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ABSTRACT

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

We propose a simple 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, our test exploits within-firm variation on wages to rank workers by their types and firm profits to rank firms. We use a panel data set that combines social security earnings records for workers in the Veneto region of Italy with detailed balance-sheet data for firms. We find robust evidence that positive assortative matching is pervasive 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.

JEL Classification: J6, J31, L2

Keywords: assortative matching, worker mobility, wages, profits, matched employer-employee data

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1 Introduction

Are better workers matched to better firms? In some labor 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. For instance, Card, Heining and Kline (2013) show that sorting plays an important role as a source of wage inequality. The strength of sorting conveys information on the relevance of any complementarities in production between workers and firms and has economy-wide efficiency implications. Knowledge on the sign of sorting is also important and policy relevant. For instance, a subsidy to education would (not) be justified in case of positive (negative) complementarity in the production function, as an increase in the worker's productivity has a positive (negative) externality on the firm's marginal productivity. Moreover, knowing the sign of sorting is important to shed light on the transmission of shocks. For instance, 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, one may expect low skill workers to be the one type of workers who will disproportionately be affected by the resulting displacements. Finally, knowing whether sorting is positive or negative is required 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 these types are straightforward to define theoretically, it is harder to agree on their empirical counterparts. A better worker should be a more productive worker but productivity is generally unobserved. Furthermore productivity is driven by many characteristics that are also unobserved or difficult to measure. The worker type is as a one-dimensional index summarizing 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

[1]For example, there are models predicting positive assortative matching as in Shimer (2005) or Lise et al. (2008), negative assortative matching as in Woodcock (2010), or random allocation of workers to firms as in Postel-Vinay and Robin (2002) or Bartolucci (2013).

(e.g. Heckman and Rubinstein 2001). Similarly, 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 sign 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 (2013) argue 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. In fact, using a search model where firms face limitations in their capacity to open vacancies, they demonstrate that the wage function may be non monotone in the firm type. In this case, the linear AKM model would be fundamentally mis-specified. Furthermore, Eeckhout and Kircher (2011) argue that it is virtually impossible to identify whether sorting is positive or negative 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, which is a distinctive advantage in light of the uncertainty surrounding the measurement of types. In fact, only local rankings of workers and firms suffice, and these can be obtained upon assuming that agents' payoffs are increasing in their own types. As we show below, this assumption implies that we can exploit within-firm variation in wages to rank co-workers by their types. Although there is a firm component in wages, this firm effect is held constant for workers in the same firm. In a similar vein, we show that aggregated profits of multi-worker firms are informative on the firm type upon assuming that the profit of the worker-firm match is increasing in the firm type. Although there is worker component in the profit of 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.

[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 2013), managerial talent and practices (e.g. Bloom and Van Reenen 2007) or organizational form (e.g. Garicano and Heaton 2010).

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, constant search costs, and job scarcity. This simple model represents an appropriate laboratory to describe how our test of sorting works in practice. The model generates 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 only basic ingredients that our test needs for identification. Our strategy imposes minimum conditions on the data generating process and is flexible enough to accommodate a large class of labor market models. This distinctive feature is appealing and arguably grants wider applicability over tests designed within more structural, highly-specified settings.

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 data for their employers. This data set is especially valuable in our application because it contains not only the universe of incorporated businesses in the 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 balance sheet data provide measures of a firm's profits, which allows us to rank firms by their types. Finally, the data-set contains information on firm closures, which we use to control for the potential endogeneity of workers' mobility.

In a set of preliminary results, we report on the performance of the AKM exercise in our data. As often found in the literature, we obtain a statistically significant negative correlation between the firm fixed effect and the worker fixed effect. Taken at face value, these results would be consistent with the existence of negative assortative matching in this labor market. However, we also report suggestive evidence of mis-specification of the AKM approach. In particular, wages are found to be non-monotone in the firm type as discussed in Eeckhout and Kircher (2011) and Lopes de Melo (2013).

These findings and related discussion motivate the alternative empirical strategy that we undertake in the rest of the paper. Our test is robust to wage non-monotonicity in the firm type, as we use firm profits - not firm average wages - to rank firms by their type. In fact we only use wages to order workers within the firm. The results we obtain with our approach are rather different than the ones obtained with the AKM approach. We 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. The same result is found across many different sub-samples, with only modest differences across gender, age, sector and occupational groups.

Our test is consistent with a popular class of models that describe the labor market. It only requires mobility of workers between firms and payoffs that are increasing in the agent's type. We present three sets of robustness checks related to these identification conditions. First, we show that our empirical results are robust to the definition of movers, and concerns related to endogenous mobility. A simplifying feature of our illustrative search model is that workers move across firms following an interim unemployment spell originated by exogenous job destruction. However, we find positive assortative matching for both movers with an interim unemployment spell and for job-to-job movers, with only minor differences. The results also hold when focusing on the sub-sample of workers who are exogenously forced to leave their firms due to a firm closure. Second, we challenge our baseline ranking of firms. It turns out that our PAM results are robust to various alternative definitions of profits that we have the privilege to observe for each firm: economic profits, accounting profits, or gross operating margins. We also show that PAM obtains irrespective of whether we rank firms using current profits or average profits across time, or profit per firm as opposed to profit per worker. A further refinement of our test is also presented to dispel concerns that profits may be uninformative of a firm's underlying productivity in the presence of differences in competition between product markets or between labor markets. Third, one may be concerned that, even *within* firm, wages do not necessarily provide a reliable order of workers for a variety of reasons, including measurement error, match effects, re-negotiation due to outside offers, or heterogeneous search intensity. We propose various refinements to our baseline specification in order to tackle each of these potential failures of our ranking of workers, and show that our PAM result is largely unaffected.

The rest of the paper is organized as follows. Section 2 presents the related literature and preliminary evidence. Our empirical strategy is 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 and the robustness checks. Section 6 offers a short conclusion.

2 Related Literature and Preliminary Evidence

Several theoretical papers analyze the conditions for the existence of assortative matching between heterogeneous agents, and whether this is positive or negative. In his seminal paper, Becker (1973) studies a frictionless economy and shows that positive assortative matching (PAM) arises if and only if the production function is supermodular.[3] Shimer and Smith (2000) extend Becker's model to account for search frictions, and show that stronger complementarities in the production function are 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 and firm types. The most influential one is AKM (1999), which makes inference on the sign and strength of assortative matching through the correlation between the worker and firm fixed effects estimated from standard Mincer-type wage equations. To estimate these models one needs longitudinal matched employer-employee data, where workers are observed as they move across different employers. The Veneto Worker History data (VWH) that we describe in more detail in Section 4 have precisely this feature. To better motivate the development of our own empirical strategy, let us preliminarily explore the performance of the classical AKM approach in our data. Hence, we begin by estimating the following standard wage equation:

$$w_{i,j,t} = x'_{i,j,t}\beta + \eta_i + \xi_j + u_{i,j,t}, \tag{1}$$

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 dependent variable is the worker's daily wage and the time-varying controls include a quadratic in the worker's age, a quadratic in the worker's tenure with the current employer, indicators for white-collar and managerial occupations, indicators for five firm-size classes and year effects. The results are presented in Table 1. As reported by many other replications of the classical AKM result, we too find evidence of a small negative correlation (-0.02) between the worker fixed effects and the firm fixed effects. Moreover, in our data-set this correlation is statistically significant. On the basis of these preliminary results, one may be tempted to conclude that there is evidence of negative assortative matching in Italy.

However, the AKM 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 data-sets from Germany, France and the United States. Second, as pointed out by Eeckhout and Kircher (2011) and Lopes de Melo (2013), the AKM correlation may be biased due to non-monotonicity of wages in the firm type. The wage could be non-monotone in the firm type for a number of reasons, such as limitations in the capacity of the firms to

[3] 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 $f_{xy} > 0$.

Table 1: OLS Estimates of Equation (1)

AKM Approach

y=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.

post new vacancies (job scarcity)[4], or on-the-job search and wage renegotiation (Postel-Vinay and Robin, 2002).[5]

In what follows, we provide evidence suggesting that in our data wages are non-monotone in the firm type. To do so, we show that workers moving to better firms can have both a wage gain or a wage cut as workers moving to worse firms. Movements across firms and the resulting wage changes can be easily observed in our data-set. However, we still need to rank firms in order to gauge whether the worker is moving to a better or a worse firm. As we explain more formally in Section 3, we use profits to rank firms according to their types. In asset pricing, expected profits are used to value firms; the higher the profit the better the firm.[6] The intuition for the validity of this index is straightforward as firms only care about maximizing profits. Notice that a more productive firm could always imitate what a less productive firm does, and still obtain higher profits; moreover, there is room for improvement. Therefore, profits represent a natural and observable measure to order firms by their types. We have access to the firms' entire balance sheets and hence have precise information on each firm's profits. This allows us to analyze whether workers who move to firms with

[4]As argued by Eeckhout and Kircher (2011) and Lopes de Melo (2013), if there is job scarcity, the value of a vacancy depends on the firm type. Then, a high-type firm may require some compensating transfer from the low-type worker to fill its vacancy. In this case, the same worker may end up receiving a lower wage in this firm than in a lower-ranked firm.

[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.

[6]Note that physical productivity is not the only determinant of profits; market power or managerial talent to reduce costs are examples of other factors influencing the firm profit. Our index of firms embeds these other factors that allow some firms to have higher profits also with the same level of physical productivity.

Table 2: Wages Non Monotone in the Firm Type

	Profits per Worker							
	Any Movers				Job-to-Job Movers & Stable Jobs			
Quality	Worse Wage		Better Wage		Worse Wage		Better Wage	
Worse	49,381	(47.1%)	55,467	(52.9%)	7,752	(39.2%)	12,032	(60.8%)
	(50.9%)		(43.9%)		(46.0%)		(43.1%)	
Better	47,680	(40.2%)	70,905	(59.8%)	9,086	(36.4%)	15,854	(63.6%)
	(49.1%)		(56.1%)		(54.0%)		(56.9%)	
	Profits							
	Any Movers				Job-to-Job Movers & Stable Jobs			
	Worse Wage		Better Wage		Worse Wage		Better Wage	
Worse	50,105	(47.1%)	56,338	(52.9%)	8,260	(38.8%)	13,040	(61.2%)
	(51.6%)		(44.6%)		(49.1%)		(46.8%)	
Better	46,956	(40.1%)	70,034	(59.9%)	8,578	(36.6%)	14,846	(63.4%)
	(48.4%)		(55.4%)		(50.9%)		(53.2%)	

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

higher profits receive higher (or lower) wages.[7] The results are presented in Table 2.

We find strong evidence of non-monotonicity of wages in the firm type. There is an association between positive changes in the firm type and positive changes in wages. However, we observe a large number of workers moving to worse firms where they receive higher wages, and workers that end up in a better firm receiving lower wages. If we consider only job-to-job movers with stable jobs[8], 36 percent of movers switching to a better firm end up receiving a wage decrease and 60 percent of movers switching to a worse firm get a wage increase.

In the tabulations presented in Table 2, we observe a surprisingly large number of workers moving to jobs with lower wages. When only considering job-to-job movements, this proportion is significantly smaller, but still large. The presence of job-related amenities is one potential candidate to explain this pattern. Notice that amenities might adversely affect the AKM measure of sorting, because this strategy infers the firm's quality using the mean wages paid by the firm. To illustrate this point, consider two identical firms with different compensation packages. One pays higher wages and offers a lower level of amenities and the other one pays lower wages with a higher level of amenities. The AKM approach would erroneously conclude that the first firm is better than the last one. A second possible explanation for job-to-job tran-

[7]Note that by tracking the same worker we keep the worker effect constant.

[8]This sample selection aims at reducing noise, but the same patterns are true for different groups of movers (see Table 2). 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.

sitions with wage cuts is the existence of on-the-job search and renegotiation (Postel-Vinay and Robin, 2002).[9]

In Section 3 we present an alternative test that uses information on workers' mobility, wages and firms' profits to identify both the sign and strength of assortative matching. As we show below, this test is robust to wage non-monotonicity in the firm type. Moreover, the test is robust to the presence of amenities that cause biases in the traditional AKM approach. In Section 5 we also present a series of refinements of the test that allow us to learn about sorting in the presence of measurement error in wages and on-the-job search with renegotiation.

Our paper contributes to a growing literature aiming at overcoming the limitations of the AKM approach to measuring sorting. 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. In a recent working paper, Hagedorn, Law and Manovskii (2012) argue that the sign of sorting can also be identified *if* the data generating process is a model as the one presented in Shimer and Smith (2000). Differently from our paper, the identification results in Eeckhout and Kircher (2011) and Hagedorn, Law and Manovskii (2012) are specific to a particular model. Although estimating such a model would imply a loss of generality, it would allow them to identify sensible primitives such as the degree of complementarities in the production function. Both papers focus on identification and do not provide empirical results. Furthermore, their empirical implementation would be challenging because they rely on the estimation of the expected wage for every worker.[10] In order to capture precisely the expected wage of a worker, we would need wage-observations with multiple employers (asymptotics here are in terms of the number of employers). Although there are data-sets containing information on the entire life-cycle of the worker, the average number of employers actually observed for each worker is typically quite low. Moreover when using data on the entire life-cycle of a worker, the assumption of time-invariant productivity is more controversial.

Lopes de Melo (2013) proposes a different strategy to measure sorting in the labor market, based on the correlation between a worker fixed effect and the average fixed effects of her coworkers. The estimates of both sets of fixed effects come from a

[9]Measurement error is also a potential candidate to explain wage cuts. The wage data used to calculate these tabulations come from administrative records, therefore measurement error should be less of a problem than in standard labor force surveys. However, in order to check whether measurement error explains these observed wage cuts, we recalculated the tabulations presented in Table 2 but only considering movements with different wages those where the difference is larger than 5%; the proportion of workers with wage cuts is somewhat smaller but still significant.

[10]In Hagedorn, Law and Manovskii (2012) the identification requires to calculate the expected value of the wage minus the minimum wage that each worker is willing to accept.

log-wage equation in the spirit of AKM. He shows that in a search model with on-the-job search, a supermodular production function and job scarcity, the proposed measure works better than the AKM correlation. He also applies his method to matched employer-employee data from Brazil, finding evidence of assortative matching. An advantage of this measure is that it can be easily estimated in many available datasets. However, it is important to note that the method proposed by Lopes de Melo can only reveal the strength of sorting but not its sign.

A different empirical strategy to measure assortative matching is to assume that all the information concerning the worker type is contained in a set of observable characteristics, such as age and education. If this is true, a measure of the firm type can be obtained through production function panel data estimation. 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 make inference on 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. Unfortunately 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.[11]

3 A Test of Assortative Matching

In this section, we present a test that uncovers the sign and the strength of assortative matching using (i) movements of workers between firms, (ii) the within-firm distribution of wages, and (iii) firm profits. To illustrate how our test works, we begin by sketching a simple matching model with search frictions. As we discuss below, our test is not specific to this particular environment. Yet, we believe this simple model is instructive for shedding light on the identification mechanisms exploited by the test and for thinking on the refinements needed to apply it in more general environments.

3.1 The Model

We build on the simple infinite-horizon model with explicit, constant search costs and job scarcity discussed in Atakan (2006) and Eeckhout and Kircher (2011). Consider a discrete time, stationary economy, populated by infinitely lived, risk neutral firms and

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

workers. Firms are a collection of jobs characterized by their productivity p. Each firm has N jobs, but not every job is necessarily matched to a worker. Worker types are denoted by ϵ. For simplicity in the exposition, consider symmetry in the distribution of jobs and workers. Denote the stationary distribution of unmatched types by $G(\cdot)$.

Unmatched workers and jobs meet a potential partner every period.[12] When two unmatched agents meet, they immediately observe each other's type. They match only if they both agree. As in Eeckhout and Kircher (2011), matched workers and jobs disappear from the market until there is an exogenous destruction of the match, at which point they return to the market. Each period a match is destroyed with probability δ.

The match (p, ϵ) produces $f(p, \epsilon)$ per period, with $f_p > 0$ and $f_\epsilon > 0$. We assume that the output of a firm p is the sum of the output of its matched jobs. A worker ϵ employed by a firm p receives $w(p, \epsilon)$ 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 pay a constant cost equal to c if they reject the potential partner that they have met. The value of being unemployed for a worker of type ϵ, $v(\epsilon)$, is given by:

$$v(\epsilon) = \int_{M(\epsilon)} \tilde{w}(p, \epsilon) g(p) dp + \int_{p \notin M(\epsilon)} [v(\epsilon) - c] g(p) dp \tag{2}$$

where $\tilde{w}(p, \epsilon) = w(p, \epsilon)/\delta$ is the expected wage over the duration of the match and $M(\epsilon)$ is the set of acceptable jobs of worker ϵ.[13] The value of a vacant job for a firm p is defined equally due to symmetry. We assume that payoffs are determined by symmetric Nash Bargaining.

Atakan (2006) shows that, if $f_{p\epsilon} > 0$, the upper and lower bounds of $M(\epsilon)$ are non-decreasing in ϵ and that $M(\epsilon)$ is convex for all ϵ. Using the proofs of Proposition 1 and 3 in Atakan (2006), it is easy to show that, if $f_{p\epsilon} = 0$, every partner is acceptable and that, if $f_{p\epsilon} < 0$, the upper and lower bounds of the acceptance set $M(\epsilon)$ are non-increasing in ϵ and $M(\epsilon)$ is convex.

3.2 Identification of Sorting

This model provides a convenient framework for describing our test. To begin with, we show that payoffs can be used to rank agents by their types. This is achieved in the following two propositions. Proposition 1 states that, conditional on the partner type,

[12]There is no on-the-job search in this simple model; hence, movements of workers between firms feature an interim unemployment spell.

[13]As noted by Eeckhout and Kircher (2011), we do not need to include the continuation value after the match breaks up exogenously because of the one-shot deviation principle. Furthermore, notice that as agents only match if they both agree, we do not distinguish between acceptance sets and matching sets (See Atakan, 2006).

the better the own type, the higher the own payoff.

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

Proof: See Appendix A.1.

Note that the monotonicity condition in Proposition 1 does not yet 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 matched with a firm less appropriate for his type. However, given that payoffs are increasing in the agent type, Proposition 2 states that the mean of payoffs can be used to rank agents.

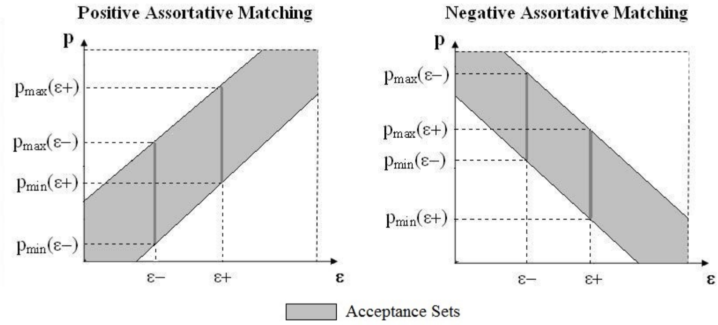
Proposition 2 *The mean of payoffs conditional on being matched are increasing in agents' own types.*

Proof: See Appendix A.1.

The worker component in the payoff of each match of a firm is integrated out and therefore, in expected terms, a better firm must do better than a worse firm. The intuition for this result is straightforward. Consider two firms p^+ and p^-, with $p^+ > p^-$. Firm p^+ could imitate the strategy (in terms of acceptance set and payoffs paid) of firm p^-. As p^+ produces more with every ϵ and pays the same, p^+ would receive more than the p^- with each worker in $M(p^-)$.

Mean payoffs are unobserved, but they can be estimated by their sample counterparts. In many data-sets, profits are observed at the firm level. Firm-level profits (Π) are the sum of profits per match, for every worker employed by 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. 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 mean wage and the sample average wage is a function of the type of the firm 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.

Figure 1: Acceptance Sets and Sorting



However, being able to rank firms allows us to use movements of workers between firms of different types to test whether there is sorting, and whether this is positive or negative. 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 $\epsilon^+ > \epsilon^-$, $p^+ \in M(\epsilon^+)$ and $p^- \in M(\epsilon^-)$ whenever $p^+ \in M(\epsilon^-)$ and $p^- \in M(\epsilon^+)$. An implication of this definition is that, if the bounds of $M(\epsilon)$ are increasing in ϵ, there is positive assortative matching and, if the bounds of $M(\epsilon)$ are decreasing in ϵ, there is negative assortative matching. Proposition 3 formalizes the way in which workers' mobility allows us to learn about the pattern of sorting in the labor market.

Proposition 3 *Consider two workers ϵ^+ and ϵ^-, with $\epsilon^+ > \epsilon^-$, who were 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: See Appendix A.1

The intuition behind proposition 3 is straightforward. If ϵ^+ and ϵ^- accepted new jobs, it is because their new employers are in their acceptance set. In the presence of PAM, the ratio between the mass of firms better than p and the mass of firms worse than p that would accept worker ϵ^+ is larger than the corresponding ratio for worker ϵ^-, while if there is NAM the opposite is true. This is because, if there is PAM, acceptance sets are increasing in the worker type, and then every firm better than p that is acceptable for ϵ^- is also acceptable for ϵ^+, while there can be some firms better than p that are acceptable for ϵ^+ but not for ϵ^-. On the other hand, every firm worse than p that is acceptable for ϵ^+ is also acceptable for ϵ^-, while there can be some firms worse than p that are acceptable for ϵ^- but not for ϵ^+ (see Figure 1).

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 than being rehired by a firm that makes more profits than firm p). This test is not feasible because ϵ^+ and ϵ^- are unobserved by the econometrician. However, if the 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 co-workers with different wages:

$$\Pr(\text{move UP} \mid p, w(\epsilon^+, p), move) > \Pr(\text{move UP} \mid p, w(\epsilon^-, p), move). \tag{3}$$

In order to test whether inequality (3) is true, we estimate the following conditional probability model:

$$\Pr(\text{move UP} \mid p, \epsilon, move) = w(\epsilon, p)'\gamma + \zeta(p) \tag{4}$$

where $w(\epsilon, p)$ is the wage of worker ϵ in firm p and $\zeta(p)$ is a firm p effect, in order to exploit only within-firm variation. Note that in the left-hand side of (4), we have the probability that a worker moves to a firm better 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.

3.3 More General Environments

As anticipated earlier, our test is not specific to the simple search model presented above. As an alternative environment, consider the search model with discounting examined by Shimer and Smith (2000). This model complicates the analysis because here some production functions generate non-convex matching sets. Therefore we can only show formally that, when the bounds of the acceptance sets are increasing, our

[14] Fixing 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 exogenous). 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.

test indicates the presence of PAM and, on the other hand, when the bounds of the acceptance sets are decreasing, our test indicates the presence of NAM. However, in Section A.2 of the Appendix we present simulations of the model presented in Shimer and Smith (2000) and show that, even when the acceptance set are not convex, our test of sorting, which is feasible with available matched employer-employee data-sets, provides the same information than the correlation between types, which is an ideal but unfeasible test of sorting. Furthermore, as pointed out in Hagedorn, Law and Manovskii (2012), in Shimer and Smith (2000) expected payoffs are not necessarily monotone due to changes in the probability of finding an acceptable partner. In Appendix A.2 we show that, if the probability of finding an acceptable worker is higher for better firms, aggregated profits are always increasing in the firm type. On the other hand, if the probability of finding an acceptable worker is lower for better firms, profits per worker are always increasing in the firm type. Therefore, in Section 5 we present results ranking firms by their aggregated profits but also but their profits per worker.

More generally, although we have shown how our test works with a particular definition of assortative matching, mobility can be used to detect the sign and strength of sorting without specifying any particular model. In such a general setting, 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 $\Psi(p|\epsilon^+) < \Psi(p|\epsilon^-)$, no sorting if $\Psi(p|\epsilon^+) = \Psi(p|\epsilon^-)$ and NAM if $\Psi(p|\epsilon^+) > \Psi(p|\epsilon^-)$, for $\epsilon^+ > \epsilon^-$. This is a broad definition of sorting which encompasses the definition of Shimer and Smith (2000). Notice that, with random or directed search (but not on-the-job search), the probability for an unmatched worker ϵ of being hired by a firm better than p conditional on a hiring is $1 - \Psi(p|\epsilon^+)$. Hence, if after an unemployment spell ϵ^+ has a higher probability to move up in the firm productivity ladder than ϵ^-, there is PAM.[16]

If there is on-the-job search, $\Psi(p|\epsilon)$ is different from the distribution of firms faced by an unemployed worker of type ϵ. However, note that if there is on-the-job search and the better the worker the higher the probability of moving upward the firm productivity ladder, the allocation of workers to firms approaches perfect sorting as the exogenous destruction rate of the match approaches zero,[17] which implies PAM (Goldmanis, Ray and Stuart, 2012).

[15]Note that in the model outlined in Section 3: $\psi(p|\epsilon) = g(p)/\phi(\epsilon)$ if $p \in M(\epsilon)$, and zero otherwise.

[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 firm p to a new firm with an interim unemployment spell.

[17]Note that, for every allocation of workers to firms at time t, if there is no exogenous destruction and the better the worker the higher the probability of moving upward the firm productivity ladder, the allocation of workers to firms in time $t+1$ is going to be more assortative than in time t.

4 Institutional Background and Data

4.1 Institutional Background

Wage setting in Italy is governed by a "two-level" bargaining system.[18] Sectoral agreements (generally negotiated every two years) establish contractual minimum wages for different occupation classes (typically 7 or 8 sector-specific classes), that are automatically extended to all employees in the sector. Unions can also negotiate firm-specific contracts that provide wage premiums over and above the sectoral minimums. During the mid-1990s such firm-level bargains covered about 40% of private sector employees nationwide (ISTAT, 2000). In addition, individual employees receive premiums and bonuses that add to the minimum contractual wage for their job. In our estimation sample nearly all employees earn at least some premium: the 5th percentile of the percentage premium is 2.5%, while the median is 24%. The combination of sector and occupation minimum wages with individual-level wage premiums means that within-firm wage variability is quantitatively significant. In particular, according to Lazear and Shaw (2008), within-firm wage variability in Italy represents about two thirds of total wage variability, in line with the international evidence reported in their study.

4.2 Data

The data set used in the paper was obtained by combining information from two different sources: individual labor market histories and earnings records, and firm balance sheet data.[19] The job histories and earnings data were derived from the Veneto Workers History (VWH) data-set, 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).[20] 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),

[18] 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.

[19] Card, Devicienti and Maida (2013) have used this data set to investigate the extent of rent-sharing and hold-up in firms' investment decisions.

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

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*).

Our balance sheet data are derived from standardized reports that firms are required to file annually with the Chamber of Commerce.[21] These data are distributed as the "AIDA" database by Bureau van Djik, and are available from 1995 onward for firms with annual sales above 500,000 euros. In principle, all (non-financial) incorporated firms with annual sales above this threshold are included in the database. The available data include sales, value added, total wage bill, the book value of capital (broken into a number of subcategories), the total number of employees, industry (categorized by 5-digit code), and the firm's tax number.[22]

Tax code identifiers are used to match job-year observations for employees in the VWH to employer information in AIDA for the period from 1995 to 2001. Additional checks of business names (*ragione sociale*) and firm location (firm address) in the two data sources were carried out to minimize false matches. The match rate was relatively high: for about 95% of the AIDA firms it was possible to find a matching firm in the VWH.[23] 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 data-set contains about 840,000 individuals aged 16-64 who were observed in about 1 million job spells (about 3 million job$\times$year observations) at over 23,000 firms.[24] On average 29% of workers in the sample are female, 30% are white collar

[21]These data are known as the Company Register database (Registro delle Imprese). Law 580 of 1993 established the Chamber of Commerce as the depository for standardized financial and balance sheet data for all incorporated firms in Italy.

[22]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).

[23]As reported by Card et al. (2013), 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.

[24]Firms in the sample 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 is significantly larger than the size of non-incorporated businesses. 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. (2013) for further details.

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 mean firm size is 69 employees. The average profit is 3.6 million Euros (in 2000 prices), and a profit per workers is 14,900 euros.

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 data set to another firm in the data set, 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.

Most of our results are based on economic profits, which are defined 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).[26] The literature on capital investment in Italy suggests that during the mid-to-late 1990s a reasonable estimate of the user cost of capital (r_t) is in the range of $8 - 12\%$. Elston and Rondi (2006) report a distribution of estimates of the user cost of capital for publicly traded Italian firms in the 1995-2002 period, with a median of 11% (Elston and Rondi, 2006, Table A4). Arachi and Biagi (2005) calculate the user cost of capital, with special attention to the tax treatment of investment, for a panel of larger firms over the 1982-1998 period. Their estimates for 1995-1998 are in the range of $10 - 15\%$ with a value of 11% in 1998 (Arachi and Biagi, 2005, Figure 2).[27] We assume that r_t is at 10% in the estimation reported below. As we

[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.

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

[27] 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

also show below, the results are not dependent on any particular definition of profit.

Table 3: Descriptive Statistics

	VWH - AIDA	
	Complete Sample	Job-Changer Sample
No. Job$\times$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 Daily Wage	69.4	61.7
Mean Daily log Wage	4.12	4.05
Mean Interim Unemployment (months)	-	7.7
Median Interim Unemployment (months)	-	2.0
Mean Firm Size	69.0	67
Mean Profit*	3,612.0	3,871.9
Mean Profit per Worker *	14.9	13.9

Note: * 1,000's euros (in 2,000 prices).

Column (2) of Table 3 reports the characteristics 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 presented in equation 4 is stylized, and hence it seems prudent to include a set of observable characteristics of the worker and the firm to control for

fell to 6% after 1997.

other confounding mechanisms.[28] 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:

$$\Pr(\text{move UP} \mid p_j, \epsilon_i, x_{i,j}, move) = x_{i,j}'\beta + w(\epsilon_i, p_j)'\gamma + \zeta_j \tag{5}$$

where $\Pr(\text{move UP} \mid p_j, \epsilon_i, x_{i,j}, move)$ is the conditional probability that an employee i whose job in firm j ended, is hired by a firm better than j. $w(\epsilon_i, p_j)$ is the wage that the worker received in firm j. ζ_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's age, age squared, tenure, tenure squared, time dummies and indicators for females, foreign-born workers, blue collar, white collars and managerial occupations.

Table 4 reports the estimates of various specifications of the conditional probability model in (5). The dependent variable is an 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). Notice that wages only provide an ordinal measure of the worker type; hence, any monotone transformation of the wage is also a valid candidate to include in the regressions. Some transformations might imply a better fit of the data than others. Entering the wage in levels (as opposed to in logs) does not affect our main results: the coefficient remains positive and statistically significant (column 1), implying PAM.[29] Columns (3) and (4) 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 effects; column 4) as opposed to the firm *and* year level (i.e. using unrestricted firm$\times$year fixed effects; column 5). Note that, since the combination of firm and year effects is very large (14,723), the average number of observations per firm$\times$year cell is only 8.84. Therefore LOGIT or PROBIT would generate biased estimates due to the presence of incidental parameters;

[28]The results from a simpler specification, which only includes log-wages and firm fixed effects as regressors, are presented in column (2) of Table 4. This specification is the direct empirical counterpart of equation (4).

[29]Most of the specifications have been replicated using wages as opposed to log-wages without significant changes in the results. In Table A2 of the Appendix we present results where we use quantiles on the within firm distribution of wages to rank workers and we also find evidence of PAM.

however, it is still possible to differentiate them out using the linear probability model.

Table 4: Different Specifications of the Probability Model

$y = \mathbb{1}(\text{next}\Pi > \text{current }\Pi)$	(1)	(2)	(3)	(4)	(5)	(6)
	Conditional Probability Model					
	LOGIT	LOGIT	LOGIT	PROBIT	Linear Probability Model	Linear Probability Model
Wage	0.0011	-	-	-	-	-
	(0.0003)	-	-	-	-	-
Log Wage	-	0.0823	0.1155	0.0668	0.0223	0.0343
	-	(0.0217)	(0.0253)	(0.0152)	(0.0050)	(0.0062)
Age	0.0023	-	0.0015	0.0010	0.0003	-0.0011
	(0.0042)	-	(0.0043)	(0.0025)	(0.0008)	(0.0010)
Age^2	$-.0001$	-	-0.0001	-0.0001	-0.0001	$3.88e^{-6}$
	(0.0001)	-	(0.0001)	(0.0001)	(0.0001)	$(1.43e^{-5})$
Female	-0.0623	-	-0.0584	-0.0346	-0.0113	-0.0134
	(0.0155)	-	(0.0155)	(0.0093)	(0.0031)	(0.0036)
Foreign-born	-0.0542	-	-0.0514	-0.0313	-0.0101	-0.0041
	(0.0218)	-	(0.0218)	(0.0131)	(0.0043)	(0.0052)
Tenure	0.0020	-	0.0019	0.0011	0.0004	0.0003
	(0.0003)	-	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Tenure^2	$-6.41e^{-6}$	-	$-6.06e^{-6}$	$-3.66e^{-6}$	$-1.16e^{-6}$	$-1.19e^{-6}$
	$(1.40e^{-6})$	-	$(1.41e^{-6})$	$(8.47e^{-7})$	$(2.79e^{-7})$	$(3.40e^{-7})$
Firm effects	yes	yes	yes	yes	yes	yes
Firm by year effect	no	no	no	no	no	yes
Observations	178,094	178,094	178,094	178,094	178,094	130,212
Number of firms	7,746	7,746	7,746	7,746	7,746	14,723
Avg. Movers per firm	22.99	22.99	22.99	22.99	22.99	8.84
Pseudo R^2	0.1732	0.1627	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. Each column represents a single regression. Controls for year and occupation are included in all regressions. Standard errors in parentheses. Number of firms in column (6), represents number of firms-years groups. Average number of movers in column (6) represents the average number of movers within a firm-year cell.

In our baseline specification, we use standard controls in order to compare workers who are similar in terms of observable characteristics. 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 to move to better firms than the rest of the workers. 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 column (2), we estimate the direct empirical counterpart of equation (4), i.e. with no controls included, and still find significant evidence of PAM.

In most of our specifications, we control for occupation by including indicators for blue collar, white collar and managerial jobs. However, one concern with these estimates is that our occupational controls may be too broad, and one may wonder whether our results are robust to a more refined way of controlling for different jobs within the firm. In Table A5 of the Appendix, we have used detailed information on each worker's collocation in the contractual "job ladder" (*livelli di inquadramento*) operating in the firm to construct a more precise classification of jobs within the firm (see Section A.3.3 in the Appendix for the details). The results strongly corroborate PAM even after including these more refined occupational controls in our regressions.

In Table A6 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 subsample of males confirms the results of PAM. 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. When we compare the size of the effect in the different groups, we find that sorting is somewhat stronger for males than for females, and for workers in the manufacturing sector than in the service sector. We also find that positive assortative matching is stronger for medium age and white collar workers.

In the tabulations presented in Table 2, there was a surprisingly large number of workers moving to jobs with lower wages. When only considering job-to-job movements, this proportion was significantly lower, but still large. Amenities were mentioned as a major candidate to explain this pattern. The data set used in this paper does not contain information on amenities. Nevertheless, as long as the level of amenities is constant within the firm$\times$occupation cluster, our measure of sorting is not affected by the presence of workers moving to firms that offer them lower wages but higher compensating differentials. This is because we only use wages to order workers in similar occupations within the firm. However, as discussed in Section 2, amenities might represent a source of bias in the AKM measure of sorting, as firm quality in AKM is inferred from the mean wage paid by the firm.

Our test of assortative matching requires that wages be 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-firm 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. To check that this is immaterial for our PAM result, we re-run our test separately for each firm, estimating the following conditional probability model:

$$\Pr(\text{move UP} \mid p_j, \epsilon_i, x_{i,j}, move) = x'_{i,j}\beta_j + w(\epsilon_i, p_j)'\gamma_j. \tag{6}$$

In Table 5 we present the average and standard deviation of γ_j. Every moment of the within-firm distribution of wages is allowed to be firm-type dependent in these specifications. Estimation requires that we restrict ourselves to the sub-sample of relatively large firms, where a minimum number of job changers can be observed (30 in our case). Albeit we loose some precision in this exercise, the results are once more suggestive of PAM.

Table 5: Within-Firm Regressions

	(1)	(2)	(3)	(4)
	Profit per Worker		Aggregated Profits	
$y = \mathbb{1}(\text{next }\Pi > \text{current }\Pi)$	Linear Probability Model	LOGIT	Linear Probability Model	LOGIT
Log-Wage	0.060	0.651	0.025	0.339
	(0.015)	(0.170)	(0.014)	(0.160)
Observations	107,110	107,110	107,110	107,110
Number of firms	1,325	1,325	1,325	1,325
Avg. Movers per firm	80.84	80.84	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. 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.

5.1 Robustness Checks: Mobility

The identification of sorting in the environment described in Section 3 relies upon observing a worker moving between two firms with an interim unemployment spell. However, a sample of workers who switch jobs with an interim unemployment spell is likely to be a selected sample. In this subsection we check whether our results change when we focus on job-to-job transitions instead. However, the sample that includes job-to-job transitions might also be a selected one. This is because our results would still be based on movers and the sorting pattern of movers might differ from the sorting pattern of stayers. Therefore, below we also run our test on a sample of workers who are forced to move due to a firm closure.

5.1.1 Job-to-Job Transitions

The model of Section 3 assumes 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. To investigate whether there are any major differences in the sorting patterns of job-to-job switchers versus workers who move between firms after transiting in unemployment, we now alternatively restrict our sample in terms of the duration of this interim unemployment spell.

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 sub-sample excluding job-to-job movers are shown in column (1) of Table 6. For robustness, column (2) adopts a more stringent requirement to identify the sub-sample of workers who have suffered a job destruction: 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 job-to-job movers are shown in column (3) of Table 6. The remaining columns consider alternative definitions of movers, as detailed in the first 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 6: Different Definitions of Movers

	(1)	(2)	(3)	(4)	(5)
LOGIT	Unemployment Duration				
$y = \mathbb{1}\,(\text{next }\Pi > \text{current }\Pi)$	$[1,\infty]$	$[3,\infty]$	$[0,1]$	$[0,3]$	$[0,6]$
Log Wage	0.1126	0.1036	0.1295	0.1278	0.1265
	(0.0296)	(0.0465)	(0.0376)	(0.0347)	(0.0329)
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

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Firms are ranked using profits per worker (ranking firms using aggregated profits delivers similar results). 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. Firms fixed effects are included in every specification. Standard errors in parentheses.

5.1.2 Movers Due to Firm Closures

Involuntary worker separations identified as in Table 6 are likely to provide reasonably good empirical counterparts of the exogenous job destruction described by the model

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

in Section 3. One concern is that, although separations with one month or even up to three months of intervening unemployment are likely to be involuntary for the worker, they may not be independent of the worker type. One may suspect that the firm selects which workers to fire according to their underlying characteristics, and therefore the workers that separate from a firm represent a non-random sample from its workforce.

Focusing on a non-random sample of workers could represent a problem if their extent of assortative matching is different from that of the other workers. In order to analyze if this is the case, we obtain estimates of the sign and strength 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. In our data it is possible to identify 710 firms that 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 7, are once again indicative of PAM. Column (1) shows the results from a LOGIT regression with firm fixed effects, while column (2) shows the results from a linear probability model with firm$\times$year fixed effects. In both cases, the wage coefficient is positive, statistically significant and similar in magnitude to the estimates reported earlier.

One concern with the results presented in columns (1) and (2), however, is that data on profits of closing firms may provide a misleading ranking of firms. Our estimates may be contaminated by the low profitability of firms that are closing down. For this reason, in columns (3) and (4), we slightly modify our test in a way that does not depend on the profit of the separating (closing) firm. Specifically, in columns (3) and (4) we run linear regression models where the dependent variable is the quantile in the distribution of firm profit of the worker's new employer. We use the same set of controls than before (including firm, or firm and year, fixed effects, respectively). Note that, in analogy with the ordinal nature of the dependent variable, the quality of the worker is represented by the worker's rank in the wage distribution of the separating firm. The results are once more supportive of PAM. After a firm closure, workers with higher wages than their former co-workers move to better firms than those co-workers do.

5.2 Robustness Checks: Order of Firms

Our test requires an ordinal measure of firms according to their type. We have argued that a better firm is one that makes more profits. However, there are many possible

[31] Cingano and Rosolia (2012) use a similar strategy to identify the strength of information spillovers on workers' unemployment duration.

Table 7: 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
			(0.008)	(0.011)
Firm Effects	yes		yes	
Firm×Year Effects		yes		yes
Obs.	10,049	12,068	10,680	10,680
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. Firms are ranked using average profits per worker (ranking firms using aggregated profits delivers similar results). Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Standard errors in parentheses.

ways to compute profits and in this section we worry that we should get a consistent set of results, no matter which specific definition we rely upon.

We have already discussed in section 3.2 that it might be prudent to use both aggregated profits and profits per worker to rank firms. Here, we also report whether the timing in the measurement of profits has any impact on our baseline results. Moreover, different measures of profits have been used in the literature: economic profits, gross operating margins and accounting profits. There are 18 possible ways to combine the definition of profit, the timing of profit, and whether or not to divide the chosen measure of profits by the number of workers in the firm. In the appendix (Table A7), we report that all these different potential indexes 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. As we show below, it is quite reassuring that, using all these 18 different measures of profits, we consistently find evidence of PAM.

Our last set of robustness checks with respect to the order of firms takes into account that our ordinal measure of firm types may be misleading if we were to compare firms that operate in different labor markets or different product markets. To uncover the sorting patterns based on a ranking of firms more connected to physical productivity, in Section 5.2.2 we only compare firms with a similar level of product market competition. Moreover, different labor markets may have different levels of competition and therefore firm aggregated profits may differ only due to differences in the proportion of workers operating in these markets. Therefore, in Section 5.2.3 we provide results robust to differences in workforce composition between firms.

5.2.1 Different Definitions of Profits

In our baseline specification, we compare the profit of the new firm measured at the time of the hiring with the profit of the old employer measured at the time of the separation. These measures of profit are firm and time specific. We think of the firm type as a fixed characteristic of 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. Hence, we also report results where the indicator variable of moving up the firm productivity ladder is defined in terms of the longitudinal 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 sample. Notice, however, that firm types might be unobserved for the workers, who may have only been able to observe the evolution of profits over time and to base their search and matching behavior on firms' past average profits. Therefore, we also present results based on past average profits, defined as:[32]

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

Table 8 shows the results obtained when firm quality is ranked using alternative measures of economic profits. 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 profit measure we use.

The specifications where we use average profits and average profits per worker to rank firms 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.[33] The results obtained when profits are defined in terms of gross operating margins (Table A3 in the Appendix) and accounting profits (Table A4) also lead us to conclude that there is PAM.

[32]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, $t \geq t_0$.

[33]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.

Table 8: Different Definitions of Firm Quality

LOGIT	(1)	(2)	(3)	(4)	(5)
	Definition of Firm Profits				
$y = \mathbb{1}$(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)
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. 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. Firms fixed effects are included in every specification. Standard errors in parentheses.

5.2.2 Accounting for Differences in Product Market Competition

In previous tables, we have ordered firms using data on profits or profits per worker. Profits provide a more comprehensive index of firm types than measures of firm physical productivity. However, it is interesting to analyze the sorting pattern derived from a metric more directly connected to the classical definition of productivity. For that purpose, we now only compare firms with similar level of product market competition. First, we focus our attention on transitions between two firms that operate in the same industry. Second, we analyze transitions between two firms in the same decile of the distribution of the Learner Index (i.e., the price-cost margin) of product market competition.

Table 9: Similar Level of Product Market Competition

LOGIT	(1)	(2)	(3)	(4)
	Old and New firm in Same 4-digit Industry		Old and New Firm with Similar Price-to-Cost Margins	
$y = \mathbb{1}$(next Π > current Π)	Average Profit	Average Profit per Worker	Average Profit	Average Profit per Worker
Log Wage	0.367	0.381	0.225	0.219
	(0.049)	(0.047)	(0.035)	(0.033)
Obs.	21,798	26,200	47,782	50,002
Pseudo R^2	0.332	0.375	0.339	0.342

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher average profits in column (1) and (3) and average profit per worker in column (2) and (4). 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. Firms fixed effects are included in every specification. Standard errors in parentheses.

The results are presented in Table 9. Both exercises are extremely data demanding because both firms, the new one and the old one, must operate in the same cluster defined in terms of industry or Learner Index. Despite the large drop in the number of valid observations, we find strong evidence of PAM. The coefficients of log-wage are positive and significant in columns (1) and (2), where we cluster firms according to a 4-digit industry index. Similarly, if we cluster firms according to the deciles in the distribution of the Learner Index, we find evidence of PAM.[34] Interestingly, the model has a significantly better fit than our baseline specification.

5.2.3 Accounting for Differences in Firms' Workforce Composition

In most of our specifications, we control for occupation and demographic characteristics when we compare workers in the conditional probability model. However, as we use profits at the firm level to rank firms, our ranking of firms may be problematic if firms have different workforce composition and employing some groups of workers is more profitable than others. Firms may make more profits by employing different groups of workers due to differences in competition between labor markets or due to differences in bargaining power.

Within sector the workforce composition can be seen as a feature that is chosen by the firm. If better firms choose more profitable workforce compositions, our index of firms holds. However, for the sake of robustness, we obtain evidence of sorting that is robust to differences in workforce composition. First, we use our test in a sub-sample of transitions where the old and the new firm are similar in terms of the proportion of blue collar workers. The results are presented in columns (1) and (2) of Table 10. Although the number of observations is significantly smaller, the probability of moving up the firm productivity ladder when both the old and the new firm have similar workforce composition is higher for better workers.

One limitation of the latter set of results, however, is that the proportion of blue collar workers may not be enough to characterize the workforce composition of the firm. In a second set of results, we instead rank firms using the firm fixed effects from a regression of profits on the characteristics of the firm's workforce. Taking advantage of the longitudinal dimension of the firm level data, we preliminarily regress firm profits or profits per worker on the proportions of workers in blue collar, white collar or managerial occupations and the proportions of female and foreign-born workers. The estimated firm fixed effects represents measures of profit that *control* for differences in the composition of the workforce. We then use these fixed effects to compare firms with similar workforce composition. In column (3) of Table 10), the fixed effects are obtained from aggregated profits; in column (4), they are obtained from profits per worker. In both cases, we still find significant evidence of PAM.

[34] The Lerner index is computed at the 4-digit industry, separately by year, and then attributed to each firm according to its industry classification.

Table 10: Firms with Similar Workforce Composition

LOGIT	(1)	(2)	(3)	(4)
	Only Old and New Firm with Similar Workforce Composition		Every Transition	
$y = \mathbb{1}$ (next Π > current Π)	Average Profit	Average Profit per Worker	Firm Effect Equation for Profit	Firm Effect Equation for Profit p.w.
Log Wage	0.239	0.167	0.127	0.122
	(0.042)	(0.039)	(0.016)	(0.016)
Obs.	29,274	29,274	176,231	171,894
Pseudo R^2	0.304	0.359	0.274	0.281

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. In columns (1) and (2) we consider two similar firms if they are in the same decile on the distribution of the proportion of blue collar workers. In column (3) we rank firms by their fixed effects in an auxiliary regression of profits (profits per worker in column (4)) on the characteristics of the workforce. 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. Firm fixed effects are also included in every specification to exploit only within-firm variation of wages. Standard errors in parentheses.

5.3 Robustness Checks: Order of Workers

In this section we challenge our assumption that wages are increasing in the worker type. Wages being monotone in the worker type is a natural assumption, which is consistent with a large family of models. In previous exercises, we control for observable characteristics of the worker, such as age, tenure, experience, occupation and migration status. However, there are reasons to believe that the residual within-firm variation of wages is not only driven by heterogeneity in worker types. We present refinements of our test to make it robust to the presence of renegotiation due to counteroffers, heterogeneity in search intensity, measurement error in wages and match effects.

5.3.1 On-the-Job Search and Wage Renegotiation

One of the critical conditions required for consistency of our measure of sorting is monotonicity of wages within the firm. If workers search on-the-job and firms match outside offers, the within-firm variation of wages is not only driven by variation in worker types. Moreover, in an environment where firms can make counter offers and workers can choose their search intensity, wages are not always increasing in the worker's type, also after conditioning on the types of the current and poaching firms (Bagger and Lentz, 2011).[35]

[35] Bagger and Lentz (2011) use the model discussed in Lentz (2010). In this environment, the firm is totally passive and sorting is a result of differential search intensities rather than matching-set variation. The environment described in Lentz (2010) implies that every worker, independently of her type, prefers to have a job in a better firm. However, this implication seems dubious in light of the evidence

In a scenario where there is on-the-job search and firms are allowed to make counter-offers (such as the model described in Postel-Vinay and Robin, 2002), when a worker meets a potential employer, the current firm and the poaching firm compete *à la* Bertrand for the worker, and the most productive firm wins. In this case, when the poaching firm is identical to the current firm, the worker extracts the full rent, and the wage is equal to the productivity of the match. This last implication can be used to order workers by their types. If the worker's previous firm is similar enough to the current firm, wages are almost identical to the productivity of the match. Therefore, we use wages to order co-workers that come from a similar firm than their current firm, without an interim unemployment spell. 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.

Table 11: On-the-job Search and Renegotiation

	(1)	(2)	(3)	(4)
LOGIT	Profit per Worker		Aggregated Profits	
$y = \mathbb{1}\,(\text{next }\Pi > \text{current }\Pi)$	Similar Firms in terms of 10 Percentiles	Similar Firms in terms of 5 Percentiles	Similar Firms in terms of 10 Percentiles	Similar Firms in terms of 5 Percentiles
Wage$\times\mathbb{1}$(Similar Firm)	0.064	0.093	0.045	0.027
	(0.024)	(0.033)	(0.024)	(0.031)
Wage$\times[\mathbb{1}$-$\mathbb{1}$(Similar Firm)]	0.017	0.018	0.047	0.048
	(0.013)	(0.013)	(0.013)	(0.013)
$\mathbb{1}$(Similar Firm)	-.272	-.392	0.112	0.010
	(0.135)	(0.186)	(0.181)	(0.134)
Observations	27,956	27,956	27,815	27,815
Pseudo R^2	0.267	0.267	0.167	0.167

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. In columns (1) and (2) firms are ordered in terms of economic profit per worker, whereas in columns (3) and (4) are ordered in terms of aggregated profit. 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. Firms fixed effects are included in every specification. Standard errors in parentheses. All specifications 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.

The 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 average profit per worker (ten groups). In column (2) homogeneous groups are defined in terms of five percentiles of the distribution of average profit per worker (20 groups). The coefficient of wages, for the workers whose previous employer was a firm similar to the current one, is significantly positive in both specifications. Moreover, the effect is stronger for this group of workers than for workers who have not firstly moved between two similar firms. In column (3) and (4), we repeat the same exercise but

presented in Table 2, 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.

with reference to aggregated average profits. In both cases, the results also suggest that there is PAM when we only consider workers who switched between two similar firms. However, these estimates are now less precise than in the previous exercises, and the coefficient of the log-wage multiplied by the indicator function of similar firm is not statistically significant in column (4).[36]

5.3.2 Heterogeneity in Search Frictions

Heterogeneity in search frictions may represent yet another reason to expect that, even within firm, wages do not provide a valid measure to order workers according to their types. This is because workers with a similar productivity ϵ but with different search abilities have different values of unemployment and, therefore, may end up having different wages even when they are hired by the same firm. If that is the case, heterogeneity in search frictions may constitute a source of omitted variable bias. Therefore, in this section we re-estimate our measure of PAM, comparing co-workers who are as similar as possible in terms of labor market frictions.

To do so, 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 8), 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.

The results of Table 12 also allow us to discuss the relevance of heterogeneity in search frictions as a potential mechanism driving the observed PAM, as argued by Mendes, van den Berg and Lindeboom (2010). Their intuition is that, even in the ab-

[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 two consecutive spells without an interim unemployment spell. 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.

sence 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. If our results of PAM were 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. Indeed, the estimated wage coefficient in Table 12 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.

Table 12: Heterogeneity in Search Frictions

	(1)	(2)	(3)	(4)
LOGIT	Definition of Firm Profit			
$y = \mathbb{1}(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per Worker	Average Profit	Average Profit per Worker
Log Wage	0.162	0.155	0.251	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)
Number of Past Employment Spells	0.006	0.027	0.041	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Number of Past Unemployment Spells	-.018	-.039	-.050	-.021
	(0.008)	(0.008)	(0.008)	(0.008)
Obs.	103,817	101,858	99,195	100,930
Pseudo R^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. 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. Firms fixed effects are included in every specification. 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. Sub-sample of 1995-2001 movers who where active in the labor market prior to 1995.

5.3.3 Match Effects and Measurement Error in Wages

Although match effects in wages have not been found to be remarkably relevant once the worker and firm effects are partialled out (Card *et al*, 2013), our ranking of workers would be incorrect if part of the within-firm variation of wages is actually driven by match effects. Similarly, the presence of measurement error, which is not expected to be significant because our data on wages come from social security records, would prevent us to use the within-firm variation of wages to rank workers. In our last set of robustness checks, we present results that are robust to measurement error and match effects. For that purpose, we re-estimate our test but now using two-stage least squares to fit the linear probability model. We instrument the worker's wage using the wage of the same worker at the previous employer. In order to guarantee that the current wage and the wage of the previous spell are only connected through the worker type, we only consider workers moving between jobs with an interim unemployment spell.

Table 13: Instrumenting Current Wages with Wages in Previous Jobs

	(1)	(2)	(3)	(4)
2SLS	Definition of Firm Profit			
$y = \mathbb{1}\,(\text{next } \Pi > \text{current } \Pi)$	Profit	Profit per Worker	Average Profit	Average Profit per Worker
Log-Wage	0.198	0.159	0.142	0.126
	(0.038)	(0.039)	(0.033)	(0.033)
Observations	43,201	43,201	43,256	43,256
Pseudo R^2	0.289	0.255	0.452	0.442

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Each column represents a single linear probability model. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Firms fixed effects are included in every specification. Standard errors in parentheses. The sample consists of workers who switch employer at least two times. We only analyze workers whose first transition had an interim unemployment spell. The wage is instrumented with the wage earned in the previous job.

The results are presented in Table 13. This exercise is also extremely data demanding, because the sample consists of workers who switch employer at least two times. Despite the large drop in the number of valid transitions, the results once again suggest that there is PAM, as the log-wage coefficients are positive and statistically significant in all specifications.

6 Conclusions

In this paper we propose a test to measure the sign 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, the main criticism to the standard AKM approach, which is empirically relevant in our data-set. Moreover, our test is robust to the presence of amenities, which represents another source of bias in the AKM approach. 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.

We use a matched data set that combines administrative earnings records for individual workers in the Veneto region of Italy with detailed financial information for their employers. Although the AKM correlation leads us to conclude that there is negative assortative matching, with our test we find strong evidence of positive assortative matching: better workers have a higher probability of moving to better firms. We run various specification checks challenging our baseline ranking of workers and firms, as well as the kind of worker mobility used to identify sorting. First, we get PAM 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. PAM is also found within narrowly defined industries, and for groups of firms sharing a similar degree of product market competition, or featuring a similar workforce composition. Second, we show that our PAM results are robust to the presence of renegotiation due to counter-offers, heterogeneity in search intensity, measurement error in wages and match effects. Third, we find that the evidence of PAM is 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.

Finally, our PAM result was found across many different sub-samples, with only modest differences across gender, age, sector and occupational groups. Overall, the bulk of our empirical evidence leads us to conclude that positive assortative matching is a pervasive feature of the Italian labor market. It would be interesting to investigate the extent to which these results generalize to the labor markets of countries characterized by different economic and institutional features.[37]

References

[1] Abowd, J., F. Kramarz, and D. Margolis (1999), "High Wage Workers and High Wage Firms". Econometrica, 67 (2), 251-334.

[2] Abowd, J., F. Kramarz, P. Lengerman, and S. Perez-Duarte, (2004) "Are Good Workers Employed by Good Firms? A Test of a Simple Assortative Matching Model for France And The United States" Unpublished Manuscript.

[3] Andrews, J., L. Gill, T. Schank and R. Upward (2008) "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?" Journal of the Royal Statistical Society: Series A, 171(3) pp. 673697.

[37] Merlino, Parrotta and Pozzoli (2013) use our test with Danish data and also find strong evidence of PAM.

[4] Arachi, G. and F. Biagi (2005), "Taxation, Cost of Capital, and Investment: Do Tax Asymmetries Matter?"Giornale degli Economisti e Annali di Economia 64 (2/3), pp. 295-322.

[5] Atakan A.E. (2006), "Assortative Matching with Explicit Search Costs", Econometrica 74, No. 3, pp. 667-680.

[6] Bagger, J., and R. Lentz, "An Empirical Model of Wage Dispersion with Sorting," University of Wisconsin mimeo 2011.

[7] Bartolucci, C (2013) "Gender Wage Gaps Reconsidered: A Structural Approach Using Matched Employer-Employee Data", Journal of Human Resources (forthcoming).

[8] Becker, G. (1964), " Human Capital; A Theoretical and Empirical Analysis, with Special Reference to Education." New York: Columbia University Press, 1964.

[9] Becker, G. (1973), "A Theory of Marriage: Part I", The Journal of Political Economy, 81, No. 4, pp. 813-846.

[10] Bloom, N. and J. van Reenen (2007) "Measuring and Explaining Management Practices across Firms and Countries." Quarterly Journal of Economics, 122(4), pp. 13511408.

[11] Bloom, N. , M. Schankerman, and J. Van Reenen. 2009. "Technology Spillovers and Product Market Rivalry" CEP working paper No 675.

[12] Caballero, R, (1994) "The Cleansing Effect of Recessions" American Economic Review, 84(5), pp. 1350-1368

[13] Cahuc, P., F. Postel-Vinay and J.-M. Robin, (2006), "Wage Bargaining with On-the-job Search: Theory and Evidence", Econometrica, 74(2), pp. 323-64.

[14] Card, D., F. Devicienti and A. Maida (2013), "Rent-sharing, Holdup, and Wages: Evidence from Matched Panel Data ", Review of Economic Studies (forthcoming).

[15] Card, D., J. Heining, and P. Kline (2013), "Workplace Heterogeneity and the Rise of West German Wage Inequality", The Quarterly Journal of Economics (forthcoming).

[16] Casadio, P. (2003), "Wage Formation in the Italian Private Sector After the 1992-93 Income Policy Agreements ". In G. Fagan, F.P. Mongelli and J. Morgan, editors, Institutions and Wage Formation in the New Europe, Cheltenham, UK: Edward Elgar, pp. 112-33.

[17] Cingano F. and A. Rosolia (2012) "People I Know: Job Search and Social Networks', Journal of Labor Economics, 30(2), pp. 291-332.

[18] Collard-Wexler, A. (2013) "Demand Fluctuations in the Ready-Mix Concrete Industry." Econometrica, 81(3), pp. 1003-1037.

[19] Daniel, C., and C. Sofer (1998) "Bargaining, Compensating Wage Dierentials, and Dualism of the Labor Market: Theory and Evidence for France", Journal of Labor Economics, 16(3), pp. 546-575.

[20] Dell'Aringa, C. and C. Lucifora. (1994). "Collective Bargaining and Relative Earnings in Italy." European Journal of Political Economy, Vol. 10, pp. 727-47.

[21] Eeckhout, J. and P. Kircher, (2011) "Identifying Sorting in Theory", Review of Economic Studies, forthcoming.

[22] Elston, J. and L. Rondi (2006). "Shareholder Protection and the Cost of Capital: Empirical Evidence from German and Italian Firms." CERIS-CNR Working Paper No. 8.

[23] Franzosi, A. (2008). "Costo del Capitale e Struttura Finanziaria: Valutazione degli Effetti di IRAP e DIT."Instituto per la Ricerca Sociale (Milano) Unpublished Manuscript.

[24] Garicano, L. and P. Heaton (2010). "Information Technology, Organization, and Productivity in the Public Sector: Evidence from Police Departments." Journal of Labor Economics, 18(1), pp. 167-201.

[25] Goldmanis, M., K. Ray, and E. Stuart (2013). "Until Death Do Us Part? The Marriage Model with Divorce", Unpublished Manuscript.

[26] ISTAT (2000). "La Flessibilit del Mercato del Lavoro nel Periodo 1995-96." Informazioni 34 Roma: ISTAT.

[27] Hagedorn, M., T. Law, and I. Manovskii (2013) "Identifying Equilibrium Models of Labor Market Sorting" Unpublished Manuscript.

[28] Hause, J.C. (1980). "The Structure of Earnings and the On-the-job Training Hypothesis", Econometrica, 48(4), pp. 1013-1029.

[29] Heckman, J. and Y. Rubinstein (2001) "The Importance of Noncognitive Skills: Lessons from the GED Testing Program" The American Economic Review, 91(2) pp. 145-149.

[30] Melitz, M. (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity" Econometrica, 71(6) pp. 16951725.

[31] Merlino, L., P. Parrotta and D. Pozzoli (2013) "Gender Differences in Sorting", Unpublished Manuscript.

[32] Lazear, E. and K. Shaw (2008) "Wage Structure, Raises and Mobility: International Comparison of the Structure of Wages Within and between Firm", The University of Chicago Press.

[33] Lentz, R. (2010) "Sorting by Search Intensity", Journal of Economic Theory 145(4) 2010, pp 1436-1452.

[34] Lillard, L. and Y. Weiss (1979). "Components of Variation in Panel Earnings Data: American Scientists 1960-1970", Econometrica 47(2), pp. 437-454.

[35] Lise, J., C. Meghir and J.M. Robin, (2011) "Matching, Sorting and Wages ", Unpublished Manuscript.

[36] Lopes de Melo, R. (2013), "Sorting in the Labor Market: Theory and Measurement", Unpublished Manuscript.

[37] Meghir, C. and Pistaferri, L. (2004). "Income Variance Dynamics and Heterogeneity", Econometrica, 72(1), pp. 1-32.

[38] Mendes, R., G. van den Berg, M. Lindeboom, (2011) "An empirical assessment of assortative matching in the labor market", Labor Economics, forthcoming.

[39] Nagypal, E. (2004), "Worker Reallocation: The Importance of Job-to-Job Transitions", Unpublished Manuscript.

[40] Postel-Vinay, F. and J.-M. Robin, (2002), "Wage Dispersion with Worker and Employer Heterogeneity", Econometrica, 70(6), pp. 2295-350.

[41] Royalty, A., (1998) "Job-to-Job and Job-to-Nonemployment Turnover by Gender and Education Level", Journal of Labor Economics 16(2), pp.392-443.

[42] Shimer, R. and Smith L., (2000) "Assortative Matching and Search ", Econometrica 68, pp. 343-369.

[43] Shimer, R., (2005) "The Assignment of Workers to Jobs in an Economy with Coordination Frictions,"Journal of Political Economy 113(5), pp. 996-1025.

[44] Syverson, c. (2001) "What Determines Productivity?", Journal of Economic Literature, 49(2), PP. 326365

[45] Tattara, G. and Valentini M. (2007) "The Cyclical Behaviour of Job and Worker Flows", Working Paper No. 16. Department of Economics Ca Foscari University of Venice.

[46] Woodcock, S, (2010) "Heterogeneity and Learning in Labor Markets" The B.E. Journal of Economic Analysis and Policy, 10(1), p. 85.

A Appendix

A.1 Proofs

Proof of Proposition 1: Wages are set by Nash-Bargaining, therefore $\tilde{w}(p,\epsilon) = \frac{S(p,\epsilon)}{2} + v(\epsilon) - c$, where $S(p,\epsilon)$ is the gain from trade of the match between a firm p and a worker ϵ. $S(p,\epsilon)$ is defined as:

$$S(p,\epsilon) = \tilde{f}(p,\epsilon) - v(\epsilon) - v(p) + 2c, \tag{7}$$

where $\tilde{f}(p,\epsilon) = f(p,\epsilon)/\delta$. Replacing $\tilde{w}(p,\epsilon)$ by $\frac{S(p,\epsilon)}{2} + v(\epsilon) - c$ in (2):

$$v(\epsilon) = \int_{M(\epsilon)} \left[\frac{S(p,\epsilon)}{2} + v(\epsilon) - c\right] g(p)dp + \int_{p \notin M(\epsilon)} [v(\epsilon) - c] g(p)dp.$$

Rearranging,

$$c = \int_{M(\epsilon)} \left[\frac{S(p,\epsilon)}{2}\right] g(p)dp, \tag{8}$$

what implies that the expected surplus is constant (Constant Surplus Condition (CSC) in Atakan, 2006). Using (7), we can write (8) as:

$$2c = \int_{M(\epsilon)} \left[\tilde{f}(p,\epsilon) - v(\epsilon) - v(p) + 2c\right] g(p)dp.$$

Taking derivatives with respect to ϵ and noting that the surplus is zero in the limits of the acceptance set:

$$\int_{M(\epsilon)} \frac{\partial \tilde{f}(p,\epsilon)}{\partial \epsilon} g(p)dp = \phi(\epsilon)\frac{\partial v(\epsilon)}{\partial \epsilon},$$

where $\phi(\epsilon) = \int_{M(\epsilon)} g(p)dp$ is the probability of finding an acceptable partner. Note that $\frac{\partial \tilde{f}(p,\epsilon)}{\partial \epsilon} > 0$ and $\phi(\epsilon) > 0$, then $\frac{\partial v(\epsilon)}{\partial \epsilon} > 0$. Therefore:

$$\frac{\partial \tilde{w}(p,\epsilon)}{\partial \epsilon} = \frac{1}{2}\frac{\partial \tilde{f}(p,\epsilon) + v(\epsilon) - v(p)}{\partial \epsilon} = \frac{1}{2}\left[\frac{\partial \tilde{f}(p,\epsilon)}{\partial \epsilon} + \frac{\partial v(\epsilon)}{\partial \epsilon}\right] > 0.$$

By symmetry $\frac{\partial \tilde{\pi}(p,\epsilon)}{\partial p} > 0$, where $\tilde{\pi}(p,\epsilon) = \pi(p,\epsilon)/\delta$. Although $\tilde{w}(p,\epsilon)$ and $\tilde{\pi}(p,\epsilon)$ are the expected profit and expected wage over the duration of the match, as the duration of each match is exogenous also the wage and profit per period are increasing in the agent own types. ■

Proof of Proposition 2:

Let us denote $\hat{v}(\epsilon)$ the value of unemployment for a worker ϵ if every agent in the economy receives a lump sum transfer of c in every period; then:

$$\hat{v}(\epsilon) = \int_{M(\epsilon)} [\tilde{w}(p,\epsilon) + \tilde{c}] g(p)dp + \int_{p \notin M(\epsilon)} \hat{v}(\epsilon) g(p)dp,$$

where $\tilde{c}$ is the expected value of c over the exogenous duration of the match. Rearranging:

$$\phi(\epsilon)\hat{v}(\epsilon) = \int_{M(\epsilon)} [\tilde{w}(p,\epsilon) + \tilde{c}]g(p)dp,$$

and then:

$$\hat{v}(\epsilon) = \int_{M(\epsilon)} [\tilde{w}(p,\epsilon)]\frac{g(p)}{\phi(\epsilon)}dp + \tilde{c}.$$

As the worker is risk neutral and the transfer is unconditional, workers and firms do not change their optimal behavior, what implies that $\frac{\partial v(\epsilon)}{\partial \epsilon} > 0 \Leftrightarrow \frac{\partial \tilde{v}(\epsilon)}{\partial \epsilon} > 0$. Therefore, as we know that $\frac{\partial v(\epsilon)}{\partial \epsilon} > 0$, the expected value of the wage conditional on employment is increasing in ϵ:

$$\frac{\partial v(\epsilon)}{\partial \epsilon} > 0 \Leftrightarrow \frac{\partial \hat{v}(\epsilon)}{\partial \epsilon} > 0 \Leftrightarrow \frac{\partial \int_{M(\epsilon)} [\tilde{w}(p,\epsilon)]\frac{g(p)}{\phi(\epsilon)}dp}{\partial \epsilon} > 0 \Leftrightarrow \frac{\partial \int_{M(\epsilon)} [w(p,\epsilon)]\frac{g(p)}{\phi(\epsilon)}dp}{\partial \epsilon} > 0.$$

By symmetry, $\frac{\partial \int_{M(p)} [\pi(p,\epsilon)]\frac{g(\epsilon)}{\phi(p)}d\epsilon}{\partial p} > 0$. ■

Proof of Proposition 3:

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

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

where $p_{max}(\epsilon) = max[M(\epsilon)]$ and $p_{min}(\epsilon) = min[M(\epsilon)]$. If ϵ^+ has higher probability of moving to a better firm than ϵ^-:

$$\frac{\int_{p_{min}(\epsilon^+)}^{p} g(p')dp'}{\int_p^{p_{max}(\epsilon^+)} g(p')dp'} < \frac{\int_{p_{min}(\epsilon^-)}^{p} g(p')dp'}{\int_p^{p_{max}(\epsilon^-)} g(p')dp'}. \tag{9}$$

Since $\frac{\partial p_{min}(\epsilon)}{\partial \epsilon} \geq 0 \Leftrightarrow \frac{\partial p_{max}(\epsilon)}{\partial \epsilon} \geq 0$ and $\frac{\partial p_{min}(\epsilon)}{\partial \epsilon} \leq 0 \Leftrightarrow \frac{\partial p_{max}(\epsilon)}{\partial \epsilon} \leq 0$, condition (9) implies that $p_{min}(\epsilon^+) \geq p_{min}(\epsilon^-)$ and $p_{max}(\epsilon^+) \geq p_{max}(\epsilon^-)$ (with at least one of the inequalities being strict) and therefore there is PAM.

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

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

what implies that $p_{min}(\epsilon^+) \leq p_{min}(\epsilon^-)$ and $p_{max}(\epsilon^+) \leq p_{max}(\epsilon^-)$ (with at least one of the inequalities being strict) and therefore there is NAM.

If the probability of moving to a better firm is independent of ϵ:

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

what implies that $p_{min}(\epsilon^+) = p_{min}(\epsilon^-)$ and $p_{max}(\epsilon^+) = p_{max}(\epsilon^-)$ and therefore there is no sorting. ■

A.2 Model with Discounting

In this section we show that our test can be used to uncover the sign and the strength of sorting in search models with discounting as the one presented in Shimer and Smith (2000). Consider the setup presented in Section 3, but let us now assume that agents discount future income at the rate $\rho > 0$ and find partners when unmatched at a rate λ.[38]

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

$$\rho U(\epsilon) = \lambda \int_{M(\epsilon)} \left[W(p,\epsilon) - U(\epsilon)\right] g(p)dp, \tag{10}$$

where $g(p)$ 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:

$$\rho W(p,\epsilon) = w(p,\epsilon) - \delta \left[W(p,\epsilon) - U(\epsilon)\right]. \tag{11}$$

The value of a vacancy and the value of a job with a worker ϵ for a firm with productivity p, $V(p)$ and $J(p,\epsilon)$, are defined equally due to symmetry. $S(p,\epsilon)$ is now given by $W(p,\epsilon) - U(\epsilon) + J(p,\epsilon) - V(p)$. The worker takes half of the surplus and the firm takes the rest. Therefore:

$$\frac{S(p,\epsilon)}{2} = W(p,\epsilon) - U(\epsilon) = J(p,\epsilon) - V(p). \tag{12}$$

Proposition 4 *Payoffs are increasing in agents' own types.*

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 $V(p^+) > V(p^-)$.[39]

[38] Although the model presented in Section 3 was in discrete time, we now write the model in continuous time as it is presented in Shimer and Smith (2000)

[39] Plugging (12) in (10) and rearranging, we can write $V(p) =$

- If $S(p^+,\epsilon) \geq S(p^-,\epsilon)$, using (12) we have: $J(p^+,\epsilon) - V(p^+) \geq J(p^-,\epsilon) - V(p^-)$. Since $V(p^+) > V(p^-)$, then $J(p^+,\epsilon) > J(p^-,\epsilon)$. Given that the value of the match is higher for p^+, but we know that $\pi(p^+,\epsilon) - \delta\frac{1}{2}S(p^+,\epsilon) > \pi(p^-,\epsilon) - \delta\frac{1}{2}S(p^-,\epsilon) > \pi(p^-,\epsilon) - \delta\frac{1}{2}S(p^+,\epsilon)$, therefore $\pi(p^+,\epsilon) > \pi(p^-,\epsilon)$.

- If $S(p^+,\epsilon) < S(p^-,\epsilon)$, using (12), we have that $W(p^+,\epsilon) < W(p^-,\epsilon)$. Therefore, from (11), $w(p^+,\epsilon) + \delta U(\epsilon) < w(p^-,\epsilon) + \delta U(\epsilon)$, and then $w(p^+,\epsilon) < w(p^-,\epsilon)$. 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 wage. Although we have shown that payoffs are increasing in the agent's type, expected payoffs are not necessarily monotone due to changes in the acceptance set. Note that in the case of firms, integrating the value of the job for the firm in the acceptance set of p and replacing in the value of a vacancy, we have that:

$$\lambda \int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon = [\rho + \frac{\rho\delta}{2} + \lambda\phi(p)]V(p) \tag{13}$$

where $\phi(p) = \int_{M(p)} g(\epsilon)d\epsilon$. Although the value of a vacancy is increasing in p, we cannot guarantee that expected profits are increasing in the firm type. This is because, without information on the primitives, we cannot state the sign of $\frac{\partial\phi(p)}{\partial p}$. It could be the case that better firms have higher or lower probability of filling a vacancy. If $\frac{\partial\phi(p)}{\partial p} > 0$, it is straightforward to show that $\int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon$ is monotonically increasing in p. Taking derivatives with respect to p in (13) and rearranging:

$$\left[\rho + \frac{\rho\delta}{2}\right]\frac{\partial V(p)}{\partial p} = \lambda\frac{\partial\left[\int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon\right]}{\partial p} - V(p)\lambda\frac{\partial\phi(p)}{\partial p}.$$

Given that the left hand side and the second term on the right hand side are positive,

$$\frac{\partial\left[\int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon\right]}{\partial p} > 0,$$

$\frac{\lambda\frac{1}{2}}{\rho}\int_{M(p)}\left[\frac{f(p,\epsilon)}{\rho+\delta} - \frac{\rho}{\rho+\delta}(V(p)+U(\epsilon))\right]g(\epsilon)d\epsilon$. 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:

$$\frac{\partial V(p)}{\partial p} = \frac{\frac{\lambda\frac{1}{2}}{\rho}\int_{M(p)}\frac{\partial f(p,\epsilon)}{\partial p}g(\epsilon)d\epsilon}{\rho + \delta + \lambda\frac{1}{2}\int_{M(p)} g(\epsilon)d\epsilon} > 0$$

and therefore expected payoffs of the firm have to be increasing in the firm type. We do not observe directly $\int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon$ but we do observe aggregated profits at the firm level. If all the firms have N jobs, aggregated profits are equal to $N\int_{M(p)} \pi(p,\epsilon)g(\epsilon)d\epsilon$, which is increasing in p. Therefore, if $\frac{\partial\phi(p)}{\partial p}$ is positive or slightly negative, aggregated profits can be used to ranks firms.

However, in the data we find a strong negative correlation between profits per worker and the size of the firm. This evidence suggests that better firms may be more selective, and therefore the probability of filling a vacancy may be decreasing in p. If $\frac{\partial\phi(p)}{\partial p} < 0$, is it straightforward to show that the expected payoff of a firm conditional on a filled vacancy is increasing in the firm type. Multiplying both sides of (13) by $\frac{1}{\phi(p)}$, taking derivatives with respect to p and rearranging:

$$\left(\frac{\rho\left[1+\frac{\delta}{2}\right]}{\phi(p)}+\lambda\right)\frac{\partial V(p)}{\partial p} = \lambda\frac{\partial\left[\int_{M(p)}\pi(p,\epsilon)\frac{g(\epsilon)}{\phi(p)}d\epsilon\right]}{\partial p} + \frac{\rho[1+\frac{\delta}{2}]}{\phi(p)}V(p)\frac{\partial\phi(p)}{\partial p}.$$

Given that the left hand side is positive and the second term on the right hand side is negative,

$$\frac{\partial\left[\int_{M(p)}\pi(p,\epsilon)\frac{g(\epsilon)}{\phi(p)}d\epsilon\right]}{\partial p} > 0.$$

Therefore, if $\frac{\partial\phi(p)}{\partial p}$ is negative or slightly positive, the average profit per worker at the firm level could be used to rank firms. Aggregated profits are robust to $\frac{\partial\phi(p)}{\partial p} < 0$ and profit per worker are robust to $\frac{\partial\phi(p)}{\partial p} < 0$. Without taking a stance on the sign of $\frac{\partial\phi(p)}{\partial p}$, in Section 5 we use both measures of expected profits. We find very similar results, irrespective of the measure of profits used.

However, it could be the case that $\frac{\partial\phi(p)}{\partial p}$ is positive or negative only in some region of the support of p.[40] Therefore, we could only guarantee that the aggregated profits or profit per worker are a correct index of firms in some region of the support of p. In order to check that a change of the sign of $\frac{\partial\phi(p)}{\partial p}$ does not drive our results, we estimate our test splitting the sample in 8 sub-samples: 4 sub-samples according to quartiles of the distribution of aggregated profits and four sub-samples according to quartiles of the distribution of profit per worker. In each sub-sample we re-estimate our test using aggregated profits and profit per worker to order firms. The results are presented in Table A1. Although these results are less precise than in previous exercises, we find a

[40] If $\frac{\partial\phi(p)}{\partial p} = 0$ both aggregated profits and profit per worker are increasing in the firm type.

positive correlation between the probability of moving up in the productivity ladder and the wage within the firm, which also suggests the existence of PAM for every sub-group of firms.

Table A1: Local Sorting

LOGIT	(1)	(2)	(3)	(4)
	Average Aggregated Profits			
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
(1)	$y = \mathbb{1}$(Profit of the New Firm $>$ Profit of the Old Firm)			
Log-wage	0.175	0.431	0.292	0.217
	(0.115)	(0.111)	(0.095)	(0.095)
Observations	12,350	12,616	22,146	16,709
(2)	$y = \mathbb{1}$(Profit p/w of the New Firm $>$ Profit p/w of the Old Firm)			
Log-wage	0.060	0.406	0.160	0.231
	(0.117)	(0.106)	(0.097)	(0.095)
Observations	11,572	13,225	13,203	20,685
	Average Aggregated Profits per Worker			
	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
(1)	$y = \mathbb{1}$(Profit of the New Firm $>$ Profit of the Old Firm)			
Log-wage	0.198	0.278	0.217	0.016
	(0.096)	(0.105)	(0.117)	(0.105)
Observations	14,932	12,676	14,007	16,709
(2)	$y = \mathbb{1}$(Profit p/w of the New Firm $>$ Profit p/w of the Old Firm)			
Log-wage	0.089	0.359	0.231	0.021
	(0.111)	(0.123)	(0.133)	(0.523)
Observations	13,359	10,740	12,568	15,085

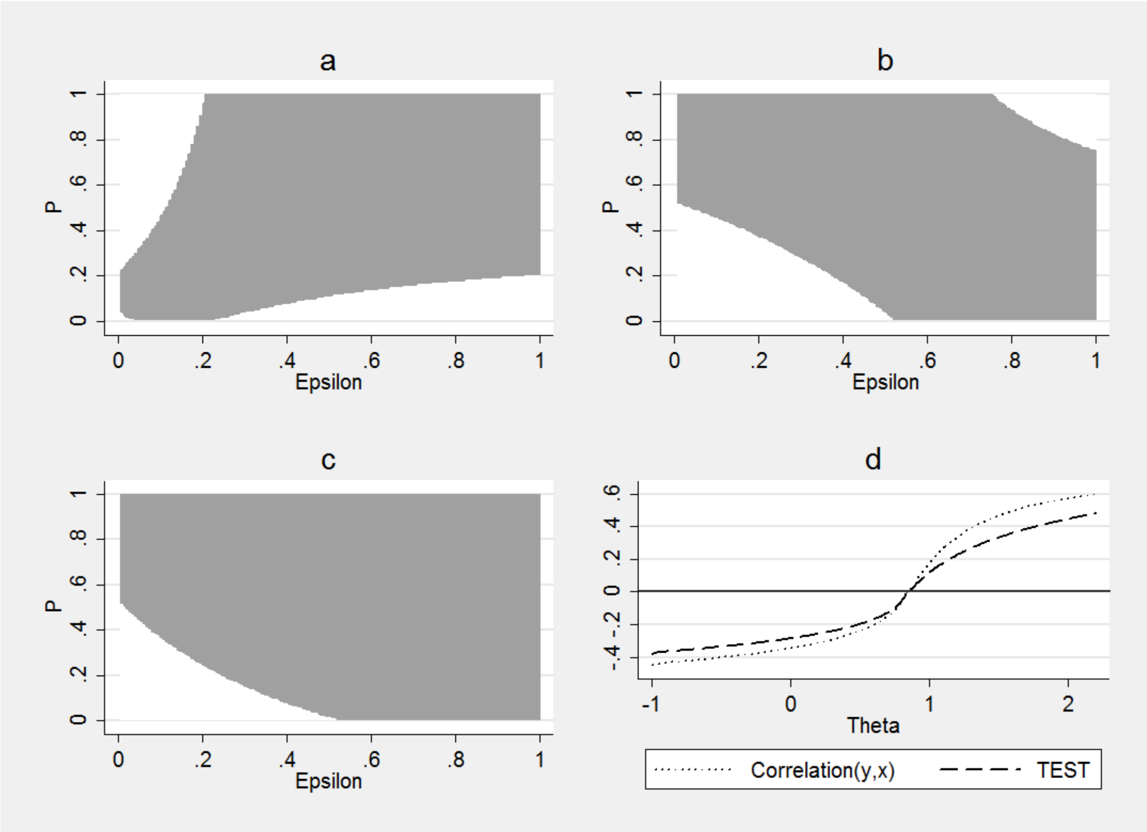
The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Profits are defined as $\Pi_{j,t} = Y_{j,t} - M_{j,t} - w_{j,t}L_{j,t} - 0.1 \times K_{j,t}$. Each coefficient comes from a single regression. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Firms fixed effects are included in every specification. Standard errors in parentheses.

A.2.1 Performance of the Test

As anticipated in Section 3.3, a model with discounting complicates the analysis because some production functions generate non-convex matching sets. In this case, we can only show formally that, when the bounds of the acceptance sets are increasing, our test indicates the presence of PAM and, on the other hand, when the bounds of the acceptance sets are decreasing, our test indicates the presence of NAM. However, using simulations we show in this section that our test of sorting, which is feasible with available matched employer-employee data-sets, provides the same information than an ideal, but unfeasible test of sorting as the correlation between types. Figure 2 presents simulations of the model described in Shimer and Smith (2000) for different production functions generating different sorting patterns.

The production function used to calculate the acceptance sets presented in Figure 2 is $f(\epsilon, p) = \epsilon + p + \theta\epsilon p$. In panel a, $\theta = 2$; then $f(\epsilon, p)$ is supermodular and the allocation of workers to firms is positively assortative. As expected, both the $correlation(\epsilon, p)$

Figure 2: Examples of Assortative Matching

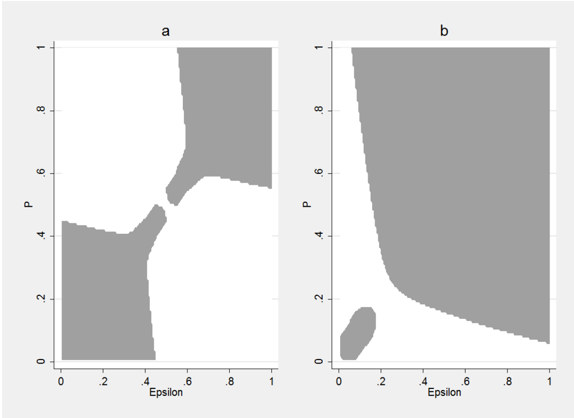


Panels a, b and c depict acceptance set for $f(p,\epsilon) = \epsilon + p + \theta\epsilon p$ with $\delta = r$, $\lambda = 100r$ and ϵ and p are uniformly distributed between 0 and 1 . In panel a, $\theta = 2$. In panel b, $\theta = -1$. In panel c, $\theta = 0$. In panel d we show the performance of our test, and the covariance between ϵ and p in equilibrium, for values of $\theta \in [-1, 2.2]$.

and our test of sorting are positive. In panel b, $\theta = -1$; hence $f(\epsilon, p)$ is submodular and the allocation of workers to firms has negative assortative matching, as indicated by our test and the correlation between ϵ and p. The production function used to calculate the acceptance sets depicted in panel c is modular ($\theta = 0$). According to our test and the correlation between types, the allocation of workers to firms has also negative assortative matching. In panel d we show the performance of our test and the correlation between types for different values of θ. We observe that our test conveys exactly the same information than the $correlation(\epsilon, p)$. For $\theta < 0.85$, the distribution is negatively assortative. For $\theta = 0.85$, every ϵ accepts every p and then both our test and the $correlation(\epsilon, p)$ are zero, indicating the absence of sorting. For $\theta > 0.85$, the allocation of ϵ and p has positive assortative matching and both our test and the $correlation(\epsilon, p)$ are positive.

Figure 3 replicates examples of the non-convex matching sets presented in Shimer and Smith (2000). Panel a presents the acceptance set for $f(\epsilon, p) = (\epsilon + p - 1)^2$. This production function is supermodular and the allocation of workers to firms is positively assortative *on average*: the correlation between types is positive and significant

Figure 3: Non Convex Matching



Panel a depicts matching set for $f(\epsilon, p) = (\epsilon + p - 1)^2$ with $\delta = r$, $\lambda = 100r$. Panel b for $f(\epsilon, p) = (\epsilon + p)^2$ with $\delta = r$, $\lambda = 35r$. In both panels ϵ and p are uniformly distributed between 0 and 1. This figure replicates Figure 3 in Shimer and Smith (2000). Although there is not sorting according to the definition in Shimer and Smith (2000) in both examples our test and the $correlation(\epsilon, p)$ indicate positive assortative matching on average.

($corr(\epsilon, p) = 0.82$). Our test also concludes that there is PAM: the correlation between the probability of moving up the firm productivity ladder and the worker type is 0.44. Panel b presents the acceptance set for $f(\epsilon, p) = (\epsilon + p)^2$. Although the acceptance set is not convex and then there is no sorting according to Shimer and Smith (2000), the allocation of workers to firms is also positively assortative on average: the correlation between types is positive and significant ($corr(\epsilon, p) = 0.33$). Our test also concludes that there is PAM, being the correlation between the probability of moving up and the worker type equal of 0.24.[41]

A.3 Additional Robustness Checks

A.3.1 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. 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.

The results are presented in Table A2, where we also find 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

[41] The code to replicate this exercise is available at *https://sites.google.com/site/cristianbartolucci.*

Table A2: Within-Firm Wage Quantiles

LOGIT	(1)	(2)	(3)	(4)	(5)	(6)
	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)
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. Controls for gender, age, age squared, migration status, tenure, tenure squared, year and occupation are included in all regressions. Firms fixed effects are included in every specification. Standard errors in parentheses.

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.

A.3.2 Different definitions of Profits: Gross Operating Margin and Accounting Profits

With the next set of estimates, we investigate the robustness of the results to the different definitions of profits used in the literature. A standard one is the gross operating surplus (GOS), defined as:

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

In Table A3 firm quality is alternatively defined in terms of 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 results support our previous finding of PAM. We do not observe significant differences in terms of fit with respect to the main specifications where we use economic profits.

An alternative measure of profits, which takes into account taxes and financial costs, is the after-tax accounting profits (AP), defined as:

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

As before, we consider six different specifications, using accounting profits or accounting profits per worker, their longitudinal averages and their past longitudinal average. The results, collected in Table A4, are consistently suggestive of PAM.

Table A3: Different definitions of Profits

LOGIT	(1)	(2)	(3)	(4)	(5)	(6)
	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)
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. Firms fixed effects are included in every specification. Standard errors in parentheses.

Table A4: Different definitions of Profits

LOGIT	(1)	(2)	(3)	(4)	(5)	(6)
	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)
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. Firms fixed effects are included in every specification. Standard errors in parentheses.

A.3.3 Differences in Occupation

Ideally, our test of sorting should be based on observing the labor market movements of workers who, prior to the move, are doing exactly the same type of job in the firm. In the previous tables, we have always included broad occupation categories (blue collar, white collar and managers), and in Table A6 we have also considered separate models for each of these occupation groups. PAM was confirmed in all cases. However, one concern with these estimates is that our occupational controls may be too broad, and one may wonder whether our results are robust to a more refined way of controlling for different jobs within the firm. While detailed occupation classification such as ISCO is missing in our data set, we can use the detailed information on "job ladders" (livelli di inquadramento) within each industry-wide collective national contract to construct a more precise classification of jobs within firms. Notice that each national contracts specifies its own job-ladder[42], and stipulates minimum wages for each of these levels. Clearly, these job ladders cannot be compared across different firms (who might be applying different national contracts), but within firms the ladder codes can be used to identify workers doing similar jobs. Hence, we have constructed dummies identifying the workers who, in any given firm, are employed under the same national contract and job ladder code. We have then run our test including these more refined controls for occupation, instead of the firm dummies as in the previous tables. The results are shown in Table A5, for both average profits and average profit per worker. Columns (1) and (2) show the results of linear probability models that absorb a large number of effects by firm$\times$(national contract)$\times$(job ladder), while in columns (3) and (4) considers linear probability models absorbing firm$\times$(national contract)$\times$(job ladder)$\times$year effects. Despite the considerable drop in the number of movers that can be observed within each type of job, as low as 5% in column (3), the results strongly corroborate PAM, and delivers similar magnitude as in previous tables.

Table A5: Controlling for Detailed Occupation Categories

	(1)	(2)	(3)	(4)
	Linear Probability Model			
$y = \mathbb{1}\,(\text{next }\Pi > \text{current }\Pi)$	Profit	Profit per worker	Profit	Profit per worker
Log wage	0.0239	0.0407	0.0302	0.0544
	(0.0076)	0.0077	0.0123	0.0116
Firm$\times$Occupation effects	yes	yes	yes	yes
Firm$\times$Occupation$\times$year effect	no	no	yes	yes
Observations	129,471	128,433	75,708	82,312
Avg. No. of Movers	9.25	9.69	5.33	5.82
Pseudo R^2	0.2174	0.2210	0.2033	0.1346

The dependent variable is a dummy that takes a value of one if the worker switches to a firm with higher profits. Each column represents a single regression. Controls for gender, age, age squared, migration status, tenure, tenure squared and year are included in all regressions. Standard errors in parentheses. The average number of movers is computed at the firm-occupation cell in columns (1) and (2), and at the firm-occupation-year cell in columns (3) and (4).

[42] Typically, there are 7 to 9 levels in each job ladder

A.4 Additional Tables

Table A6: Different Groups of Workers and Firms

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	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
(1)	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)
(2)	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)
(3)	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)
(4)	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)
(5)	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)
(6)	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)
(7)	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)
(8)	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. Firms fixed effects are included in every specification. Standard errors in parentheses.

Table A7: 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