Identifying Sorting in Practice*

Cristian Bartolucci
Collegio Carlo Alberto

Francesco Devicienti
University of Torino and Collegio Carlo Alberto

May 2011 - Preliminary

Abstract

Eeckhout and Kircher (2011) argue that using wage data alone, it is virtually impossible to identify whether assortative matching between worker and firm types is positive or negative. This paper proposes to use workers mobility to identify the sign of assortative matching. In order to understand the nature of sorting, we directly analyze the matching process between firms and workers. In the absence of assortative matching we should observe that the probability that workers leave a firm to go to a firm of different quality is independent of the worker type. 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. We only assume that agents' payoffs are partially monotone on their types, which allows us to use within firm variation on wages to order workers. While we index the quality of the firm by its profits. We use a matched data set that combines administrative earnings records for individual employees with detailed balance sheet data for their employers in the Veneto region of Italy. We find strong evidence of positive assortative matching. Better workers are found to have higher probability to move to better firms.

1 Introduction

In this paper we are interested in the measurement of assortative matching between firms and workers. In order to measure the existence and the direction of sorting,

*We thank Stephane Bonhomme, Jan Eeckhout, Claudio Michelacci and Nicola Persico for helpful comments. We are also extremely grateful to Giuseppe Tattara for making available the dataset and to Marco Valentini and Carlo Gianelle for assistance in using it.

we analyze mobility of workers across firms. The intuition is that in the absence of assortative matching we should observe that the probability that workers leave a firm to go to a firm of different quality is independent of the 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. Our measures of sorting are robust to wages non-monotone on the firm type, which is the main criticism to the existing measures.

It is controversial to empirically define the firms and workers types. There is only agreement in the statements that given the worker type, better firms should produce more and given the firm type, better worker should also produce more. There are many characteristics that might affect agents productivity. The worker type is in general an unknown function of the worker cognitive skills but also other soft skills such as her ability to communicate or her ability to work in teams. Likewise, the firm type is a one dimensional index that collapses information on many firm characteristics; such as the firm technology, its market power or managerial skills of its CEO. One of the advantages of the identification strategy presented in this paper, is that it does not require cardinal measures of workers and firms types. We only require measures that under some conditions, allow us to order agents by their types.

To order workers according to their types is straightforward in this context. As we use mobility of workers across firms as the dependent variable, we can use wages to index worker quality. Although there is a firm component in the wage, this firm effect is held constant by exploiting variation in wages of coworkers. If wages are partially monotone on the worker type, within the firm a better worker should have a better wage. Therefore, if workers with higher wages than their coworkers have higher probability of moving to firms of different quality, there is evidence of assortative matching.

To index firms, we use firm's profits. The convenience of having information on the firm's output or profit to characterize the firm type has already been mentioned before, see for example Eeckhout and Kircher (2011). That for a given worker type the firm profit is monotone on the firm type is generally acknowledged. But the problem is that in practice output and profit measures are usually only provided at the firm level, and attributing them to each individual worker is difficult. In this paper we show that for multi-worker firms, only assuming that profit are partially monotone on the firm type and that workers and firms are distributed in the data according to a steady state equilibrium distribution, expected profits of the firm are monotone on the firm type.

The last essential assumption for identification is that the steady state equilibrium joint distribution of workers and firms implies some mismatches. If workers are always in their optimal firm type, identification of sorting may be complicated because both sources of heterogeneity contain the same information, and are then empirically indistinguishable. As in Eeckhout and Kircher (2011) we use a broad definition of mismatch. Without specifying how matches are created and destroyed. We start from the premise that mismatches are observed occasionally, and that some mechanism moves workers and firms toward the optimal allocation. This gives additional variation that is crucial for identification. This concept of worker mismatches has a close connection to the mismatch that occurs in search models with on-the-job search. A worker coming from unemployment is going to accept an offer from a firm that provides him a value as good as the value of the unemployment. This firm will not necessarily be the optimal firm given the worker type. If this is true, the worker may continue searching on-the-job and occasionally he will move in the direction of the optimal allocation. Movements as the latter one, generate the variation in the data used in this paper to identify the direction of assortative matching.

Assortative matching between firms and workers generates two kinds of questions intrinsically related. The first question is positive and addresses the existence and the direction of an association between workers and firms types. The second one is normative and is related with the economic implications of sorting as for example: How large are the gains from matching workers to the appropriate firm. The second kind of questions, which are more relevant from an economic perspective, are hard to answer without a model. They aim to produce policy recommendation and, therefore they need to calculate counterfactual scenarios. In order to design a model to answer normative questions we first need to understand the nature of sorting, that is to know the strength and the direction of this association.

If one of the purposes of the positive question is to provide insights on modeling the matching process, it is prudent to use an empirical strategy as flexible as possible. This is because the empirical strategy should be consistent with mechanisms able to generate different patterns of sorting. There are many modeling assumptions that in one direction or in the other, shape the matching process, such as: supermodular or submodular production function, type dependent or type independent value of the vacancy, type dependent or type independent unemployment flow utility, search effort and search cost, among others. The approach presented in this paper is as agnostic as possible in terms of the labor market model that generates the data. It takes no stance on the possible mechanisms that are driving sorting. It only assumes few general assumptions that are: (i) Partialling out the firm component in the wage, better workers have better wages (*ie:* it requires partial monotonicity of wages in the worker type, but not monotonicity of wages on the firm type). (ii) Better firms are able to obtain higher profits (*ie:* it requires partial monotonicity of profits in the firm type). (iii) There is some mechanism in the labor market that generates mismatches and transitions of workers across firms.

We use a unique matched data set that combines administrative earnings records for individual employees with detailed balance sheet data for their employers in the Veneto region of Italy. This dataset is specially valuable in our application because it contains the universe of incorporated business in this Italian region but also information on every single employee working in these firms. We implement our test for the presence of assortative matching, finding strong evidence of positive assortative matching. Better workers are found to have higher probability to move to better firms. This result is remarkably robust to different specification of the conditional probability model, different definitions of firm profits and different group of workers.

The rest of the paper is organized as follows. Section 2 presents the related literature. The empirical strategy is described in Section 3. Section 4 presents the data. In Section 5 we show the results. In Section 6 we compare our results with results obtained using the AKM strategy. Section 7 offers a short conclusion.

2 Related Literature

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

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

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

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

Given AKM's shortcomings there have been some responses in the literature. Eeckhout and Kircher (2011) argue that using wage data alone, it is virtually impossible to identify whether Assortative Matching between worker and firm types is positive or negative. It proposes a method to measure the strength of sorting using information on the range of accepted wages of a given worker. The intuition behind their method is that if a worker is only willing to match with a small fraction of firms, for a given level of frictions (which can also be identified from the data) the complementarities must be large. Their strategy is elegant but its empirical feasibility is questionable. We first need panel data with long longitudinal dimension in order to capture precisely individual's range of wages. The within worker variation of wages, depends on complementarities on the production function but also on the primitive distribution of firm's types, productivity shocks, friction patterns and therefore to backup the strength of sorting from information on individual wage-gaps we need to make assumptions on the latter ones. Nevertheless, the measure proposed by Eeckhout and Kircher (2011) is an indicator of the presence of an association but not the direction.

In a recent paper, Lopes de Melo (2011), proposes a different strategy to measure the degree of sorting, based on the correlation between a worker fixed effect and the average fixed effects of his coworkers. Fixed effect estimates come from log-wage equation in the spirit of AKM. The paper shows that simulating a simple search model where positive assortative matching is driven by a supermodular production function and firm-type dependent values of vacancies, the proposed measure works better than the AKM correlation.[1] Although this measure is relatively easy to obtain from the data,

[1] The AKM measure of sorting does not perform well because the model generate a wage function that is non-monotone on the firm type. Nevertheless, the wage function is monotone on the worker type, the firm profit function is monotone on the firm type, and there are mismatches due to frictions.

as in Eeckhout and Kircher (2011), the worker-coworker measure of sorting cannot detect the "sign of sorting". The approach presented in this paper complements the strategies presented in Eeckhout and Kircher (2011) and Lopes de Melo (2011), in the sense that it, is not only able to measure the existence of sorting but also the direction of assortative matching.

A different strategy to measure assortative matching is to assume that all the information concerning the worker type is contained in a set of observable characteristics, such as age or education. If this is true, a measure of the firm type can be obtained through production function panel data estimation. The firm specific effect in the production function is informative about the firm type. This was proposed by Mendes, van den Berg and Lindeboom (2010). The latter paper, imposing a production function with fixed marginal productivity of each worker type, finds evidence of positive assortative matching.[2] Although this strategy is more natural, it has two main limitations. First, the estimation of production functions only using within firm variation, in order to partial out the firm fixed effect, is not generally trouble-free.[3] Moreover, the estimation of the production function could be more problematic if it allows enough flexibility to be consistent with any sign of the cross derivative between firms and workers types. Second, only a small fraction of the workers wage variation is explained by observable characteristics. There is strong evidence suggesting that observable characteristics are not sufficient statistics of workers unobserved fixed heterogeneity in wage regression.[4]

3 The Empirical Model

In order to describe the empirical strategy let us use the following notation. Every firm is characterized by its productivity (p). Let $\Psi(p)$ be the cumulative distribution function of p. Workers types are denoted by ϵ. The distribution of ϵ in the population of workers is $\gamma(\epsilon)$, with cumulative distribution function $\Gamma(\epsilon)$ and support $[\epsilon_{\min}, \epsilon_{\max}]$. We assume that workers and firms are distributed following an unknown steady state joint equilibrium distribution. That means that given the firm type there is an expected composition of workers. There might be assortative matching, therefore $\Gamma(\epsilon) \neq \Gamma(\epsilon|p)$. $\gamma(\epsilon|p)$ and $\psi(p|\epsilon)$ are assumed to be non degenerate, this condition means that there are mismatches, and therefore there is overlapping between the within firm equilibrium distributions of ϵ for firms of different types.

The productivity of the match (p, ϵ) is $f(p, \epsilon)$ and the wage, $w(p, \epsilon)$. As usual $\partial \frac{f(p,\epsilon)}{\partial p}\Big|_{\epsilon} > 0$, $\partial \frac{f(p,\epsilon)}{\partial \epsilon}\Big|_{p} > 0$. We assume that $\partial \frac{w(p,\epsilon)}{\partial \epsilon}\Big|_{p} > 0$, but $\partial \frac{w(p,\epsilon)}{\partial p}\Big|_{p} \gtreqless 0$. The latter inequality is because a firm with a higher p produce more but also might have higher outside option. If the difference in outside options is larger than the difference in output and the surplus remains positive, the worker transfers part of his utility to compensate a part of the loss. This is the basic mechanisms explained in Eeckhout and Kircher (2011) and in Lopes de Melo (2011).

Given that $\partial \frac{w(p,\epsilon)}{\partial \epsilon} > 0$, for fixed p, the higher the wage, the higher the worker type. Therefore, within the firm we can use wages to index the worker quality. Wages been

Therefore, the measure of sorting propose in this paper would perfectly hold.

[2]Note that in the presence of assortative matching, worker productivity depends on the firm type.

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

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

monotone in the worker type is a generally accepted assumption which most of the models used in the literature comply with. There are only few exceptions. Shimer (2005) proposes a model with directed search and ex post screening where wages could be non monotone in the worker type. The intuition is that a better worker may have a lower wage at a given firm being compensated by a higher probability of getting hired. Eeckhout and Kircher (2010) show that if there is negative assortative matching there could be decreasing wages for better workers in a model with directed search but without ex post screening.

Given the worker type, better firms have higher profits. Therefore if it exist a steady state equilibrium joint distribution of workers and firms, profits can be used to index firm quality. This can be shown noting that:

$$E(\pi(p,\epsilon)|p) = E(f(p,\epsilon)|p) - E(w(p,\epsilon)|p) \tag{1}$$

which is the same that

$$E(\pi(p,\epsilon)|p) = \int_{\epsilon_{min}}^{\epsilon_{max}} [f(p,\epsilon) - w(p,\epsilon)]\, d\Gamma(\epsilon|p) \tag{2}$$

By the Leibniz integral rule:

$$\frac{\partial E(\pi(p,\epsilon)|p)}{\partial p} = \int_{\epsilon_{min}}^{\epsilon_{max}} \partial \frac{\{[f(p,\epsilon) - w(p,\epsilon)]\, \gamma(\epsilon|p)\}}{\partial p} d\epsilon \tag{3}$$

In order to index the firm's quality, p, by the firm's profit, we need to show that the derivative of the expected profits with respect to p is positive. Assuming that $\partial \frac{\pi(p,\epsilon)}{\partial p}\Big|_{\epsilon} > 0$, we can show that (3) is higher than zero rewriting (3) as

$$\frac{\partial E(\pi(p,\epsilon)|p)}{\partial p} = \int_{\epsilon_{min}}^{\epsilon_{max}} \partial \frac{[\pi(p,\epsilon)]}{\partial p} \gamma(\epsilon|p) d\epsilon + \int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p,\epsilon)] \partial \frac{\gamma(\epsilon|p)}{\partial p} d\epsilon \tag{4}$$

The first term in right hand side of 4 is positive. This means that for every worker ϵ working in a firm p (*ie:* $\gamma(\epsilon|p) \neq 0$), the derivative of the profit function with respect to p is positive.

The second term in the right hand side of 4 is more delicate but it can be shown to be positive. Compare two firms, p and p^+, where $p < p^+$. The output that a worker ϵ produces in firm p^+ is higher than the output than the same worker produces in p. We know that for a given ϵ, if a worker was feasible for p, meaning that he produces enough to generate a positive surplus, the same worker is going to be attainable for p^+, in the sense that if the firm offers the same wage to the worker, the firm is obtaining more than before, and the worker is as happy as it is with p. It may be the case that for the firm p^+ is not profitable to have that worker, due to its different value of a vacancy, but if the firm p^+ does not hire the worker is in its own interest. On the other hand, if a worker was working in p^+, is not necessarily true that he is attainable for p, because as $f(p,\epsilon) < f(p^+,\epsilon)$ we cannot guarantee that p is able to pay $w(p^+,\epsilon)$. Therefore there might be some worker which are happy to work in p^+ but not in p. Formally, as $f(p^+,\epsilon) - w(p^+,\epsilon) > 0$ for every ϵ with $\Gamma(\epsilon|p^+) > 0$:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+,\epsilon) - w(p^+,\epsilon)\right] d\Gamma(\epsilon|p^+) > \int_{\epsilon_{min}}^{\epsilon_{max}} \left[f(p^+,\epsilon) - w(p^+,\epsilon)\right] d\Gamma(\epsilon|p) \tag{5}$$

Which is the same that:

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

When p^+ converges to p:

$$\int_{\epsilon_{min}}^{\epsilon_{max}} [\pi(p^+,\epsilon)]\partial\frac{\gamma(\epsilon|p)}{\partial p}d\epsilon > 0 \tag{7}$$

Therefore, assuming that the firm's profits are only partially monotone on the firm type, firms profits are going to be monotone in the firm type. If this is true, we can use firm's profits to order firm according to their types.

Under these conditions, the identification of sorting is straightforward. We basically aim to estimate the within-firm effect of wages on the probability of observing a job-switcher moving from a firm j to a firm with better quality than j. We estimate the following equation on a sample of movers:

$$Prob(move\ to\ \pi^+|p_j, movement) = wage'_{i,j}\gamma + \eta_j + u_i \tag{8}$$

where π^+ is the profit of the new firm, and π_j is the profit of the current firm, $\pi^+ > \pi_j$, $wage_{i,j}$ is the wage of the worker i in firm j, η_j is the firm j effect, in order to exploit only within-firm variation. Note that the dependent variable is the mean of an indicator function that takes the value one if the worker moves to a firm with better quality than the current one and zero if the worker moves to a firm with worse quality than the current one.

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

4 Data

The data set used in the paper was obtained by Card, Devicienti and Maida (2010) by combining information from two main types of information: individual labor market histories and earnings records, and firm balance sheet data. The job histories and earnings data were derived from the Veneto Workers History (VWH) dataset, constructed by a team leaded by Giuseppe Tattara, at the University of Venezia 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).[5] Specifically, it includes register-based information for any job that lasts at least one day. On the employee side the VWH includes total earnings during the calendar year for each job, the number of days worked during the year, the code of the appropriate collective national contract and level within that contract (i.e., a "job ladder" code), and the worker's gender, age, region (or country) of birth, and seniority with the firm. On the employer side the VWH includes industry (classified by 5-digit ATECO 91), the dates of "birth" and closure of the firm (if applicable), the firm's location, and the firm's national tax number (*codice fiscale*).

Firm-level balance sheet information was obtained from AIDA (*analisi informatizzata delle aziende*), a database distributed by Bureau Van Dijk that includes information for incorporated non-financial firms in Italy with annual sales of at least 500,000

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

Euros.[6] AIDA contains the official balance sheet data for these firms, and is available starting in 1995. The AIDA data include sales, value added, total wage bill, capital, the total number of employees, industry (categorized by 5-digit code), and the firm's tax number.

Tax code identifiers are used to match job-year observations for employees in the VWH to employer information in AIDA for the period from 1995 to 2001. Additional checks of business names (*ragione sociale*) and firm location (firm address) in the two data sources were carried out to minimize false matches. As reported by Card et al. (2010), the match rate was relatively high: for about 95% of the AIDA firms it was possible to find a matching firm in the VWH.[7] The characteristics of our initial sample - potential matches between VWH and AIDA - is reported in column 1 of Table 1. Over the 1995-2001 period, the matched data contains about 850,000 individuals aged 16-64 who were observed in about 3 million job spells at about 12,000 firms.[8] On average 29% of workers in the sample are female, 20% are white collars and a tiny minority, about 1%, are managers. The mean age is 35, mean tenure is 8.5 years and the mean daily wage was 69 Euros. While the median firm size is 69, the presence of a small number of relatively large firms raise the mean at 190 employees.

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

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

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

The literature on capital investment in Italy suggests that during the mid-to-late 1990s a reasonable estimate of the user cost of capital (r_t) is in the range of $8 - 12\%$. Elston and Rondi (2006) report a distribution of estimates of the user cost of capital for publicly traded Italian firms in the 1995-2002 period, with a median of 11% (Elston and Rondi, 2006, Table A4). Arachi and Biagi (2005) calculate the user cost of capital, with special attention to the tax treatment of investment, for a panel of larger firms

[6]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).

[7]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.

[8]These represent about 10% of the total universe of firms contained in the VWH. The vast majority of the unmatched firms are non-incorporated, small family business (*societa' di persona*) that are not required by existing regulations to maintain balance sheets books, and are therefore outside the AIDA reference population. The average firm size for the matched sample of incorporated businesses (about 200 employees) is therefore substantially above the average for all firms (incorporated plus non-incorporated businesses) in the VWH (7.0 employees). Mean daily wages for the matched sample are also higher than in the entire VWH, while the fractions of female and younger workers are lower. See Card et al. (2010) for further details.

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).[9] We assume that r_t is at 10% in the estimation reported below. As we show below, the results are not dependant on any particular profit definition. Four additional profitability measures from the firm's profit and loss report are reported in Table 1: gross operating surplus (GOS):

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

after-tax accounting profits (AP):

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

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

From the set of potential matches we made a series of exclusions to arrive at our estimation sample. First, we considered only those workers who - at any time within the 1995-2001 period - switched employer. 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).[10] We also eliminated unusually high wages by dropping wages higher than the top 1% of the overall wage distribution.

Column 2 of Table 4 reports the characteristics of the job-switcher sub-sample that we use in the estimation of equation (8). 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 the overall sample (mean age in column 2 is 31), have lower tenure (less than 3 years) and earn comparatively less than the rest of the population (62 euro daily). The percentage of female, white collars and managers is 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 to a new one. The median of this variable (labeled "lag" for short) is only 2 months. However, reflecting the existence a relatively large fraction of long-term unemployed, the mean lag is at 7.7 months.

5 Results

The model imposes very few restrictions on the data generating process. Consequently, it is a very general model that says little on the empirical counterpart of equation 8.

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

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

Table 1: Descriptive Statistics

	VWH - AIDA	
	Complete Sample	Movers sample
no. Job*year obs	3,088,113	214,588
no. individuals	838,619	166,192
no. firms	12,013	11,030
mean age	35.2	31.1
% female	29.3	27.1
% white coll	29.6	25.4
% manager	1.1	0.3
mean tenure (months)	102.5	36.5
mean wage	69.4	61.7
mean log wage	4.12	4.05
mean lag (in months)		7.7
median lag		2.0
mean firm size	191	209
median firm size	69.0	67
mean profit*	3612.0	3871.9
mean profit p.w.*	14.9	13.9
mean GOS*	2781.9	2829.5
mean GOS p.w.*	11.4	9.8
mean account. profit*	1245.8	1091.3
mean acc. profit p.w. (after tax)*	4.1	1.6

Note: * 1000's of real euros

The model is obviously incomplete as every stylized model, and hence, it seems prudent to include a set of observable characteristics of the worker and the firm to *control* for other confounding mechanisms.[11] Therefore, on a sample of movers we estimate the following conditional probability model:

$$Prob(move\ to\ \pi^{+}|p_j, movement) = x'_{i,j}\beta + wage'_{i,j}\gamma + \eta_j + u_i \tag{9}$$

where $Prob(move\ to\ \pi^{+}|p_j, movement)$ is the probability that an employee i who was working in a firm j, moves to a firm better than j conditioning on a movement. $wage_{i,j}$ is the wage that the worker receives in the firm j. η_j is a firm effect in order to partial out between firm variation. $x_{i,j}$ are characteristics of the worker i and her job in the firm j. $x_{i,j}$ includes measures of the worker age, age squared, tenure, tenure squared, time dummies and indicators for females, migrants, blue collar, white collars and managerial occupations. Table 2 shows the results obtained when firm quality is defined in terms of economic profits. In column 1 the dependent variable is a dummy 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). Workers may have been able to observe the evolution of profits over time and base their search and matching behavior according to firms' time averaged profits. In column 2 the same dummy is therefore defined in terms of average profits, computed

[11]There are many worker characteristics that might affect wages and worker mobility, such as age, gender or migration status.

as:

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

Note that in column 4 only past profits are used to compute average profits, namely:

$$AvProfit_{j} = \frac{\Sigma_{t=1}^{T}\pi_{j,t}}{T}$$

Finally, columns 3 and 5 consider average profit and average profit per worker, respectively. The LOGIT estimates of columns 1-5 show that the log wage has a positive and significant impact on the probability of the worker moving to a firm with higher profits, no matter the definition of profit we refer to. This implies PAM: better workers are more likely to move to better firms.

Table 2: Different definitions of Firm Quality

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

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

The models that use average profit and average profit per worker as a measure of firm quality have a significant better fit of the data than the altertative 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 idyosincratic shocks to productivity. In the presence of shocks to productivity, the average profit is a more stable function of the time invariant firm type. This is because the variance of the average shock is of order $1/T_j^2$ than the variance of the idyosincratic shocks.[12]

Note that there appears to be some heterogeneity in the conditional probability of moving to a better firm for workers belonging to various sub-groups, although in many

[12]Where T_j is the number of periods where the firm j is observed.

cases the impact of worker characteristics is not clearcut and is not always precisely estimated. After conditioning for wages, female and migrant workers seem to be less likely than the rest of workers to move to better firms. The effect of age and tenure is instead more dubious, with only very weak evidence that more mature and workers with a longer tenure are more likely to improve the quality of their employers.

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

5.1 Different Specifications of the Conditional Probability Model

In Table 3 firms' quality is defined in terms of current profit per worker, but different specifications of the probability model are compared. Wages are only an ordinal measure of the worker type. Any monotone transformation of wages is also a valid candidate to include in the regressions. Some transformations might imply a better fit of the data than others. Entering the wage in levels (as opposed to in logs) does not affect our main result: the coefficient remains positive and statistically significant (column 1).[13] Columns 2 and 3 compare PROBIT and LOGIT estimates, showing that the PAM result is robust to these alternative distributional assumptions. We next take on board a linear probability model, which allows us to show that the results are insensitive to partialling out wages at the firm level (i.e. inserting in the model firm fixed effect; column 4) as opposed at the firm *and* year level (i.e. using unrestricted firm*year fixed effects, as in column 5). Note that, as the combination of firm and year effect is very large (14,723), the average number of observations per firm-year cell is only 8.84. Therefore LOGIT or PROBIT would generate biased estimated due to the presence of incidental paramemeters; however, it is still possible to differentiate them out using the linear probability model.

5.2 Different Definitions of Movers

In the previous tables we have considered both job-to-job changes and job changes with an intervening spell of non-work. We are unable to distinguish between voluntary and involuntary separations in our data. However, given that we observe the number of months between one's separation from the current employer and association to a new employer, we can define job-to-job changers as those with no more than 1 month between the two jobs.[14] The results for the sub sample of job-to-job changers are shown in column 2 of Table 4. The remaining columns consider alternative definitions of movers, as detailed in the last row of the table: those with an intervening spell of up to three months (column 3), those with a spell up to six months (column 4) and those

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

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

Table 3: Different Specifications of the Probability Model

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

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

with more than six months of non-work before getting a new job (column 6). As before wages significantly increase the probability to move to a firm with higher profit per worker, and are therefore consistent with PAM. There are no major differences in the various definitions of movers, with the exception of those with a very long non-work spell: for those with a lag exceeding 6 months the wage coefficients is smaller, albeit still positive, and barely significant. This is perhaps not surprising given that the wage in the former employer becomes a noisier signal of the worker quality as the worker spends a long time out of work, or has (short) job experiences in sectors not covered by our data.[15]

5.3 Different Definitions of Profits

Our next set of estimates further investigate the robustness of the results to different definitions of profits. In Table 5 firm quality is alternatively defined in terms of gross operating surplus (GOS), GOS per worker. Average GOS and average GOS per worker

[15] As in many other social security data, the VWH data does not allow us to distinguish between unemployment and inactivity. Private sector workers who move to the public sector, self-employment or to the informal (black) sector will also be recorded as in non-work

Table 4: Different definitions of movers

LOGIT	(1)	(2)	(3)	(4)	(5)
	Definition of firm quality ($\pi_{j,t}$)				
$y = 1(\pi_{i,t+1} > \pi_{j,t})$	Current profits per worker	Current Profit per worker	Current Profit per worker	Current Profit per worker	Current Profit per worker
Log Wage	0.1155	0.1295	0.1278	0.1265	0.0157
	(0.0253)	(0.0376)	(0.0347)	(0.0329)	(0.0094)
age	0.0015	0.0029	0.0054	0.0035	-0.0013
	(0.0043)	(0.0080)	(0.0073)	(0.0068)	(0.0013)
age^2	$-.0002$	-0.0002	-0.0002	-0.0002	$8.18e^{-6}$
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	($1.79e^{-5}$)
Female	0.0584	-0.1110	-0.1224	-0.1220	-0.0062
	(0.0155)	(0.0256)	(0.0231)	(0.0215)	(0.0051)
Migrant	-0.0514	-0.0021	-0.0679	-0.0455	-0.0047
	(0.0218)	(0.0379)	(0.0332)	(0.0301)	(0.0072)
Tenure	0.0019	0.0011	-0.0013	0.0017	0.0003
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0001)
Tenure^2	-6.06e^{-6}	-3.54e^{-6}	-4.26e^{-6}	$-7.15e^{-7}$	-7.47e^{-6}
	($1.41e^{-6}$)	($2.02e^{-6}$)	($1.88e^{-6}$)	($1.79e^{-6}$)	($5.37e^{-7}$)
firm effects	yes	yes	yes	yes	yes
Observations	178,094	76,800	90,614	102,256	68,834
Number of firms	7,746	5,616	6090	6,397	4,976
Av. Movers per firm	22.99	13.68	14.88	15.98	13.83
Pseudo R^2	0.1732	0.2038	0.2033	0.2317	16.52
definition of switchers (lag)	$\in [0, \infty]$	$\in [0, 1]$	$\in [0, 3]$	$\in [0, 6]$	$\in (6, \infty)$

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

are also considered, using either the whole sequence of observed GOS or only GOS up to the time of the worker separation (see section 4 for details). The same set of estimates are reported in Table 6 but with reference to accounting profit measures (AP). In the appendix (Table A.1) we show that all these different measures of firm quality are positively correlated; however the range of the correlation coefficients (as low as 0.3 for some measures) suggest that they may convey non-redundant information. It is reassuring that in all these cases we find robust evidence of PAM.

5.4 Within Firm Regressions

We have only assumed that wages are partially monotone on the worker type. This assumption implies that within the firm, worker types can be indexed by their wages. In previous specification we have included a firm fixed effect in the conditional probability model in order to have wages relatives to the mean wage of every firm. It could be the case that other moments of the within firm distributions of wages are firm specific. For example in models with between firms Bertrand Competition and two-sided heterogeneity, such as Cahuc, Postel-Vinay and Robin (2006), the within firm variance and skewness are associated with the firm type. If this is the case, the effect of wages on the probability of a transition could be heterogeneous across firms. In Table (7) we show results obtained with within-firm regressions. In particular, we run linear probability models or LOGIT models firm-by-firm. In these specification every moment of the within-firm distribution of wages is allowed to be firm-type dependent.

Table 5: Different definitions of Profits

LOGIT $y = 1(\pi_{i,t+1} > \pi_{j,t})$	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
	Gross Operating Surplus	GOS per worker	Average GOS	Average GOS per worker	Past Av. GOS	Past Av. GOS per worker
Log-wage	0.154	0.102	0.231	0.184	0.236	0.186
	(0.03)	(0.029)	(0.032)	(0.031)	(0.031)	(0.03)
Age	0.014	0.0007	0.027	0.005	0.011	-.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age^2	-.0003	-.0001	-.0005	-.0002	-.0003	-.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.038	-.075	0.022	-.084	0.048	-.103
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
Migrant	-.152	-.051	-.162	-.046	-.147	-.069
	(0.03)	(0.03)	(0.032)	(0.032)	(0.031)	(0.031)
Tenure	0.0004	0.002	0.0005	0.002	0.0009	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-1.07e-06	-6.37e-06	-4.26e-06	-7.10e-06	-4.20e-06	-7.42e-06
	(1.83e-06)	(1.78e-06)	(1.98e-06)	(1.91e-06)	(1.92e-06)	(1.85e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	103,214	102,441	98,131	95,594	100,435	99,109
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
Lag	$\in [0, 6]$	$\in [0, 6]$	$\in [0, 6]$	$\in [0, 6]$	$\in [0, 6]$	$\in [0, 6]$

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

Estimation requires that we restrict ourselves to the subsample of relatively large firms where a minimum number of job changers can be observed (30 in our case). The estimated coefficients for each firm were then averaged across firms and reported in the table, along with the standard deviation of the average. Albeit we loose some precision in this exercise, the results are once more suggestive of PAM.

5.5 Within firm Wage Quantiles

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

Results are presented in Table 8. We observe that if we do not include the worker's wage but its quantile on the within firm distribution of wages, we also obtain evidence of PAM. The coefficient of the wage quantile is significantly positive in every specification, with the exception of Column (1) which uses aggregated economic profit as a measure

Table 6: Different definitions of Profits

LOGIT $y = 1(\pi_{i,t+1} > \pi_{j,t})$	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
	Accounting Profits	Accounting Profits per worker	Average AP	Average AP per worker	Past Av. AP	Past Av. AP per worker
Log-wage	0.156	0.126	0.063	0.058	0.124	0.097
	(0.029)	(0.028)	(0.032)	(0.031)	(0.031)	(0.03)
Age	0.0009	-.007	0.015	0.011	0.001	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age^2	-.0001	-1.00e-05	-.0004	-.0003	-.0001	-.0002
	(0.00009)	(0.00009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.016	-.030	0.004	-.051	0.019	-.048
	(0.021)	(0.02)	(0.023)	(0.022)	(0.022)	(0.021)
Migrant	-.112	-.062	-.108	-.089	-.097	-.099
	(0.03)	(0.03)	(0.032)	(0.032)	(0.031)	(0.031)
Tenure	0.0007	0.001	0.0003	0.002	0.001	0.002
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Tenure^2	-2.00e-06	-4.62e-06	-1.18e-06	-4.67e-06	-2.47e-06	-7.32e-06
	(1.80e-06)	(1.74e-06)	(2.02e-06)	(1.89e-06)	(1.91e-06)	(1.81e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	104,733	103,198	98,533	95,929	101,379	98,874
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
Lag	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$

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

of the firm quality. As noted before, when we use average profits or average profits per worker as a measure of firm quality, we generally get a better fit of the data and more stable results.

6 Discussion

6.1 Firm Fixed Effects and Worker Fixed Effects in Wage Equations

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

$$w_{i,j,t} = x'_{i,j,t}\beta + \eta_i + \xi_j + u_{i,j,t}, \tag{10}$$

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

The results are presented in Table 9. We find the standard result of a negative and significant correlation between the worker fixed effects and the firm fixed effects. It is surprising that using our approach we find significant evidence of PAM and using the AKM approach we find significant evidence of NAM. In the rest of this section we provides some insights on the potential mechanism that generates this difference.

Table 7: Within Firm Regressions

$y = 1(\pi_{i,t+1} > \pi_{j,t})$	(1)	(2)	(3)	(4)
	Profit per Worker			
	Linear Probability Model	LOGIT	Linear Probability Model	LOGIT
Log-Wage	0.058	4.125	0.060	0.651
	(0.022)	(2.550)	(0.015)	(0.170)
Age	0.003	-6.205	0.003	-0.637
	(0.003)	(1.951)	(0.002)	(0.189)
Age^2	-6.20e-5	0.087	-5.57e-5	0.009
	(5.17e-5)	(0.028)	(3.52e-5)	(0.003)
Female	-0.009	0.138	0.001	-0.039
	(0.011)	(0.113)	(0.008)	(0.052)
Migrant	-0.029	-0.018	-0.017	-0.125
	(0.011)	(0.081)	(0.008)	(0.048)
Tenure	0.0003	-0.167	0.001	-0.014
	(0.0004)	(0.067)	(0.0003)	(0.007)
Tenure^2	3.98e-6	0.003	-9.04e-6	0.001
	(1.03e-5)	(0.001)	(8.96e-6)	(0.0002)
Observations	47,459	47,459	107,110	107,110
Number of firms	713	713	1325	1325
Av. Movers per firm	66.56	66.56	80.84	80.84
definition of switchers (lag)	$\in [0, 6]$	$\in [0, 6]$	$\in [0, \infty]$	$\in [0, \infty]$

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

Both tests of assortative matching exploit similar variation in the data. The identification of both sets of fixed effects in the AKM approach is only based on workers who move across firms. But in addition, our test exploits data on firms' profits. Therefore the two tests are not nested.

One intermediate step that helps to understand the difference between our test and AKM's, is to use the measures of firm quality obtained from the equation (10), namely the estimated firm fixed effect, to perform our test of assortative matching. It is not clear under which assumptions the AKM measure of firm quality is going to be valid to perform this test,[16] but at this stage it is only used for illustrative purposes.

Results are presented in the Column (1) of Table 10. We find that wages are positively associated with the probability of moving to a better firm according the AKM metric of firm quality. This is not surprising if we consider that using our strategy we have found significant evidence of PAM. Under PAM better workers are working in better firms and therefore better firms pay better wages. We concequently expect a strong positive association between the firm type and the firm fixed effect $(ie : \xi)$ in this case.

In Column (2) of Table 10, we presente results where the woker fixed effect of AKM, η_i, is included in the mobility regression as a measure of the worker type instead of the worker wage. The coefficient of η_i is negative and significant. This result goes in

[16]Under NAM, best firms have worse workers and therefore they might also pay lower wages than bad firms. In the latter scenario, the average wage paid by the firm is not a monotone transformation of the firm type.

Table 8: Within firm Wage Quantiles

LOGIT	(1)	(2)	(3)	(4)	(5)	(7)
	Definition of firm Profit					
$y = 1(\pi_{i,t+1} > \pi_{j,t})$	Profit	Profit per worker	Average Profit	Average Profit per worker	Past Av. Profit	Past Av. Profit per worker
Wage Quantile	0.008	0.091	0.153	0.216	0.052	0.152
	(0.023)	(0.023)	(0.025)	(0.025)	(0.024)	(0.024)
Age	-.021	0.001	0.131	0.129	-.033	0.005
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Age^2	0.0002	-.00009	-.002	-.002	0.0004	-.0002
	(0.00006)	(0.00006)	(0.00007)	(0.00007)	(0.00006)	(0.00007)
Female	0.034	-.063	-.092	-.208	0.043	-.113
	(0.016)	(0.015)	(0.018)	(0.017)	(0.016)	(0.016)
Foreign	-.081	-.052	-.206	-.125	-.078	-.070
	(0.022)	(0.022)	(0.024)	(0.024)	(0.023)	(0.023)
Tenure	0.001	0.002	-.002	-.0003	0.0009	0.002
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Tenure^2	-2.20e-06	-5.92e-06	8.55e-07	-2.94e-06	-1.52e-06	-7.00e-06
	(1.45e-06)	(1.42e-06)	(1.58e-06)	(1.50e-06)	(1.50e-06)	(1.46e-06)
firm effects	yes	yes	yes	yes	yes	yes
Observations	177740	178144	175040	171782	175695	174517
No of firms	7,746	7,746	7,746	7,746	14,723	
Av. Movers per firm	22.99	22.99	22.99	22.99	8.84	
Pseudo R^2						
Switchers (lag)	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$	$\in [0,6]$

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

line with the negative covariance between η and ξ reported in Table 9. If the point made by Eeckhout and Kircher (2011) and Lopes de Melo (2011) is correct, equation (10) is misspecified and therefore η and ξ are wrongly measured. From this execise we learn that in our application this misspescification does not have important effects on the recovered measures of the firm type (ξ) but it significantly disturbs the recovered measures of the worker type (η). One potential reason to explain this pattern is the fact the firm is observed many more times than the worker, and therefore its fixed effects absorb the firm type but also the mean of the worker types working there.

6.2 Wages non monotone on the firm type

One of the potential explanations of the divergence in results, is the one proposed by Eeckhout and Kircher (2011) and Lopes de Melo (2011). They argue that if wages are non-monotone in the firm type, equation (10) is misspecified. There are good reasons to expect wages non-monotone on the firm type, such as limitations in the firms' capacity to post new vacancies.[17] In this subsection, we analyze whether workers that move to better or worse firms according to our metric of firm quality, receive higher or lower wages.

[17]Limitations to post new vacancies may be consistent with free entry. Note that if firms invest to acquiry its type, there might be ex-ante free entry with ex-post firm dependent value of vacancies.

Table 9: OLS estimates of equation(10)

AKM Approach

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

Results are presented in Table 11. Considering that our measure to orders firms by their quality is correct, we find strong evidence of non-monotonicity of wages in the firm type. There is an association between positive changes in firm type and positive changes in wages. But we observe a large number of worker moving to worse firms having better wages and workers that end in a better firm receiving lower wages.

6.3 Amenities

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

However, amenities might affect the AKM measure of sorting. This is due to the fact that firm quality is inferred from mean wages paid by the firm. To illustrate this point, consider to identical firms with different compensations strategies. One pays higher wages and lower level of amenities and the other one pays lower wages with higher level of amenities. The AKM approach would wrongly conclude that the first one is a better firm than the last one.

7 Conclusions

In this paper we propose a test to measure the strength and the direction of assortative matching between firms and workers. We analyze mobility of workers across firms, exploiting the fact that in the absence of assortative matching we should observe that the probability that workers leave a firm to go to a firm of different quality is independent of the 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

Table 10: Using ξ as the firm quality index

LOGIT	(1)	(2)
	$y = 1(\xi_{i,t+1} > \xi_{j,t})$	
Log-Wage	0.152	
	(0.026)	
η		-0.231
		0.032)
Age	-.139	0.141
	(0.005)	(0.005)
Age^2	0.0002	-.0020
	(0.00007)	(0.00007)
Female	-0.228	-.286
	(0.017)	(0.017)
Foreign	-.0203	-.227
	(0.023)	(0.023)
Tenure	0.002	-0.001
	(0.0003)	(0.0003)
Tenure^2	-2.25e-06	-2.12e-08
	(1.44e-06)	(1.43e-06)
firm effects	yes	yes
Observations	170,546	170,242
No of firms	7,393	7,392
Av. Movers per firm	23.07	23.03
Pseudo R^2	0.2373	0.2375
Switchers (lag)	$\in [0, 6]$	$\in [0, 6]$

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

data generating process. Our measures of sorting are robust to wages non-monotone on the firm type, which is the main criticism to the existing measures.

Our test does not require cardinal measures of quality of workers and firms. We only make the general assumption that the payoffs of the players are partially monotone on the players' types. If given the firm type, wages are monotone on the worker type, we can use within firm variation on wages, that by definition partials out the firm effect, to order workers by their type within the firm. While we show that assuming that profits are partially monotone on the firm type and that the equilibrium distribution of workers into firms is in steady state, we can use firm profits to order firms by their types.

We use a matched data set that combines administrative earnings records for individual employees with detailed balance sheet data for their employers in the Veneto region of Italy. We implement our test for the presence of assortative matching, finding strong evidence of positive assortative matching. Better workers are found to have higher probability to move to better firms. This is understood as evidence of positive assortative matching. This finding is remarkably robust to different definitions of firm quality, different definitions of movers and different specifications of the conditional probability model.

We replicate the AKM strategy in our data, and we find the standard result of a significantly negative correlation between firm's and worker's fixed effects from a log-wage equation. We also observe that a significant number of workers are moving to worse firms but receiving higher wages. This evidence goes in line with the mechanism described in Eeckhout and Kircher (2011) and Lopes de Melo (2011), and could be one of the reasons of the downward bias in the AKM measures.

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.

[4] Arachi, G. and F. Biagi (2005), "Taxation, Cost of Capital, and Investment: Do Tax Asymmetries Matter?"Gionale 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] Becker G.S. (1973), "A Theory of Marriage: Part I", The Journal of Political Economy, 81, No. 4, pp. 813-846.

[7] 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.

[8] Card, D., F. Devicienti and A. Maida (2010), "Rent-sharing, Holdup, and Wages: Evidence from Matched Panel Data ", NBER Working Paper No. 16192.

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

[10] Eeckhout, J. and P. Kircher, (2010) "Sorting and Decentralized Price Competition", Econometrica 78(2), pp. 539-574.

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

[12] Hause, J.C. (1980). "The one structure of earnings and the on-the-job training hypothesis", Econometrica, 48(4), pp. 1013-1029.

[13] Hellerstein, J., Neumark, D. (1998) "Wage discrimination, segregation, and sex differences in wage and productivity within and between plants, "Industrial Relations 37, pp. 232-260.

[14] Lillard, L. and Weiss, Y. (1979). "Components of variation in panel earnings data: American scientists 1960-1970", Econometrica 47(2), pp. 437-454.

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

[16] Lopes de Melo, R. (2011), "Sorting in the Labor Market: Theory and Measurement", Unpublished Manuscript.

[17] Meghir, C. and Pistaferri, L. (2004). “Income variance dynamics and heterogeneity”, Econometrica, 72(1), pp. 1-32.

[18] Mendes, R., G. van den Berg, M. Lindeboom, (2011) “An empirical assessment of assortative matching in the labor 0market”, Labor Economics, forthcoming.

[19] Nagypal, E. (2004), “Worker Reallocation: The Importance of Job-toJob Transitions”, Unpublished Manuscript.

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

[21] 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.

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

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

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

A Appendix

A.1 Additional Tables

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

	Profits per Worker					
	Any Movers		Job-to-Job Movers		Stable Jobs	
	Worse Wage	Better Wage	Worse Wage	Better Wage	Worse Wage	Better Wage
Worse Quality	49,381	55,467	19,981	26,257	7,752	12,032
%	47.1	52.9	43.21	56.79	39.18	60.82
Better Quality	47,680	70,905	21,186	34,633	9,086	15,854
%	40.21	59.79	37.95	62.05	36.43	63.57
Total	97,061	126,372	41,167	60,890	16,838	27,886
%	43.44	56.56	40.34	59.66	37.65	62.35
	Profits					
	Any Movers		Job-to-Job Movers		Stable Jobs	
	Worse Wage	Better Wage	Worse Wage	Better Wage	Worse Wage	Better Wage
Worse Quality	50,105	56,338	20,760	27,713	8,260	13,040
%	47.07	52.93	42.83	57.17	38.78	61.22
Better Quality	46,956	70,034	20,407	33,177	8,578	14,846
%	40.14	59.86	38.08	61.92	36.62	63.38
Total	97,061	126,372	41,167	60,890	16,838	27,886
%	43.44	56.56	40.34	59.66	37.65	62.35

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.

Table A1: Correlations between Different Measures of Profits

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