firms of different types, and payoffs that are increasing in the agent's type, but not necessarily monotone in the partner type. These are the basic ingredients that our test needs for identification. Our test however is not specific to this model, but it is consistent if this model is the data generating process.

Our strategy imposes minimum conditions on the data generating process and is fully compatible with most of the popular classes of mechanisms that generate sorting. 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), and search effort and search cost (Lentz, 2010). The approach presented in this paper is agnostic with regards to the labor market model that generates the data. In particular, we take no stance on the possible mechanisms that drive sorting. Our test only requires that agents' payoffs are monotone in their own types, which is a condition consistent with most of the popular classes of labor market models in the literature.

To implement our test, we exploit a unique panel data set that combines Social Security earnings records and labor market histories 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. Hence, it allows us to observe the within-firm wage distribution that we use to rank workers by their types. Moreover, the richness of the balance sheet data allows us to compute various proxies of a firm's profits, which we use to rank firms by their types. Finally, the dataset contains information on firm closures, which we use to control for the potential endogeneity of workers' mobility.

Our empirical results show that positive assortative matching is a pervasive feature of the labor market: better workers are found to have higher probability to move to better firms. This result is robust to various model specifications, variable definitions and different sub-samples. In particular, we find similar results if, instead of using the within-firm variation on wages, we use log-wages or the within-firm wage quantiles. 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. Our results are also robust to the definition of movers: positive assortative matching is found for movers with an interim unemployment spell but also for job-to-job movers. The results also hold 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, for workers in the manufacturing sector than for the service sector, for medium-age than for younger or more mature workers, and for white-collar than blue-collar workers.

Using the same data set, we also perform the test proposed by Abowd, Kramarz and Margolis (1999). As commonly reported in this literature, 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 correlation or our measure of sorting. First, we provide evidence suggesting that wages are not always monotone in the firm type and, therefore, firm fixed effects in AKM wage regressions do not necessarily reflect a firm's underlying type. Our results are instead robust to wage non-monotonicity in the firm type, as we use firm profits - not firm average wages - to rank firms by their type. Second, we find evidence suggesting that amenities play an important role in explaining differences in the compensating packages across jobs. Whenever the level of amenities is constant within the firm, our measure of sorting is not affected by the existence 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, between-firm differences in amenities may bias the AKM test of sorting. Third, as argued by Bagger and Lentz (2011), the AKM test may also be biased when sorting is generated by models with endogenous search effort. We then present results using slightly modified versions of our basic test, which are consistent with models with heterogeneous search intensity. These additional results also suggest the existence of 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 the conditions for the existence of assortative matching between heterogeneous agents, and whether this is positive or negative. The seminal paper of Becker (1973) studies a frictionless economy and establishes that positive assortative matching (PAM) arises if the production function is supermodular.[4] 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. As frictions add noise to the matching process, stronger complementarities than those incorporated in a supermodular production are now required to guarantee PAM. 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 worker types and firm types. The most influential one is AKM (1999), which makes inferences on the direction and strength of assortative matching through the correlation between the worker and firm fixed effects estimated from standard Mincer-type wage equations. However, 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 (2004) find that, although the bias can be considerable, it is not sufficiently large to remove the negative correlation in datasets from Germany, France and the United States. Second, as pointed out by 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, which in turn imply that firm average wages do not necessarily reflect the firm's underlying type. The wage could be non-monotone in the firm type for a number of reasons, such as limita-

[4] If $f(p, \epsilon)$ is the output of the match between worker ϵ and firm p and f is smooth, then supermodularity is equivalent to $f_{xy} > 0$.

tions 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)).[5]

Given AKM's shortcomings, there have been a number of responses in the literature. Eeckhout and Kircher (2011) 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 derive the strength of sorting from information on individual wage-gaps, one needs to also make assumptions about these features of the model. 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 fact, they argue that, using wage data alone, it is virtually impossible to identify whether assortative matching between worker and firm types is positive or negative.

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/her coworkers. The 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 job scarcity, the proposed measure works better than the AKM correlation. 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. Our approach complements the strategies presented in Eeckhout and Kircher (2011) and Lopes de Melo (2011): 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

[5]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.

can be obtained through production function panel data estimation. After conditioning on the observed characteristics of the firm's workforce, 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), who estimate the sign and degree of sorting from the correlation between the estimated firm fixed effect and the (observed) skill level of the firm's workforce. They find evidence of positive assortative matching using Portuguese longitudinal data. Although this strategy is appealing, it has two main limitations. First, the estimation of production functions using within-firm variation to partial out the firm fixed effect is not generally trouble-free.[6] 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 for workers' unobserved fixed heterogeneity.[7]

3 The Model

In this section, we sketch a simple matching model with search frictions to illustrate how movements of workers between firms can be used to uncover the sign and the strength of assortative matching. The model is a slightly modified version of the matching model presented in Shimer and Smith (2000), to make it consistent with multi-worker firms. Let us consider a continuous time, infinite horizon, stationary economy, populated by infinitely lived firms and workers. Agents are risk neutral and discount future income at the rate $\rho > 0$. Firms are characterized by their productivity p, distributed according to the probability density function $\psi(p)$. Each firm has N jobs, but not every job is necessarily matched to a worker. Worker types are denoted by ϵ distributed according to the probability density function $\gamma(\epsilon)$ and support $[\epsilon_{\min}, \epsilon_{\max}]$.

Matches 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. When two unmatched agents meet, they immediately observe each other's type. They match only if they are both unmatched and they

[6] 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). 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 of output with respect to the firm and worker types.

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

both agree.[8]

The output of the match (p, ϵ) is $f(p, \epsilon)$. We assume that the output of a firm p is the sum of the output of its matched jobs and that a worker contacts a job, rather than a firm. Therefore, the output of the match (p, ϵ) and the outside options depend only on the types of the firm p and the worker ϵ. A worker ϵ employed by a firm p receives wage $w(p, \epsilon)$ and the firm receives $\pi(p, \epsilon)$. Since payoffs exhaust match output, $f(p, \epsilon) = w(p, \epsilon) + \pi(p, \epsilon)$. Unemployed workers and vacancies produce nothing when unmatched.

The behavior of the agents is described by their acceptance sets, which specify with whom they are willing to match. Let $M_w(\epsilon)$ be the set of firms with whom the worker ϵ is willing to match and $M_f(p)$ be the set of workers with whom the firm p is willing to match. Since we assume transferable utility, a firm p is in the acceptance set of worker ϵ if and only if worker ϵ is in the acceptance set of firm p.

One important difference from standard matching models is that we do not impose a free entry condition of firms. As in Shimer and Smith (2000), we assume that there are fixed stocks of heterogeneous agents in both sides of the market. When firms are scarce, the value of the vacancy depends on the type of the firm. In this case, not every firm is willing to match with the same workers and not every worker is willing to match with the same firms, which makes the model a convenient framework to analyze sorting.

The value of the unemployment for a worker of type ϵ, $U(\epsilon)$, solves the following Bellman equation:

$$\rho U(\epsilon) = \lambda \int_{M_w(\epsilon)} \left[W(p', \epsilon) - U(\epsilon) \right] v(p') dp', \tag{1}$$

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

$$\rho W(p, \epsilon) = w(p, \epsilon) - \delta \left[W(p, \epsilon) - U(\epsilon) \right]. \tag{2}$$

The value of a vacancy for a firm with productivity p, $V(p)$, solves the following Bellman equation:

$$\rho V(p) = \lambda \int_{M_f(p)} \left[J(p, \epsilon') - V(p) \right] u(\epsilon') d\epsilon', \tag{3}$$

[8] There is no on-the-job searching; hence the model features movements of workers between firms with an interim unemployment spell.

where $u(\epsilon)$ is the density of unemployed workers, 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:

$$\rho J(p,\epsilon) = \pi(p,\epsilon) - \delta \left[J(p,\epsilon) - V(p) \right]. \tag{4}$$

We assume that payoffs are determined by splitting the surplus of the match by the Generalized Nash Bargaining Solution.[9] Let $S(p,\epsilon)$ be the surplus of the match between a firm p and a worker ϵ. $S(p,\epsilon)$ is given by $W(p,\epsilon) - U(\epsilon) + J(p,\epsilon) - V(p)$. Let β be the bargaining power of the worker, then the standard solution implies that the worker takes a fraction β of the surplus and the firm takes the rest. Therefore:

$$S(p,\epsilon) = \frac{W(p,\epsilon) - U(\epsilon)}{\beta} = \frac{J(p,\epsilon) - V(p)}{1-\beta}. \tag{5}$$

Since we present the model only to illustrate how our test works, for simplicity we assume symmetry between firms and workers. This implies that $\psi(p) = N\gamma(\epsilon)$ and that workers and firms have the same bargaining power. Under these additional assumptions the model is equivalent to the one in Shimer and Smith (2000) and their proof of the existence of an equilibrium holds.

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 necessary for assortative matching; hence acceptance sets can be characterized by their bounds. Therefore, there exist bounds $p_{min}(\epsilon)$ and $p_{max}(\epsilon)$ such that $p \in M_w(\epsilon)$ if and only if $p_{min}(\epsilon) \leq p \leq p_{max}(\epsilon)$.

3.1 Identification of Sorting

This model provides a convenient framework for describing our test. Although types are in general unobserved by the econometrician, payoffs of agents can potentially be used to rank firms and workers by their types, as long as payoffs are monotone on the agents' own types.

Proposition 1 *Payoffs are increasing in the agents own types.*

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

Proof: consider two firms, p^- and p^+ matched to a worker of type ϵ. p^+ produces more, but not necessarily $S(p^+,\epsilon) > S(p^-,\epsilon)$ because $V(p^+) > V(p^-)$.[10]

- If $S(p^+,\epsilon) > S(p^-,\epsilon)$, using (5) we have: $J(p^+,\epsilon) - V(p^+) > J(p^-,\epsilon) - V(p^-)$. Since $V(p^+) > V(p^-)$, then $J(p^+,\epsilon) > J(p^-,\epsilon)$. Given that the value of the match is higher for p^+, using (3) and (4) we know that $\pi(p^+,\epsilon) - \delta(1-\beta)S(p^+,\epsilon) > \pi(p^-,\epsilon) - \delta(1-\beta)S(p^-,\epsilon) > \pi(p^-,\epsilon) - \delta(1-\beta)S(p^+,\epsilon)$, therefore $\pi(p^+,\epsilon) > \pi(p^-,\epsilon)$.

- If $S(p^+,\epsilon) \leq S(p^-,\epsilon)$, using (5), we have that $W(p^+,\epsilon) \leq W(p^+,\epsilon)$. Therefore, from (2), $w(p^+,\epsilon) + \delta U(\epsilon) < w(p,\epsilon^-) + \delta U(\epsilon)$, and then $w(p^+,\epsilon) < w(p^-,\epsilon)$.[11] Since $f(p^+,\epsilon) - \pi(p^+,\epsilon) = w(p^+,\epsilon) < w(p^-,\epsilon) = f(p^-,\epsilon) - \pi(p^-,\epsilon)$ and $f(p^+,\epsilon) > f(p^-,\epsilon)$, then $\pi(p^+,\epsilon) > \pi(p^-,\epsilon)$. ■

The same result can be easily established for the worker's wages. Note that 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, which is not deterministic due to frictions in the matching process. For example, there can be a bad worker receiving a higher wage than a good worker simply because the latter ended up match with a firm less appropriate for his type.

Nevertheless, given that payoffs are increasing in the agent type, the better the type, the higher the mean of the payoffs. Let $\Pi(p) = \int_{M_f(p)} \pi(p,\epsilon')u(\epsilon')d\epsilon'$ be the mean-payoff of firm p. This represents the mean of the match profits for all workers that could potentially be matched to firm p. Although there is worker component in the payoff of each match, in expected terms a better firm must do better than a worse firm. The intuition of this result is straightforward. A firm p^+ could imitate the strategy (in terms of acceptance set and payoffs paid) of a firm p^-. p^+ produces more with every ϵ and could pay the same, therefore p^+ would receive more than the p^- (with each partner of that acceptance set).[12] The

[10] Plugging (5) in (1) and rearranging, we can write $V(p) = \frac{\lambda(1-\beta)}{\rho} \int_{M_f(p)} \left[\frac{f(p,\epsilon)}{\rho+\delta} - \frac{\rho}{\rho+\delta}(V(p) + U(\epsilon)) \right] u(\epsilon')d\epsilon'$. Therefore, if $f(p,\epsilon)$ is differentiable, using the Leibniz integral rule and noting that the surplus is zero at the bounds of the integral:

$$\frac{\partial V(p)}{\partial p} = \frac{\frac{\lambda(1-\beta)}{\rho} \int_{M_f(p)} \frac{\partial f(p,\epsilon)}{\partial p} u(\epsilon')d\epsilon'}{\rho + \delta + \lambda(1-\beta) \int_{M_f(p)} u(\epsilon')d\epsilon'} > 0$$

[11] In this case, wages are decreasing in the firm type. This is the basic criticism of AKM presented in Eeckhout and Kircher (2011) and in Lopes de Melo (2011).

[12] In the Appendix, we include a proof of monotonicity of the mean of payoffs that is not specific to this model.

same is true for the mean-wage of the worker. Therefore, mean-payoffs could be used to rank firms and workers.

Mean-payoffs are unobserved, but they can be estimated by their sample counterparts. In many datasets, firm's profits are observed. These firm-level profits are the sum of the profits per match, for every matched worker in the firm. As long as there is a large number of workers per firm, a precise estimate of the mean-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 200 workers, see Table 1). On the other hand, workers are normally matched with one firm per spell and the longitudinal dimension does not help much (in our sample workers are, on average, with 1.3 employers along the 7-year duration of our panel). Therefore, the average wage for a worker estimated in a sample over all her job spells is not a good measure of her mean-wage. Moreover, the difference between the average-wage and the mean-wage is a function of the type of the firms that hired the worker. Therefore, the measurement error in the estimate of the mean-wage is correlated with the firm type, and then a correlation between the average wage of the worker 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 to test 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 $p^- \in M_w(\epsilon+)$. An implication of this definition is that there is PAM when the bounds of the acceptance set are increasing in type and there is negative assortative matching (NAM) when the bounds are decreasing in type.

Proposition 2 *Consider two workers ϵ^+ and ϵ^-, with $\epsilon^+ > \epsilon^-$, who where working in a firm p and are now hired by new firms. If ϵ^+ has higher (lower) probability than ϵ^- of being hired by a firm better than p, there is positive (negative) assortative matching.*

Proof: The probability of being hired by a firm better than p, conditional on being hired by some firm is:

$$\frac{\lambda \int_{p}^{p_{max}(\epsilon)} v(p')dp'}{\lambda \int_{p_{min}(\epsilon)}^{p_{max}(\epsilon)} v(p')dp'} = \frac{\int_{p}^{p_{max}(\epsilon)} v(p')dp'}{\int_{p}^{p_{max}(\epsilon)} v(p')dp' + \int_{p_{min}(\epsilon)}^{p} v(p')dp'} = \frac{1}{1 + \frac{\int_{p_{min}(\epsilon)}^{p} v(p')dp'}{\int_{p}^{p_{max}(\epsilon)} v(p')dp'}}$$

If ϵ^{+} has higher probability of moving to a better firm than ϵ^{-}:

$$\frac{\int_{p_{min}(\epsilon^{+})}^{p} v(p')dp'}{\int_{p}^{p_{max}(\epsilon^{+})} v(p')dp'} < \frac{\int_{p_{min}(\epsilon^{-})}^{p} v(p')dp'}{\int_{p}^{p_{max}(\epsilon^{-})} v(p')dp'} \tag{6}$$

Since the upper and the lower bound move in the same direction,[13] condition (6) implies that $p_{min}(\epsilon^{+}) > p_{min}(\epsilon^{-})$ and $p_{max}(\epsilon^{+}) > p_{max}(\epsilon^{-})$ and therefore there is PAM.

If ϵ^{-} has higher probability of moving to a better firm than ϵ^{+}:

$$\frac{\int_{p_{min}(\epsilon^{+})}^{p} v(p')dp'}{\int_{p}^{p_{max}(\epsilon^{+})} v(p')dp'} > \frac{\int_{p_{min}(\epsilon^{-})}^{p} v(p')dp'}{\int_{p}^{p_{max}(\epsilon^{-})} v(p')dp'}$$

what implies that $p_{min}(\epsilon^{+}) < p_{min}(\epsilon^{-})$ and $p_{max}(\epsilon^{+}) < p_{max}(\epsilon^{-})$ and therefore there is NAM. ■

Therefore, to identify whether there is PAM or NAM, we compare the probabilities of going up the firm productivity ladder for two workers ϵ^{+} and ϵ^{-}, with $\epsilon^{+} > \epsilon^{-}$, who both move out of a firm of type p due to a match destruction:

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

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. However, 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

[13] This is because $p_{max}(\epsilon) = \epsilon_{min}^{-1}(p)$, therefore $\frac{\partial p_{max}(\epsilon)}{\partial \epsilon} = \left[\frac{\partial \epsilon_{min}(p)}{\partial \epsilon}\right]^{-1}$. Given symmetry of the acceptance set, $p_{min}(\epsilon) = \epsilon_{min}(p)$ and therefore $\frac{\partial p_{max}(\epsilon)}{\partial \epsilon} = \left[\frac{\partial p_{min}(\epsilon)}{\partial \epsilon}\right]^{-1}$.

wages:

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

With some structure in the conditional probability model:

$$\Pr(\text{move UP} \mid p, \epsilon, move) = w(\epsilon, p)'\gamma + \psi(p) \tag{7}$$

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.[14]

We make inference about the existence and the sign of assortative matching by 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 of assortative matching.

Note that our test is not specific to the simple search model presented above. Although we have shown how the test works with a particular definition of assortative matching, mobility can be used to detect the strength and the direction of sorting in a more general setting. Without specifying a particular model, let us define the density of firms conditional on the worker type $\psi(p|\epsilon)$ with cumulative $\Psi(p|\epsilon)$.[15] In Lentz (2010) assortative matching is defined in terms of stochastic dominance. According to Lentz's definition, there is PAM if $\Psi(p|\epsilon^+) < \Psi(p|\epsilon^-)$, whenever $\epsilon^+ > \epsilon^-$ (and NAM otherwise). This is a broad definition of PAM which encompasses the definition of PAM presented in Shimer and Smith (2000). Notice that, for an unmatched worker ϵ, the probability of being hired by a better firm than p conditional on a hiring is $1 - \Psi(p|\epsilon^+)$. Hence, if ϵ^+ has a higher conditional probability to move up in the firm productivity ladder than ϵ^-, there is PAM (and NAM otherwise).[16]

[14] To fix our attention on movers is not strictly required in this model, because the probability of a movement is independent of the worker type (the probability of destruction of the match is δ). Nevertheless, it seems prudent to include that condition because there are many mechanisms, such as on-the-job search, that can generate dependence between the worker type and the probability of a match destruction.

[15] Note that in the model outlined in this paper $\psi(p|\epsilon) = \frac{v(p)}{\int_{p_{min}(\epsilon)}^{p_{max}(\epsilon)} v(p')dp'}$.

[16] This probability is conditional on being unmatched and conditional on a hiring. As we compare workers originally working in the same firm p, this probability is conditional on a movement from the firm p to a new firm with an interim unemployment spell.

We finally discuss the requirement that payoffs are increasing in the agents' own types for our test to be valid. Wages being monotone in the worker type is a natural assumption, which is consistent with a large 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 them, 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. Finally, in the Appendix we show without using the structure of the model that mean-payoffs are increasing in the own type whenever payoffs are increasing in the own type.

4 Institutional Background, Data and Definitions

4.1 Institutional Background

Wage setting in Italy is governed by a "two-level" bargaining system.[17] 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

[17]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.

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 combining information from two different sources: individual labor market histories and earnings records, and firm balance sheet data.[18] 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).[19] 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 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.[20] 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 ad-

[18]Card, Devicienti and Maida (2010) have used this data set to investigate the extent of rent-sharing and hold-up in firms' investment decisions.

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

[20]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).

dress) in the two data sources were carried out to minimize false matches. The match rate was relatively high: for about 95% of the AIDA firms it was possible to find a matching firm in the VWH.[21] 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 840,000 individuals aged 16-64 who were observed in about 1 million job spells (about 3 million job*year observations) at over 23,000 firms.[22] On average 29% of workers in the sample are female, 30% are white collars and a tiny minority, about 1%, are managers. The mean age is 35, mean (median) tenure is 106 (75) months and the mean daily wage is 69 Euros. The median firm size is 69 employees and mean size is 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:

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

where $Y_{j,t}$ denotes total sales of firm j in year t, $M_{j,t}$ stands for materials and $w_{j,t}L_{j,t}$ are firm labor costs, all 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).[23]

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

[21] As reported by Card et al. (2010), 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.

[22] 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.

[23] In the AIDA data, capital is measured as the book value of past investments.

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).[24] 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. These are the gross operating surplus (GOS):

$$GOS = Sales - Materials - LaborCosts - Depreciation,$$

the after-tax accounting profits (AP):

$$AP = Sales - Materials - LaborCosts - Depreciation - DebtServices - Taxes,$$

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 is 1,2 million, and 4,100 euros 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 - ever switched from a firm in the dataset to another firm in the dataset, with or without an intervening spell of unemployment. 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).[25] We also eliminated unusually high wages by dropping wages higher than the top 1% of the overall wage distribution.

[24] 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.

[25] Information about contractual minimum wages (inclusive of any cost-of-living allowance and other special allowances) were obtained from records of the sector-wide national contracts.

Table 1: Descriptive Statistics

	VWH - AIDA Complete Sample	VWH - AIDA Job-changer 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 interim unemployment (months)	-	7.7
Median interim unemployment	-	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 euros (in 2000 prices).

Column (2) of Table 1 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 years), have lower tenure (less than 3 years) and earn comparatively less than the rest of the population (62 euros 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 duration of this interim unemployment is only 2 months. However, the mean unemployment duration is 7.7 months, which is consistent with a large fraction of workers with long-term unemployment (ISTAT, 2000).

5 Results

The empirical model in section 3.1 (equation 7) 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.[26] 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 with different tenure and experience. Therefore, using a sample of movers we estimate the following conditional probability model:

$$\Pr(\text{move UP} \mid p_j, \epsilon_i, x_{i,j}, move) = x_{i,j}'\beta + w(\epsilon_i, p_j)'\gamma + \psi_j \tag{8}$$

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

Table 2 shows the 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 these measures of profit are 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 than current profit does. In column (2), the indicator variable is therefore defined in terms of average profits, computed as:

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

where T_j is the total number of periods where we observe firm j in the sam-

[26]Results from a simpler specification, only including log-wages and firms fixed effects as regressors, are presented in row (1) of Table A1 in the Appendix. That specification is the direct empirical counterpart of equation (8). Results in row (1) of Table A1 also give significant evidence of positive assortative matching.

ple. However, workers may have been able to observe the evolution of profits over time and to base their search and matching behavior on firms' time-averaged profits. Therefore columns (4) presents results with past average profits, namely:[27]

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

Finally, columns (3) and (5) consider average profit per worker and past 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.

Table 2: Different definitions of Firm Quality

	(1)	(2)	(3)	(4)	(5)
LOGIT	Definition of firm quality ($\pi_{j,t}$)				
$y = \mathbb{1}$ (next Π > current Π)	Profits	Average Profit	Average Profit per worker	Past Average Profit	Past Avg. 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	0.0014	−0.0838	−0.2039	−0.0501	−0.1099
	(0.0157)	(0.0177)	(0.0174)	(0.0164)	(0.0165)
Foreign-born	−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 a value of one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - M_{j,t} - w_{j,t}L_{j,t} - 0.1 \times K_{j,t}$. Each column represents a single logistic regression. Year and occupation dummies are included in all regressions. Standard errors in parentheses.

The specifications where we use average profit and average profit per worker

[27]More precisely, the profit of the incumbent firm is measured up to the time of the worker's separation, say $t = t_0$. The profit of the new firm where the worker eventually moves is measured up to the moment of hiring, $t \geq t_0$.

as a measure of 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.[28]

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 foreign-born 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 no clear evidence that more mature workers and those with a longer tenure are more likely to improve the quality of their employers.

In Table A1 we show that the 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. Assortative matching is also positive for both blue collar and 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 estimations by sector confirm that assortative matching is positive in both the manufacturing and the service sector.

Comparing the size of the effect in different groups, we find that 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.

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 transforma-

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

tions 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).[29] 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 to 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 estimates due to the presence of incidental parameters; however, it is still possible to differentiate them out using the linear probability model.

Table 3: Different Specifications of the Probability Model

	(1)	(2)	(3)	(4)	(5)
	Conditional Probability Model				
$y = \mathbb{1}$ (next Π	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)
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
Avg. 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 a value of one if the worker switches to a firm with higher profits. Profits are defined as $\Pi = Y_{j,t} - M_{j,t} - w_{j,t}L_{j,t} - 0.1 \times K_{j,t}$. Each column represents a single regression. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation 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 within a firm-year cell.

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

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

defined in terms of gross operating surplus (GOS) and GOS per worker. Average GOS and average GOS per worker are also considered, using either the whole sequence of observed GOS or only past GOS. 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

	(1)	(2)	(3)	(4)	(5)	(6)
LOGIT	Definition of firm Profit					
$y = \mathbb{1}$ (next Π > current Π)	Gross Operating Surplus	GOS per worker	Average GOS	Average GOS per worker	Past Avg. GOS	Past Avg. 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)
Firm effects	yes	yes	yes	yes	yes	yes
Observations	103,214	102,441	98,131	95,594	100,435	99,109
No. 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 a value of one if the worker switches to a firm with higher profits. Gross Operating Surplus is defined as the value of sales minus the cost of materials, labor costs and depreciation of capital. Each column represents a single logistic regression. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses.

Table 5: Different definitions of Profits

	(1)	(2)	(3)	(4)	(5)	(6)
LOGIT	Definition of firm Profit					
$y = \mathbb{1}$ (next Π > current Π)	Accounting Profits	Accounting Profits per worker	Average AP	Average AP per worker	Past Avg. AP	Past Avg. 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)
firm effects	yes	yes	yes	yes	yes	yes
Observations	104,733	103,198	98,533	95,929	101,379	98,874
No. 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 a value of one if the worker switches to a firm with higher profits. Accounting profits are defined as value of sales minus cost of materials, labor costs, depreciation of capital and debt services. Each column represents a single logistic regression. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses.

5.3 Within-Firm Regressions

Our test of assortative matching 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 specifications we have included a firm fixed effect in the conditional probability model in order to have wages relative 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 specifications 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). 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.

Table 6: Within-Firm Regressions

	(1)	(2)
	Profit per Worker	
$y = \mathbb{1}(\text{next } \Pi > \text{current } \Pi)$	Linear Probability Model	LOGIT
Log-Wage	0.060	0.651
	(0.015)	(0.170)
Observations	107,110	107,110
Number of firms	1325	1325
Movers per firm	80.84	80.84

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - M_{j,t} - w_{j,t}L_{j,t} - 0.1 \times K_{j,t}$. Each column presents the average and the standard deviation of the average of coefficients estimated in individual regressions at the firm level. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions.

5.4 Within-Firm Wage Quantiles

Assuming that wages are monotone in the worker type allows us to use within-firm variation in wages to order workers relative to their co-workers. Hence, wages are used as an ordinal measure of worker types. A different possibility is to include in the regressions the quantile in the within-firm distribution of wages. Using the wage-quantile instead of the wage 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.

Table 7: Within-Firm Wage Quantiles

	(1)	(2)	(3)	(4)	(5)	(6)
LOGIT	Definition of firm Profit					
$y = \mathbb{1}$ (next Π > current Π)	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Avg. Profit	Past Avg. 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)
Firm effects	yes	yes	yes	yes	yes	yes
Observations	177,740	178,144	175,040	171,782	175,695	174,517
No. of firms	7,656	7,750	7,597	7,409	7,409	7,345
Movers/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 a value of 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. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses.

Results are presented in Table 7, where we also show 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 be more confident 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. In addition, we ask how our results change if instead of movers that comes from a match destruction, we consider job-to-job movers.

As in most administrative data sets, we are unable to distinguish between voluntary and involuntary worker separations. 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 as voluntary (job-to-job) movers those with no more than 1 month between the two jobs.[30] 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 jobs 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 4) and those with a spell up to six months (column 5). As before wages significantly increase the probability of moving to a firm with higher profit per worker, which is consistent with PAM. There are no major differences in the various definitions of movers.

Table 8: Different Definitions of Movers

	(1)	(2)	(3)	(4)	(5)
LOGIT	Definition of firm quality ($\Pi_{j,t}$)				
$y = \mathbb{1}$ (next Π	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)
Firm effects	yes	yes	yes	yes	yes
Observations	133,711	98,820	76,800	90,614	102,256
No. of firms	6,945	6,021	5,616	6090	6,397
Movers/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	$[1, \infty]$	$[3, \infty]$	$[0, 1]$	$[0, 3]$	$[0, 6]$

The dependent variable is a dummy that takes a value of 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 is the number of months between two consecutive job spells. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses.

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

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.

Focusing on a non-random sample of workers could represent a problem if their extent of assortative matching is different from the other workers. In order to analyze if this is the case, we 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.[31] 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 columns (1) and (2) are obtained using our test of assortative matching and data on movers originated by a firm closure. With this test, we make inference on assortative matching by analyzing how the probability of moving up in the firm productivity ladder differs for co-workers of different types. Data on profits of closing firms may be a misleading ordinal measure of their types. Even though we are using average profits (instead of current profits) to order firms in columns (1) and (2), 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

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

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.

Table 9: Exogenous Match Destruction

	(1)	(2)	(3)	(4)
	$y = \mathbb{1}(\text{next } \Pi > \text{current } \Pi)$		$y = \text{next } \Pi$	
	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)
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 a value of 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. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation 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:

$$w_{i,j,t} = x'_{i,j,t}\beta + \eta_i + \xi_j + u_{i,j,t}, \tag{9}$$

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

The results are presented in Table 10. We find the standard result of a small negative correlation between the worker fixed effects and the firm fixed effects.

Table 10: OLS estimates of equation (9)

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-Collar	0.0510	(0.000734)
Manager	0.2879	(0.003016)
Firm Fixed Effects ξ_j	11,985	
Worker Fixed Effects η_i	778,388	
Observations	2,672,812	
$Correlation(\xi_j, \eta_i) = -0.0216$ with $p - value < 0.0001$		

Note: Year dummies and dummies for firm size (5 categories) included.

Moreover, in our dataset this correlation is statistically significant. It is striking that using our 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 provide some insights into the potential mechanisms that may generate 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 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 to every worker. A type-dependent value of vacancies is consistent with firms investing to acquire their type.[32] If wages are non-monotone in the firm type, equation (9) is mis-specified. In this subsection, we provide 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 A2.

On the premise that our measure to orders firms by their quality is correct,

[32] Even with ex-ante free entry, the value of the vacancy will depend on the firm's productivity after the investment in type is made.

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. However, 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 lower wages. If we consider only job-to-job movers with stable jobs,[33] 36 percent of movers going to a better firm end up receiving a wage decrease and 60 percent of movers going to a worse firm get a wage increase.

6.3 Amenities

In the tabulations presented in Table A2, 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 a major candidate 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 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 because, in the AKM approach, a firm's quality is inferred from the mean wages it pays. To illustrate this point, consider to identical firms with different compensations packages. One pays higher wages and lower level of amenities and the other one pays lower wages with a higher level of amenities. The AKM approach would wrongly conclude that the first firm is better than the last one.[34]

6.4 Endogenous Search Intensity

The model presented in Section 3 emphasizes the role of the limitations on firms to post new vacancies as the mechanism that generates sorting in the labor market, as in Eeckhout and Kircher (2011) and Lopes de Melo (2011). Alternatively, sorting can be generated by allowing endogenous search intensity in standard

[33]This sample selection aims at reducing noise, but the same patterns are true for different groups of movers (see Table A2). 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.

[34]Moreover, amenities might not simply mean different compensating packages: good working conditions may have a positive impact on firm-level productivity (see Daniel and Sofer (1998) for a discussion).

equilibrium search models. This mechanism is proposed in Lentz (2010). In this case the firm is totally passive and sorting is a result of differential search intensities rather than matching-set variation. This model is fundamentally asymmetric in that sorting is driven by worker behavior only.

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 A2, 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. 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 monotonicity of wages on the worker type. As it is pointed out in Bagger and Lentz (2011), endogenous search intensity generates wages that are not always increasing in the worker type, even after conditioning on the firm type. Bagger and Lentz (2011) show that, if the production function is supermodular, the present values of future outcomes is more valuable for a high skilled worker than for a low skilled worker. Hence, 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.[35] When one worker meets a potential employer, the current firm and the poaching firm compete for the worker, and the most productive

[35] This wage setting scenario has been proposed in Postel-Vinay and Robin (2002). An extension where the worker bargaining power is allowed to be different from zero was presented in Flinn and Dey (2005) and Cahuc, Postel-Vinay and Robin (2006)

Table 11: Endogenous Search Intensity

$y = \mathbb{1}$ (next Π $>$ current Π)	(1) Similar firms in terms of 10 percentiles	(2) Similar firms in terms of 5 percentiles	(3) Top firms in terms of 10 percentiles	(4) Top firms in terms of 5 percentiles
Wage$\times\mathbb{1}$(Similar firm)	0.064	0.093	-	-
	(0.024)	(0.033)	-	-
Wage$\times$[1-$\mathbb{1}$(Similar firm)]	0.017	0.018	-	-
	(0.013)	(0.013)	-	-
$\mathbb{1}$(Similar firm)	-.272	-.392	-	-
	(0.135)	(0.186)	-	-
Wage	-	-	0.0510	0.0407
	-	-	(0.0096)	(0.011)
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 a value of 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. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses. Columns (1) and (2) consider workers who switch at least three times. $\mathbb{1}$(Similar firm) is an indicator that takes a value of one if the worker comes from a firm in the same group than the current firm. Columns (3) and (4) present results only for the right tail of the distribution of firms types.

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 11. In column (1), we define approximately homogeneous groups of employers as firms in the same decile of the distribution of profit per worker (ten groups). In column (2), homogeneous groups are defined in terms of five percentiles of the distribution of 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.[36]

[36]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, we need to identify these workers who come from a firm similar to the current one. For that purpose, we need to track workers in

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[37], 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.[38] In this case we perform our test but only including firms in the right tail of the distribution of firm's profit. Results are shown in Table 11. In column (3) of Table 11, 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 11, 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 with the probability of moving to a better firm.

6.5 Heterogeneity in search frictions

The results presented in Table 11 were primarily intended to show that our PAM result is robust to sorting generated by endogenous search intensity, where wages are not always monotone in the worker type. Nevertheless, these results 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.

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.

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

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

Their intuition is that, even in the absence of complementarities 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 A2, 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 11 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 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 12. 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 these additional sources 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.

Table 12: Heterogeneity in Search Frictions

	(1)	(2)	(3)	(4)
LOGIT	Definition of Firm Quality ($\Pi_{j,t}$)			
$y = \mathbb{1}(\text{next } \Pi > \text{current } \Pi)$	Profit per worker	Average Profit	Average Profit per worker	Past Avg. Profit per worker
Log wage	0.162	0.15	0.2	0.214
	(0.034)	(0.037)	(0.036)	(0.035)
Avg. past tenure /100	0.006	0.018	0.053	0.023
	(0.035)	(0.038)	(0.038)	(0.037)
Avg. past unemployment duration /100	-0.114	-0.148	-0.180	-0.127
	(0.046)	(0.050)	(0.051)	(0.049)
No. past employm. spells	0.006	0.027	0.041	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
No. past unempl. 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 a value of 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. Controls for age, age squared, migration status, tenure, tenure squared, year and occupation 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.

7 Conclusions

In this paper we propose a test to measure the direction and strength of assortative matching between firms and workers. We analyze the mobility of workers across firms, exploiting the idea that in the absence of assortative matching we should observe that the probability that workers leave one firm to go to another one 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 wage non-monotonicity in the firm type, which is the main criticism to the standard AKM approach used in the literature. 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 their own types. If, given the firm type, wages are monotone in the worker type, we can use within-firm variation in wages, which by definition partials out the firm effect, to order workers within the firm by their types. As for firms, if match profits are monotone in the firm type, we can rely on observed measures of profit at the firm level to order them 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 finds strong evidence of positive assortative matching: better workers have a higher probability of moving to better firms. We obtain similar results if instead of using the within-firm variation on wages, we use logwages or the within-firm wage quantiles. We get positive assortative matching irrespective of whether 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 the firm and worker fixed effects from a log-wage equation. We discuss a number of reasons that can explain the divergence in the results obtained with our test and with the AKM method. First, we observe that a significant number of workers in our data move to worse firms with wage gains or to better firms with wage losses. This evidence suggests that wages are non-monotone in the firm type, as described in Eeckhout and Kircher (2011) and Lopes de Melo (2011). Second, there is a large proportion of workers with job-to-job movements that result in 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. Third, heterogeneity in search intensity has been mentioned as a additional 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 in the labor market is consistent with 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. This proof is not specific to the model presented in Section 3. We focus the discussion in the case of a firm, but the same is true for the worker. As at the end of Section 3, let us define the density of employees conditional on the firm type $\gamma(\epsilon|p)$ with cumulative $\Gamma(\epsilon|p)$.[39] The expected profit of a firm with productivity p is:

$$\Pi(p) = \int_{\epsilon_{min}}^{\epsilon_{max}} [f(p,\epsilon) - w(p,\epsilon)]\, d\Gamma(\epsilon|p) \tag{10}$$

By the Leibniz integral rule and as $\partial \frac{\pi(p,\epsilon)}{\partial p}\Big|_{\epsilon} > 0$, it is straightforward to show that $\frac{\partial \Pi(p)}{\partial p}$ is higher than zero:

$$\frac{\partial \Pi(p)}{\partial p} = \int_{\epsilon_{min}}^{\epsilon_{max}} \partial \frac{[\pi(p,\epsilon)]}{\partial p} \gamma(\epsilon|p) d\epsilon + \int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p,\epsilon)] \partial \frac{\gamma(\epsilon|p)}{\partial p} d\epsilon \tag{11}$$

[39] Note that in the model outlined in Section 3, $\gamma(\epsilon|p) = \frac{u(\epsilon)}{\int_{\epsilon_{min}(p)}^{\epsilon_{max}(p)} u(\epsilon') d\epsilon'}$.

The first term on the right hand side of (11) is positive whenever payoffs are increasing in the agent own type. The second term in the right hand side of (11) 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 $\Gamma(\epsilon|p^+) > 0$:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+,\epsilon) - w(p^+,\epsilon)\right] d\Gamma(\epsilon|p^+) > \int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+,\epsilon) - w(p^+,\epsilon)\right] d\Gamma(\epsilon|p) \tag{12}$$

Which is the same as:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} \left[\pi(p^+,\epsilon)\right] \gamma(\epsilon|p^+) d\epsilon > \int_{\epsilon_{min}}^{\epsilon_{max}} \left[\pi(p^+,\epsilon)\right] \gamma(\epsilon|p) d\epsilon \tag{13}$$

When p^+ converges to p:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p^+,\epsilon)] \partial \frac{\gamma(\epsilon|p)}{\partial p} d\epsilon > 0 \tag{14}$$

A.2 Additional Tables

Table A1: Different Groups of Workers and Firms

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of Firm Profit					
$y = \mathbb{1}(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Avg. Profit	Past Avg. Profit per worker
(1)	Full Sample Without Covariates					
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)
(2)	Only Male workers					
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)
(3)	Only White-Collar Workers					
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)
(4)	Only Blue Collar Workers					
Log-wage	-.038	0.131	0.022	0.253	-.020	0.154
	(0.036)	(0.036)	(0.04)	(0.039)	(0.037)	(0.037)
(5)	Only Young Workers (20-35 Years Old)					
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)
(6)	Only Mid-Career Workers (35-50 Years Old)					
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)
(7)	Only Older Workers (50-65 Years Old					
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)
(8)	Only Firms in the Manufacturing Sector					
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)
(9)	Only Firms in the Service Sector					
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)

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - M_{j,t} - w_{j,t}L_{j,t} - 0.1 \times K_{j,t}$. Each coefficient comes from a single regression. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions, with the exception of the specification without covariates in row (1). Standard errors in parentheses.

Table A2: 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			
Firm Quality	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			
Firm Quality	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: The 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.

Table A3: Correlations Between Different Measures of Profits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Profits	1.00																	
(2) Profits/W	0.55	1.00																
(3) Avg. profits	0.62	0.35	1.00															
(4) Avg. Profits/W	0.32	0.52	0.54	1.00														
(5) Avg. Past Profits	0.78	0.45	0.69	0.33	1.00													
(6) Avg. Past Profits/W	0.45	0.70	0.37	0.66	0.52	1.00												
(7) GOS	0.82	0.51	0.56	0.30	0.68	0.41	1.00											
(8) GOS/W	0.49	0.79	0.31	0.46	0.39	0.61	0.58	1.00										
(9) Avg. GOS	0.58	0.34	0.87	0.53	0.62	0.36	0.59	0.35	1.00									
(10) Avg. GOS/W	0.28	0.48	0.49	0.83	0.29	0.56	0.32	0.50	0.55	1.00								
(11) Avg. past GOS	0.72	0.43	0.63	0.32	0.84	0.49	0.75	0.46	0.68	0.34	1.00							
(12) Avg. past GOS/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						
(13) 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					
(14) 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				
(15) Avg. 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			
(16) Avg. 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		
(17) Avg. 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	
(18) Avg. past AP/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