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High Wage Workers and High Wage Peers

Michele Battisti

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Abstract

This paper investigates the effect of co-worker characteristics on wages, measured by the average person effect of coworkers in a wage regression. The effect of interest is identified from within-firm changes in workforce composition, controlling for person effects, firm effects, and sector-specific time trends. My estimates are based on a linked employer employee dataset for the population of workers and firms of the Italian region of Veneto for years 1982–2001. I find that a 10 percent increase in the average labour market value of co-workers' skills is associated with a 3.6 percent wage premium. I also find that around one fourth of the wage variation previously explained by unobserved firm heterogeneity is actually due to variation in co-worker skills, and that between 10 and 15 percent of the immigrant wage gap can be explained by differences in co-worker characteristics.

JEL Code: J31, J79.
Keywords: Spillover effects, linked employer-employee dataset, skill segregation.

Michele Battisti
Ifo Institute – Leibniz Institute
for Economic Research
at the University of Munich
Poschingerstr. 5
81679 Munich, Germany
Phone: +49(0)89/9224-1324
battisti@ifo.de

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1 Introduction

It has long been hypothesised that externalities among people working together may be important (Marshall, 1890, p. 12). Understanding spillover effects among co-workers is important for our general understanding of the labor market. It is also likely to shed light on findings such as those of Abowd et al. (1999) that firms are important determinants of wage variation across workers, controlling for individual characteristics and type. This topic is increasingly important as firm segregation by worker characteristics rises (Kremer and Maskin 1996 and Hellerstein and Neumark 2008 for the US; Kramarz et al. 1996 for France; Lopes de Melo 2009a for Brazil; Bagger and Lentz 2008 for Denmark) and may play a role for the recent growth in wage inequality (Edin et al., 2008).

The issue of spillover effects in the workplace has attracted some interest among empirical economists. However, most of the existing research is based on small datasets and narrow economic sectors and tasks, and focuses on the effect of peers operating through effort and on the role of team production in specific firms.[1] Previous studies typically find that peer pressure and team-based work matter: observed effort levels are higher when a worker is paired with higher-productivity individuals. The reason for the scarcity of results on the labour market as a whole is related to the complexity of statistically identifying spillover effects, which generates steep data requirements. First, workers in the same firm tend to have similar wages even in the absence of social interactions because they share similar characteristics and because they operate in the same environment, which can generate an upward bias in the estimated of peer effects. This suggests that spillover effects ought to be estimated from changes in workforce composition within firms, for which we need a panel dataset. Secondly, some of the relevant co-worker characteristics may be unobserved to the econometrician, and their exclusion might generate a downward bias of the estimate of the role of

[1] Using panel data from 20 steel mills, Boning et al. (2007) investigate the effects of the adoption of problem-solving teams, and find a significant positive effect on productivity. More recently, Chan et al. (2012) focus on a different question and investigate the role of compensation schemes on peer effects and on the level of cooperation inside the firm, using data from a Chinese department store. Hamilton et al. (2003) investigate the effect of group composition on the productivity of teams using data from a garment plant, and find evidence of large and heterogenous spillover effects. Bandiera et al. (2009) focus on the effects of social connections between workers and managers on productivity using data from a soft fruit picking farm. They find that social connections increase the productivity of workers. Ichino and Maggi (2000) look at the role of social interaction for shirking behaviour in a large Italian bank, and find group interactions to be very important. On the other hand, Guryan et al. (2009) test for the presence of peer effects in productivity using a dataset of professional golf players, and find no evidence of significant peer effects in that context.

spillovers in the labour market.

Until recently, virtually all observational data on the labour market were individual surveys, household surveys or population censuses, making it impossible to link firm's characteristics and characteristics of co-workers to any specific worker. Recently, the advent of linked employer-employee panel datasets (LEED), which include information on many workers inside the same firm and follow the same workers over time, made it possible to investigate spillover interactions within firms and to account for the role of unobservables, which is the main goal of this paper.

A stream of literature has emerged in recent years from the availability of LEEDs focusing on the role of labour market networks on the diffusion of information across workers. For a great example and for references to other constributions see Cingano and Rosolia (2012), who focus on the role of employment status of former colleagues on unemployment duration. To the best of my knowledge there are only two other studies that estimate wage spillover effects in the workplace using a representative sample of workers and a comprehensive measure of co-worker skills,[2] and both have important methodological limitations relative to this paper. Shvydko (2007) specifies the peer effect via co-workers' wages, which raises concerns about endogeneity, because all of the unexplained within-firm wage variation that is common across co-workers will be part of the estimated spillover coefficient. Lengermann (2002) estimates spillover effects operating through observable and unobservable co-worker characteristics, similarly to this paper. He finds that a one standard deviation increase in an index of co-worker skill is associated with wage increases of 3 to 5 percent. However, Lengermann (2002) uses a different estimator from the one I use in this paper, and his estimator's statistical properties are unknown.

I estimate a log-linear wage regression that enriches the person and firm effects model of Abowd et al. (1999). My regression includes fixed individual effects that capture the return to time-invariant worker characteristics and fixed firm effects that allow for unobserved firm-level heterogeneity. In addition, I include a measure of co-worker characteristics parameterised as the average of the fixed individual effect among people working at the same firm in the same time period. This represents

[2] Battu et al. (2003) measure spillover effects in the UK operating through the level of education of co-workers, but cannot control for the role of unobservables at the worker or firm level. In a related contribution, Navon (2010) investigates the effect of knowledge diversity on within-plant human capital spillovers using a panel dataset for Israel.

a proxy measure for the labour market value of co-workers' "portable" skills (i.e., the returns to characteristics that are person-specific and employer-invariant). I estimate the spillover effect arising from co-workers' observable and unobservable time-invariant characteristics simultaneously with the other parameters, using an estimator based on Arcidiacono et al. (2012). The spillover effect is identified from changes in the composition of the workforce for the same worker in the same firm, controlling for sector-specific time trends and firm size.

I estimate the model using the Veneto Worker History (VWH) dataset, a longitudinal linked employer employee dataset that covers the population of private-sector workers of the Italian administrative region of Veneto for the years 1982-2001.[3] I find that spillover effects are an important determinant of wage variation: a 10-percent increase in my measure of co-worker 'labour market quality'[4] is associated with a 3.6-percent wage premium. This means that increasing co-worker 'quality' by one standard deviation is associated with a real wage increase between 4 and 8 percent. Through a simple variance decomposition, I also find that including spillover effects reduces the overall wage variation explained by firm effects by about one fourth, suggesting that a substantial component of firms' contributions to wages is determined by the composition of a firm's workforce. I also investigate the role of skill segregation on wage inequality for specific groups of workers in the presence of spillover effects. I find that around 12 percent of the gender wage gap and from 10 to 15 percent of the immigrant wage gap is due to the labour market characteristics of peers. Finally, I present evidence about the extent to which high-wage workers are employed by high-wage firms looking at the dynamics of wage segregation over time. Consistent with Bagger et al. (2013), I find that wage segregation varies within the sample period, and that higher-wage workers are increasingly matched to high-paying firms.

[3] VWH includes wages and individual characteristics of all workers in each firm. Other datasets, such as the Longitudinal Employer-Household Dynamics (LEHD) dataset for the US and the LIAB dataset of the Institut für Arbeitsmarkt- und Berufsforschung (IAB) for Germany, could be used for this study with relatively simple modifications to my strategy. I intend to work on those datasets in the future.

[4] I borrow this term from Borjas (1987), meaning here a summary measure of time-invariant skills that are valued by the labour market in terms of wages.

2 Theoretical Background

The theoretical literature has identified a number of means through which the labour market quality of co-workers could affect a worker's wage. First, there may be complementarities in the production function for each worker, such that a worker's marginal productivity may depend on the characteristics of her co-workers. One channel that has received some attention is the possible effect of human capital heterogeneity at the firm level on productivity, which is analysed in Kremer (1993), Davis and Haltiwanger (1991), Kremer and Maskin (1996) and Dunne et al. (2000). Navon (2010) finds that knowledge heterogeneity within a firm matters for spillover effects across workers. In a related contribution, Moretti (2004) tests for the existence of human capital spillover effects across firms within cities and finds productivity spillovers to be positive and significant for hi-tech plants in the US.[5]

The characteristics of peers might play a role in wage determination even in the absence of complementarities in the production function. Recent work examines the role of peer pressure in the workplace using laboratory and field data for isolated tasks. Falk and Ichino (2006) use a laboratory experiment to investigate social pressure spillovers, and find that productivity is higher and less dispersed when subjects work in pairs. Mas and Moretti (2009) use field data from a large US supermarket chain where worker pairs are varied. Their estimates show that individual effort is positively correlated with the productivity of nearby workers.

The average labour market quality of co-workers might also affect individual wages through a worker's reservation wage, which may operate through preferences and social norms. Workers may have a preference for working with a certain type of co-workers, and may be willing to accept a lower wage for that because of compensating differentials considerations, and this may generate either positive or negative spillover effects depending on workers' preferences. Kremer and Maskin (1996) discuss evidence of social pressure for wage equality within the firm. Reference points may also be important for wage determination (see Dittrich et al. 2011 for an overview of the literature on the role of relative wages). If the wage structure within the firm provides a reference point for all

[5] In a recent paper, Kurtulus (2011) investigates the role of demographic dissimilarity among co-workers using data from a large U.S. firm. She finds that age and tenure dissimilarity are associated with lower worker performance. On the other hand, wage dissimilarities are associated with higher worker performance.

workers, wages will be affected by the skill composition inside the firm. For instance, Kronenberg and Kronenberg (2011) find that workers are more likely to leave a firm as wage inequality in the firm increases. As firms react, wages of low-skill workers will be positively affected by the average level of skills in the firm.

co-workers' skills may also affect wages through bargaining externalities. If high-skill workers are able to extract a higher share of the surplus through bargaining, and bargaining outcomes are positively correlated within a firm, a worker's wage will increase with co-worker skills. Conversely, in a context where wages are a fixed share of total revenues, there may be negative bargaining externalities and negative spillover effects if some groups or workers have a higher bargaining power than others.

Incentive schemes within the firm can also generate interactions between wages and peer characteristics. In tournament models,[6] effort (and thus wages) is a function of the characteristics of all workers in the firm. However, the relationship between labour market quality of co-workers and individual effort does not need to be positive or monotonic, as discussed in Becker and Huselid (1992), because of the *discouragement effect*: low ability workers may choose zero effort if they perceive their probability of winning to be very low.[7] In addition, the expected level of cooperation among workers (and thus total output and individual wages) may also depend on the distribution of types. Investigating the existence and magnitude of spillover effects empirically allows us to assess the relative importance of these different channels.

3 Empirical Model

My empirical model builds upon the structure of the model of Abowd et al. (1999). In the following, let i denote a worker, j denote a firm and t a time period.[8] A worker i working at a firm j in period t shares that same employer j with other workers, which I refer to as i's set of current co-workers,

[6] Initiated by the seminal work of Lazear and Rosen (1981).

[7] Harbring and Irlenbusch (2003) offer an excellent review of the literature and also present compelling experimental evidence showing that in a variety of different treatments agents tend to choose very low levels of effort in general, and very often zero.

[8] Since the estimation follow workers over time, a more precise notation defines the firm where worker i is employed at the t as $J(i, t)$, I use j for simplicity.

or current peer group. I denote the set of workers employed by firm j at time t with $\mathcal{N}_{ijt}$, with cardinality N_{ijt}. One of worker i's co-workers is denoted by p. My main regression model is

$$w_{ijt} = \mathbf{X_{it}}\beta + F_{jt}\kappa + \theta_i + \left(\frac{1}{N_{ijt\sim i}} \sum_{p \in \mathcal{N}_{ijt\sim i}} \theta_p \right) \eta + \psi_j + \tau_t + \epsilon_{ijt} \tag{1}$$

where the outcome of interest is worker i's log wage w_{ijt}. I denote time-variant individual characteristics of worker i by $\mathbf{X_{it}}$, firm size by F_{jt}, individual time-invariant characteristics by θ_i, whose average among peers[9] is $\frac{1}{N_{ijt\sim i}} \sum_{p \in \mathcal{N}_{ijt\sim i}} \theta_p$. Invariant firm characteristics are captured in ψ_j and industry-specific time trends are controlled for by τ_t. The $b \times 1$ column vector[10] β and the scalars κ and η are parameters to be estimated. The scalar η captures the effect of average time-invariant individual characteristics of peers on individual i's log wages, which is the my the parameter of interest. Finally, ϵ_{ijt} is a transitory mean-zero error term.

As discussed in Manski (1993) and Bramoulle et al. (2009) there are significant challenges for identifying peer effects in a linear-in-means model. The steps below are aimed at addressing the main identification challenges. Individual covariates $\mathbf{X_{it}}$ are included because individual characteristics that have an effect on wages might also be correlated with the average labour market quality of a worker's peer group. I also include firm size, denoted by F_{jt}, so that my estimates of peer effects are not driven by growth and decline in the number of employees of a firm, which could introduce bias if firms paid higher wages but attracted lower-ability workers when they grew in size. There may also be common-environment effects ('correlated effects', Manski 1993): some firms might be systematically better at attracting high-wage workers and might also give out higher wages, conditional on a worker's fixed effect. I address this issue by including time-invariant firm effects denoted by ψ_j in equation (1).

Moreover, I include time effects to control for trends in the average ability of peers and in the

[9] Sometimes I refer to this measure as peer 'quality' or 'labour market quality'. The reader should be cautions with its interpretation however. The parameter θ will capture all of the characteristics that make a worker more productive and the return to those characteristics as well as the characteristics that will make him/her more able to extract rents. My estimates of θ capture the market value of portable skills, and so it does not address the underlying mechanisms through which that market value may be different for different workers. If a group of workers receives lower wages even when I control for their individual characteristics, they will have a lower θ.

[10] Where b is the number of individual time-variant characteristics included in the model.

outcome variable, which could affect my estimates of spillover effects. For example, during a boom firms may pay higher wages but may also see the average ability of their workforce decrease, which would be the case if marginal workers had lower-than-average skills. In order to allow for time trends to be different by economic sector,[11] I include industry-specific year fixed effects, denoted by τ_t in equation (1). The individual fixed effect θ_i measures the 'market value of portable skills' or 'portable component of individual wages'. Equivalently, $\frac{1}{N_{ijt}} \sum_{p \in \mathcal{N}_{ijt}} \theta_p$ measures the mean of θ among people working with worker i at time t. For notational convenience I define $\bar{\theta}_{ijt} \equiv \frac{1}{N_{ijt\sim i}} \sum_{p \in \mathcal{N}_{ijt\sim i}} \theta_p$.

The nonlinear least squares problem derived from equation (1) is then

$$\min_{\beta,\kappa,\theta,\eta,\psi,\tau} \sum_i \sum_t \left[w_{ijt} - \mathbf{X_{it}}\beta - F_{jt}\kappa - \theta_i - \bar{\theta}_{ijt}\eta - \psi_j - \tau_t \right]^2 \tag{2}$$

Equation (2) is written under a 'proportionality' assumption on the characteristics included in θ_i, which is also made in Arcidiacono et al. 2012 and Altonji et al. 2010. This assumption gives a structure to the relationship between the coefficients on each of the components of θ_i in the direct effect on w_{ijt} as opposed to its indirect effect through peers. The proportionality assumption states that the relevant importance of each of these components is the same in the direct effect on own wages and in the peer effect. For example, if two characteristics that are part of θ_i have the same effect on the log wage of worker i, those same two characteristics will also have the same effect when operating through peers.

Under the proportionality assumption I can apply Theorem 1 of Arcidiacono et al. (2012) for consistency and asymptotic normality of $\hat{\eta}_{NLS}$, the nonlinear least squares estimate of η. The key assumption of Theorem 1 requires residuals across any two observations to be uncorrelated:[12] $E(\epsilon_{ijt}|\mathbf{X_{it}}, \mathbf{F}_{jt}, \theta_i, \bar{\theta}_{-ijt}, \psi_j, \tau_t) = 0$. Net of person effects, firm effects, time effects and spillover effects, all of the remaining wage variation is assumed to come from random shocks. This assumption implies that workers may be different in their unobserved ability, firms may be systematically different in the average ability of their workforce, there might be yearly time trends that are different

[11] In the period of my panel different economic sectors have been exposed to labour market regulations, and to exposure to global markets in a very heterogeneous way, and so an average time trend would not adequately control for the relevant macroeconomic context of each industry.

[12] I am writing this assumption as mean-independence for simplicity.

for different sector. The remaining intertemporal changes in peer 'quality' within a firm, controlling for all of the other covariates, are assumed to be orthogonal to the error term ϵ_{ijt}. This is equivalent to assuming that there are no time-varying unobservables driving changes in the composition of the peer group of worker i while at the same time systematically affecting worker i's wage.[13]

Under the assumption stated above, the nonlinear least squares solution $\hat{\eta}_{NLS}$ is a consistent and asymptotically normal estimator of the true parameter η as the number of individuals goes to infinity for a fixed number of time periods. The key elements that allow Arcidiacono et al. (2012) to prove this theorem is that the vector of individual fixed effects can be written as a function of the spillover parameter and of the data, so that the Least Squares problem above can be formulated as an optimization problem with only one minimand, η. Arcidiacono et al. (2012) can then use Theorem 12.2 of Wooldridge (2002) for consistency of M-estimators establishing identification and uniform convergence, and Theorem 12.3 for asymptotic normality. Even though my problem is complicated by the presence of additional sets of fixed effects, the main logic of their proofs applied here.

There are reasons why equation (2) is still restrictive. First, the model is specified as a linear-in-means model,[14] so that I cannot investigate spillover effects operating through a different moment of the relevant distribution, and I am also not exploring possible heterogeneity in spillover effects. In addition, I assume away endogenous effects: peers' wages affect a worker's wage only through the effect of peers' ability, not directly via their own wages, for example through effort.[15] If peers' effort choice positively affected a worker's effort choice, and effort and ability were correlated, my estimates of η in equation (2) would be upward biased.[16]

In order to estimate equation (2) I find the vector of parameters θ and the parameter η that

[13]Thereom 1 of Arcidiacono et al. (2012) also requires either homoskedasticity within each peer group or that heteroskedasticity is uncorrelated with the number of observations available for each worker. In addition to these assumptions, we also need a few standard assumptions: $Corr(\theta, \epsilon) = 0$, $E(\theta_i^4) < \infty$, $E(\epsilon_{ijt}) = 0$, $E(\epsilon_{int}^4) < \infty$. Finally we need η to lie in the interior of a compact parameter space Γ where the largest element of Γ needs to be smaller than 2. See Arcidiacono et al. (2012) page 7 for details on these assumptions

[14]This is by far the most common choice in the peer effects literature. There are a few exceptions that are worthy of being mentioned because of their role in the peer effects literature. Brock and Durlauf (2001, 2003) use the nonlinearity arising in discrete-choice models to distinguish endogenous effects from exogenous effects.

[15]Without this assumption on endogenous effects, my estimates can be viewed as a combination of exogenous and endogenous effects, i.e. effects operating through peer characteristics and through behaviour.

[16]In my context endogenous effects are likely to be a function of time-varying covariates, and so there would be endogeneity problems including them in my wage regression.

minimise equation (2) iteratively.[17] Intuitively, I start from a model without spillover effects by setting $\hat{\eta}^0 = 0$ to get a first set of estimate of all fixed effects. I then use these first estimates to get a first set of estimates of the regression parameters β, κ and η. I then use these estimates to update the fixed effects to be used in the next step of the procedure, switching between updating the fixed effects and updating the parameters, until convergence is reached.[18] Each iteration consists of four steps.[19] For a general iteration α the four steps are as follows:

1. Estimate $\hat{\eta}^{\alpha}_{OLS}$, $\hat{\beta}^{\alpha}_{OLS}$ and $\hat{\kappa}^{\alpha}_{OLS}$ from $\theta^{\alpha-1}$, $\psi^{\alpha-1}$, $\tau^{\alpha-1}$ using Ordinary Least Squares;

2. Estimate θ^{α} from $\theta^{\alpha-1}$, $\psi^{\alpha-1}$, $\hat{\eta}^{\alpha}_{OLS}$, $\hat{\beta}^{\alpha}_{OLS}$ and $\hat{\kappa}^{\alpha}_{OLS}$ using equation (A.2);

3. Estimate ψ^{α} from θ^{α}, $\tau^{\alpha-1}$, $\hat{\eta}^{\alpha}_{OLS}$, $\hat{\beta}^{\alpha}_{OLS}$ and $\hat{\kappa}^{\alpha}_{OLS}$ using equation (A.3);

4. Estimate τ^{α} from θ^{α}, ψ^{α}, $\hat{\eta}^{\alpha}_{OLS}$, $\hat{\beta}^{\alpha}_{OLS}$ and $\hat{\kappa}^{\alpha}_{OLS}$ using equation (A.4).

4 Data and Institutional Background

I estimate my model using the Veneto Worker History (VWH) dataset,[20] which includes virtually all private-sector workers of the Italian region of Veneto[21] for years 1982-2001.[22] The VWH dataset includes register-based information on all firms and employees that have been hired by those firms for at least one day during the period of observation. The entire employment history in the period 1982-2001 has been reconstructed for each employee.[23] The full sample contains around 3.6 million

[17]Estimating equation (2) in one step is not computationally feasible with a large dataset. Because of the spillover effect the outcome of person i at time t is a function of the ability of all of i's co-workers, which are themselves estimated within the model. The inclusion of additional covariates compared to Arcidiacono et al. (2012) and in particular of firm effects and year by sector effects does not affect the main logic of the estimation. When the θs are updated, all of the other fixed effects and covariates are treated as columns of data. For additional details see my Appendix.

[18]The specific iterative procedure described below builds upon that of Arcidiacono et al. (2012) adapting it to the labour market context and in particular to the inclusion of firm effects.

[19]See the Appendix for details and for the updating equations I use.

[20]This panel dataset has been constructed by a team led by Prof. Giuseppe Tattara of the University of Venice, using the Social Security administrative data of the *Istituto Nazionale per la Previdenza Sociale* (INPS).

[21]State and local government employees, farm workers and some category of professionals, such as doctors, lawyers, notaries and journalists, are not included because they have alternative social security funds. Additional information on the dataset available in Card et al. (2010) and in Tattara and Valentini (2010)

[22]The period covered by the dataset is 1976-2001, but because coding errors concerning wages have been found for the period 1976-1981, I will only use the 20-year period between 1982 and 2001. The VWH dataset has not been updated for the years after 2001.

[23]Considering the occupational spells out of the region of Veneto as well for individual regressors.

workers and 46 million observations at the worker by year level over 20 years.[24]

The region of Veneto, in the North East of Italy, is the third Italian region by GDP and has a population of around 5 million people, around 8 percent of the country's total. Its economy is characterised by small manufacturing businesses which are organised on a regional basis by specialisation and with local integration. Immigrants currently represent around 10 percent of the population of Veneto, which is well above the Italian average.[25] The equivalent figures for 1991 are 25,000 in absolute number, around one percent of the total population.

Estimating the effects of co-worker characteristics on wages requires a certain degree of wage flexibility. Italy is often viewed as a country where collective bargaining is the main mechanism for wage determination. In reality however, and especially for small firms, which dominate the labour market of Veneto, there are many sources of wage heterogeneity across workers. National regulations are typically silent about compensation levels. Trade union contracts specify non-binding minimum wages at the industry level. Although these are relevant for bargaining inside the firm, they only represent an industry-specific floor for total compensation, and in Veneto compensation are almost always higher, as discussed in Bartolucci and Devicienti (2012), who find for the same population that almost all employees earn a wage premium, and that the median wage premium is 24 percent. Individual bargaining is very important: wage variability within firms is around two thirds of overall wage variability in Italy (Lazear and Shaw, 2008). Wage premia are also highly heterogeneous across firms (Erickson and Ichino, 1994), and higher for small firms (Cingano, 2003).

[24] Additional details on the structure of the dataset are available in the Appendix.

[25] Data from various Italian censuses available from http://www.istat.it/ show that the proportion of foreign residents (defined as people residing in Italy while not holding an Italian citizenship) increased slowly from 1.2 percent in 1961 to 2.2 percent in 1971 to 3.7 percent in 1981, after which it soared to 6.1 percent in 1991 and to an estimated 7.5 in 2001 (and on a positive and sharp trend in the last decade). According to Istat (2011) data, the total number of immigrants in Veneto at the end of 2009 is 489,000, 10 percent of the total population. Employed immigrants in 2009 are around 11 percent of all employed. These figures do not include undocumented migrants. According to Anastasia et al. (2009) however the proportion of irregulars and temporary migrants in Veneto is less than 10 percent of the total number of immigrants, which is a much lower proportion than many other Italian regions. And in the future there will be a very large proportion of the whole labour force that will be constituted by second generation immigrants, since in 2009 the percentage of children whose parents are not Italian citizens is 21.2 percent Istat (2010). A synthetic account of the development of migration to Italy is offered in Colombo and Sciortino (2004).

5 Sample Restrictions

In order to estimate my model, it is necessary to identify a specific time dimension for the panel dataset such that in each time period there is at most one observation for each worker.[26] I choose to construct a dataset where there is at most one observation for each worker in each year.[27] I create a wage variable that measures average monthly wages for full time employment (FTE), so that my estimates of wages are driven by variation in compensation per unit of time rather than by labour supply variations. My main regressor of interest is a measure of co-worker labour market skills, which can be constructed only if the firm has at least two workers. Therefore, I drop all firms with only one employee.[28]

Separately identifying firm effects and person effects requires employment histories to be sufficiently connected. A connected group of firms and workers contains all the workers that ever worked for any of the firms in the group and all the firms where any of the workers were ever employed (Abowd et al., 2002). I use an algorithm to identify connected groups of observations.[29] Abowd et al. (2002) then proceed by estimating person and firm effects within each group to maintain the representativeness of the sample. I simply drop all observations that are not part of my main connected sample before estimating my model.[30]

[26]Failing to do so would result in higher weights given to more mobile individuals, and it would make it impossible to include a control for time trends.

[27]I thus eliminate the case in which there is more than one observation for each worker in the same year. See the Appendix for details.

[28]This eliminated around three percent of all observations, where firms only had one employee. I also construct a variable for labour market experience and for firm size, please see the Appendix for details.

[29]I use the algorithm "a2group" written by Ouazad (2007), who in turn develops it from a Fortran implementation written by Robert Creecy. I had to make only minor changes to their code to deal with a larger number of firms. The basic functioning of the algorithm mirrors the definition of connected groups: starting from a single firm, the algorithm finds the set of workers that worked for that firm in any time period, and includes those as part of the connected graph. The algorithm then adds all of the firms that set of workers ever worked for, and add all of the workers that worked for those firms to the connected graph. This procedure continues until no additional worker is added to the connected graph.

[30]Only around 9,000 observations out of over 28 million are excluded from the main connected graph, i.e. just over 2,000 workers are outside the main connected group out of over 3 million, and only around 1,000 firms out of over 230,000.

6 Summary Statistics

My regression sample has 28,115,529 yearly observations for 231,195 firms and 3,180,714 workers. Of these workers, 40.8 percent are female, 8.2 percent are foreign born, 31.2 percent are white collar workers. There is substantial worker mobility in my sample: I observe around two thirds of the workers in more than one firm.[31] Figure 1 plots average monthly FTE wages (in 2003 Euros) by gender and share of females. Monthly real wages increased both for females and males, but we observe a break in the trend around 1991, with real wages increasing at 2.41 percent a year on average for females and 2.15 percent for males in the years 1982-1991, and only 0.37 percent for females and 0.10 percent for males a year in the period 1992-2001. The gap between monthly wages of males and females decreased slightly from 24.3 percent in 1982 to 20.4 percent in 2001. The proportion of females increases from 35.5 percent in 1982 to around 40 percent from 1997 onwards.

Figure 2 compares workers born in Italy with workers born abroad. The bar chart shows that proportion of foreign-born workers increases dramatically, from 2.6 percent in 1982 to 9.8 percent in 2001.[32] The chart shows the first large influx of foreign born workers and the first sizeable arrival of people of different ethnicities around 1990, driven mostly by immigrants from Morocco and Albania. The unconditional wage gap between foreign born and Italian born was relatively constant at around 400 Euros in the period 1982-1989. Afterwards, it increases dramatically, driven largely by falling real wages of foreign born.[33] While in 1982-1989 average yearly growth rates of gross real wages are 1.70 percent for Italian born and 1.98 percent for foreign born, in the period 1990-2001 the equivalent figures are 0.71 percent for Italian born and -0.33 percent for foreign born.

Looking at wage heterogeneity, Figure 3 plots the standard deviation of the natural logarithm of monthly wages in each year within and across firms, both normalized to 100 in 1982.[34] There

[31] For 25 percent of all workers I observe two employers, for around 16 percent I observe three employers, for around 10 percent I observe four employers. Five percent of individuals work for 5 firms within the period of my data, and a further 6 percent has 6 or more employers.

[32] Up to 1989, foreign born are between 2 and 4 percent of the total, many of which are individuals born abroad with Italian parents returning from Switzerland, Germany and Latin America.

[33] In 1990, foreign born would earn on average 2,700 Euros for each month they work full time. As everywhere else in the paper, the reader should bear in mind that these wages are gross of taxes and for full-time months. An earner that earns 2,700 Euros per full-time month probably earns around 1,000 or 1,100 Euros net of taxes in a normal month. By 2001, eleven years later, their average wages had fallen to 2,600 while those of Italian born are over 3,300 Euros, for a staggering gap of 23 percent.

[34] I calculate the average of the within-firm standard deviation and the standard deviation of the average wage of

is a clear upward trend for both measures. Wage dispersion within firms is generally higher than wage dispersion across firms, and it increases by around 8 percent from 0.379 in 1982 and peaks at 0.414 in 1997. Wage inequality across firms rose relatively more, (consistent with the finding of Kremer and Maskin 1996 for the US) from 0.331 in 1982 to a maximum of 0.393 in 1999 (an 18 percent increase from 1982), slightly dropping afterwards. The overall standard deviation of log monthly wages rises by 11 percent in the same period.

The average number of employees of a firm is 21.6 in 1982, falls gradually to 18.1 in 1993 and then levels off, attaining 18.5 in 2001. The median size of firms in my sample is 6 throughout the period, with a dip at 5 in 1998 only. In 2001, out of 83,173 firms, 25 percent of all firms have either 2 or 3 employees, 75 percent of the firms have 15 employees or less, only one percent of all firms have more than 200 employees. The largest economic sectors in terms of total number of firms are commerce, bars and hotels (28 percent of all firms), construction (20 percent of all firms), construction of metal products (7 percent) and banking and insurance (6 percent).[35]

7 Regression Results

My estimates of equation (1) are presented in Table 2. I report heteroskedasticity-robust standard errors and t-statistics for my coefficients.[36] Column 1 estimates a model with a firm fixed effect, a worker fixed effect and a year by industry effect only. Column 2 adds firm size and a second-order polynomial in labour market experience. Controlling for firm effects, the effect of firm size and labour market experience on wages is very small.[37] In Column 3 I add a the average person effect of peers, $\bar{\theta}$. Its estimated coefficient $\hat{\eta}$ is 0.358, which implies that, using the overall standard

each firm. Figure 3 is constructed from a dataset that has one observation for each worker in each year. If I had one observation per firm the statistics on the chart would be entirely driven by small firms.

[35] See table 1 for more information.

[36] Arcidiacono et al. (2012) gives no guidance on how to calculate the exact standard errors and so show standard errors and t statistics from the OLS regression of the last iteration. While these are only approximate standard errors, given the size of the t-statistics, this is very unlikely to make any difference for inference.

[37] Both in terms of coefficients and in terms of its effect on R^2. This is consistent with the discussion in Abowd et al. (1999) firm size is a proxy for something else in the firm that we typically do not observe, and this is what is driving large estimates of firm size when we use cross sectional variation in wages only. Large firms seem to be systematically different from small firms but firms do not pay systematically higher wages when they grow. Because my experience measure is in part imputed, this may be lower than what I would obtain if I could observe labour market experience from the beginning of their careers for all of the workers in my sample.

deviation of $\bar{\theta}$, which is 0.218, a one-standard-deviation increase in the average person effect of a worker's peers is associated with a wage gain of 7.81 percent. I also calculate the cross-sectional standard deviations of $\bar{\theta}$ for three representative years, which are equal to 0.221 for 1982, 0.201 for 1991 and 0.199 for 2001. Estimates associated wage gain for either of these are between 7.12 percent (using the 2001 standard deviation) and 7.89 percent (using the 1982 standard deviation). An alternative reference distribution is the average standard deviation of $\bar{\theta}$ within a person's career, which is 0.104. This might be more intuitively appealing since the overall distribution of peer labour market quality in the population may not be the natural reference for considering the changes in co-worker composition that workers in my data might actually experience. Using this alternative reference distribution a one standard deviation increase in peer characteristics is associated with a more conservative wage increment of 3.7 percent. In this case, the conditional wage effect of having a group of peers that is one standard deviation higher than average is similar to the effect of two years of labour market experience. Finally, from the perspective of a worker considering a move to a different firm, the relevant measure might be the standard deviation of $\bar{\theta}$ across firms, which is 0.19 using a dataset with one observation per firm. The associated wage premium in this case is 6.8 percent. [38]

8 Post-estimation Analysis

8.1 Fixed Effects across Specific Groups

Table 3 presents the average of wages and of the estimated fixed effects across genders and immigrant status. On average, female workers have 25 percent lower wages, 20 percent lower 'market value of portable skills' measured by the fixed person effect θ, 8 percent lower co-worker 'labour market quality' and work in firms that pay conditionally slightly lower wages. On the other hand, on average a foreign born worker has a wage that is 13 percent below that of a native worker; her person effect θ is 15 percent lower and co-worker 'labour market quality' is 9 percent lower. Her firm

[38] My estimates of 3.7 and 7.9 percent effects may be seen as lower and upper bounds. In Appendix D, I include robustness checks running the same regression on a subsample of the population, to investigate how much my estimates vary by firm size.

effect ψ is on average 2 percent lower. The person effect θ includes skills as they are valued in the labour market, and the potential effect of specific groups being discriminated in the labour market is included in the person effect θ. In order to partially address this concern, I regress the individual person effect θ on gender and immigration status in Table 4. I find that foreign birth status and gender together explain less than 5 percent of the variation in θ across workers. Therefore, the extent to which θ is driven by gender and immigrant discrimination seems to be limited.

8.2 Variance Decomposition

Beyond the estimates discussed above, I decompose the variance of log wages from equation (1):

$$\begin{aligned}
Var(w_{ijt}) &= Cov(w_{ijt}, w_{ijt}) = Cov(w_{ijt}, \mathbf{X_{it}}\beta + F_{jt}\kappa + \theta_i + \bar{\theta}_{ijt}\eta + \psi_j + \tau_t + \epsilon_{ijt}) \\
&= Cov(w_{ijt}, \mathbf{X_{it}}\beta) + Cov(w_{ijt}, F_{jt}\kappa) + Cov(w_{ijt}, \theta_i) + Cov(w_{ijt}, \bar{\theta}_{ijt}\eta) \\
&\quad + Cov(w_{ijt}, \psi_j) + Cov(w_{ijt}, \tau_t) + Cov(w_{ijt}, \epsilon_{ijt})
\end{aligned}$$

This can be normalised dividing both sides by $Var(w_{ijt})$:

$$\begin{aligned}
&\frac{Cov(w_{ijt}, \mathbf{X_{it}}\beta)}{Var(w_{ijt})} + \frac{Cov(w_{ijt}, F_{jt}\kappa)}{Var(w_{ijt})} + \frac{Cov(w_{ijt}, \theta_i)}{Var(w_{ijt})} + \frac{Cov(w_{ijt}, \bar{\theta}_{ijt}\eta)}{Var(w_{ijt})} \\
&\quad + \frac{Cov(w_{ijt}, \psi_j)}{Var(w_{ijt})} + \frac{Cov(w_{ijt}, \tau_t)}{Var(w_{ijt})} + \frac{Cov(w_{ijt}, \epsilon_{ijt})}{Var(w_{ijt})} = 1
\end{aligned} \tag{3}$$

The bottom section of Table 2 presents estimates of each element of equation (3). The contribution of individual time-invariant characteristics to the variance of individual wages is between 44 and 49 percent. Sector-specific year effects, on the other hand, explain between 5 and 6 percent of wage variation. Experience and firm size are of marginal importance. Firms' heterogeneity accounts for around 20 percent of wage variation in column 1 of Table 2,[39] falling to 18 percent in column 2. Once we control for peer 'quality', the proportion of wage variation that is explained by firm effects decreases by about 28 percent. In turn, the average labour market quality of peers explain around 5 percent of the overall wage variation.[40] The R^2 of column 3 is very similar to that of column

[39] Gruetter and Lalive (2009) estimate a similar model as column 1 of my model and finds an estimate of 27 percent.

[40] Adding complexity to the functional form used and including a function of peers' worker effect beyond he first moment is likely to increase this estimate, which should therefore be seen as a lower bound of the effect of peers'

2: the additional 5 percent of the variance of log wages explained by peer labour market quality is associated with a similar decrease in the proportion of the variance explained by the firm effect. An important portion of what our usual firm effects pick up is driven by the level of skills of that firm's labour force.

8.3 Wage Sorting Dynamics

The findings above are in line with most of the literature on wage determination using panel data: both worker and firm heterogeneity are important for wages. It is then natural to investigate the presence of wage sorting, defined as the correlation between worker and firm fixed effects as in Bagger and Lentz (2008). I calculate the degree of wage sorting for the different models I estimate, and present the results at the bottom of table 2. When I do not include peer effects in my model, I find a positive albeit modest estimate of 0.160: high-wage workers tend to work in high-wage firms. Abowd et al. (1999) finds small negative correlation coefficients, which is at odds with much of the theoretical literature which predicts assortative matching between workers and firms, and generated a large and unsettled debate. Note that the comparison is highly imperfect because I use wages per unit of time while the literature typically uses total annual compensation. Once I include peer effects in the model, as in column 3 of table 2, the correlation between θ and ψ is driven very close to zero at just 0.012. Most of the correlation between θ and ψ found in column 2 is driven by high-wage workers having high-wage peers: the correlation between θ and $\bar{\theta}$ is 0.420.[41] My estimates of the correlation between θ and ψ and between θ and $\bar{\theta}$ are consistent with the discussion in Lopes de Melo (2009b): sorting in the labour market seems to operate largely through workers with similar levels of productivity sharing the same employer.[42]

In figures 5 and 6 I investigate the correlation between worker quality and firm quality further,

ability.

[41] Prior to this study the two available studies that calculate the equivalent correlation find values between 0.3 and 0.4 for Brazil (Lopes de Melo, 2009a) and Denmark (Bagger and Lentz, 2008).

[42] Lopes de Melo (2009b) argues that a better measure of sorting is the correlation between the fixed effect of a worker and that of her co-workers because of possible non-monotonicities between the firm effect and a firm's productivity. Lopes de Melo (2009b) discusses a theoretical model based upon Shimer and Smith (2000), which implies that correlation between person effect and firm effect underestimates the extent of sorting in the labour market. In a related contribution, Eeckhout and Kircher (2009) also find non-monotonicities of wages around the equilibrium point, reflecting the structure of the firm's opportunity cost.

by looking at how wage sorting evolved over time.[43] Figure 5 is constructed using the estimates of the AKM model without spillover effects, i.e. those of column 2 of table 2. Figure 6 on the other hand uses estimates of the full model with spillovers. The correlation levels (solid lines of figures 5 and 6) vary greatly between the two models, as discussed above. In figure 5 the correlation ranges between 0.064 in 1982 and 0.211 in 1995. After we take account of spillover effects the degree of wage sorting is lower, as discussed above and shown in figure 6, ranging between -0.068 in 1982 and 0.075 in 1997. In terms of trends however the two figures look very similar. The correlation between the firm effect and the person effect varies greatly within the sample period, growing until around 1997 and declining afterwards. Bagger et al. (2013) present equivalent estimates with data for Denmark, and find remarkably similar trends. Card et al. (2012) use data from the German Social Security system and also find that the extent of assortative matching between workers and firms increased in Germany in the period 1985-2009, from 0.03 in 1985-1991 to 0.25 in 2002-2009 (0.10 in 1990-1996, 0.17 in 1996-2002). The strong similarities between the results of this paper (from the model without spillovers) and those of Bagger et al. (2013) and Card et al. (2012) suggest that the observed increase in wage sorting is not driven by idiosyncratic elements of my dataset and of Veneto. On the contrary, it seems to reflect structural changes in the labour market, which may be associated with rising wage inequality, suggesting that this deserves further attention in future work.

The dynamics of wage sorting over time shown by the solid line of Figures 5 and 6 are driven both by initial allocation of workers, and by new firms and new workers entering the dataset. I thus include correlations calculated only for the firms that are active in 1982 to isolate the role of inter-firm mobility. The dashed lines of figures 5 and 6 follow the same pattern as the solid line, and exhibits only slightly higher correlation coefficients: using a constant pool of firms, the increase in assortative matching across the sample period is stronger.[44] Figures 5 and 6 also includes the correlation between the person effect and the firm effect using the sample of workers that are active in 1982 only. The dotted lines follow a similar trend but levels are consistently lower: among workers

[43] Both θ and ψ are time-invariant to any changes across years are driven by mobility as well as entry and exit.

[44] This is consistent with the results in Mendes et al. (2010) of stronger assortative matching among long-lived firms using data from Portugal.

with high levels of labour market experience mobility may be lower and changes in wage sorting are less pronounces. Overall, the movement towards assortative matching is disproportionally driven by "old" firms and by "new" workers.

8.4 Decomposing the Gender Wage Gap

In order to further investigate the role of peers on the gender wage gap I documented in my data, I decompose the average wage gap between wages of male and female workers. Consider the following simple decomposition of the average gender wage gap based on estimating equation (1):

$$\begin{aligned} E(w_{ijt}^M - w_{ijt}^F) = \; & E(\mathbf{X_{it}^M}\beta - \mathbf{X_{it}^F}\beta) + E(F_{jt}^M\kappa - F_{jt}^F\kappa) + E(\theta_i^M - \theta_i^F) + E(\bar{\theta}_{ijt}^M\eta - \bar{\theta}_{ijt}^F\eta) \\ & + E(\psi_j^M - \psi_j^F) + E(\tau_t^M - \tau_t^F) + E(\epsilon_{ijt}^M - \epsilon_{ijt}^F) \end{aligned} \tag{4}$$

where the exponents F and M stand for 'Female' and 'Male' respectively. This decomposition shows that around 85 percent of the overall wage gap between female and male workers is due to differences in θ, i.e. differences in individual characteristics and their returns in the labour market.[45] Differences in peer 'quality' explain 12 percent of the overall gap: one eighth of the gender wage gap is due to the fact that females have on average co-workers with lower person effect θ. All other covariates as well as the unexplained component are very small. To assess the role of gender on peer exposure in more detail, I regress average peer 'quality' on gender and a series in controls:

$$\bar{\theta}_{ijt} = Female_i\delta_0 + \theta_i\delta_1 + \mathbf{X_{ijt}}\delta_2 + P_{ijt}\delta_3 + \psi_j\delta_4 + \upsilon_{ijt} \tag{5}$$

where θ, $\bar{\theta}$ and ψ are those I estimated my main model and $Female$ is a dummy for gender. The matrix $\mathbf{X_{ijt}}$ includes a constant, experience and firm size. In addition, P_{ijt} denotes the proportion of females among worker i's co-workers at time t. Finally, υ_{ijt} is a transitory mean-zero error term and δ_0, δ_1, δ_2, δ_3 and δ_4 are parameters to be estimated. Table 5 presents the estimates from equation (5). Column 3 shows that once I control for the proportion of females among peers, female

[45] Note this component of the gap does not necessarily reflect differences in skills, since it is itself a combination of skills and their wage returns. Foreign born may have lower labour market skills but are also likely to have lower returns to those unobserved labour market skills, for many reasons which may include labour market discrimination as found in audit studies.

workers have conditionally higher-θ peers compared to males.[46]

8.5 The Immigrant Wage Gap

Figure 2 and Table 3 documented a large and growing wage gap between foreign born and native born workers.[47] Figure 4 shows that foreign born and native workers are also segregated across firms: in 2001, while native workers work in firms where around 9 percent of workers are foreign born (the corresponding median is around 5 percent), foreign born workers work in firms where 22 percent of workers are foreign born (corresponding median is 16 percent). This patterns suggest that peer effects may contribute substantially to the wage gap between them.

Figure 7 shows a simplified graphical representation of the decomposition in equation (4) over time. As shown in Figure 2, the overall gap in log monthly wages between foreign born and Italian born rises during the period covered by my dataset. The majority of the gap is driven by differences in the person effect θ. Average peer characteristics explains between 10.4 percent in 1982 and 15.9 percent in 1987 of the overall wage gap. My decomposition also shows that a large part of the wage gap (19 percent on average) is explained by the firm effect ψ: foreign born disproportionately work in firms that pay lower wages.

Next I regress peer characteristics on a dummy for foreign born and on other covariates:

$$\bar{\theta}_{ijt} = (Foreign\ born)_i\delta_0 + \theta_i\delta_1 + \mathbf{X_{ijt}}\delta_2 + P_{ijt}\delta_3 + \psi_j\delta_4 + \upsilon_{ijt} \tag{6}$$

where P_{ijt} denotes the proportion of foreign born among worker i's peer group and all other covariates and parameters are defined as in equation (5). Table 6 displays the estimates for equation (6). Even controlling for own unobserved 'type' θ_i, the proportion of foreign born among the peer group, experience, firm size and firm effects, foreign born still have peers that have lower average person effects. Column 5 shows that wages of foreign born workers lower by around 0.5 percent

[46] Column 4 introduces controls for experience and firm size, column 5 adds the firm effect as well, and shows that ceteris paribus higher-paying firms have lower-θ workers on average. The main insights from column 3 are confirmed in columns 4 and 5.

[47] I focus on the simplest case and simply divide my sample of workers in foreign born and Italian born. The analysis of the role of peers for different groups of immigrants is left to future work. The reader should be also aware that my foreign -born dummy includes second generation Italians born abroad, and thus it is not equivalent to an immigrant dummy.

due to the characteristics of their peers.

9 Concluding Remarks

In this paper I estimate the effect of co-workers' characteristics on wages. I address the main sources of possible bias due to group selection (by which workers with certain characteristics are non randomly distributed across firms) and to the role of unobservables, by using within-firm variation in the peer group composition net of time trends and allowing peer effects to operate through all relevant time-invariant worker characteristics. I use a large panel dataset of workers of the Italian region of Veneto for years 1982-2001. I find peer characteristics to be an important factor for wage determination: a 10-percent increase in co-worker 'quality' is associated with a rise in real monthly wages of 3.6 percent. In addition, I find that after controlling for peer 'quality' the effect of firms' unobservables on wages decrease by more than one fourth. I also offer evidence of rising wage sorting in the sample period: high-wage workers are increasingly likely to be employed at high-wage firms, even controlling for co-worker characteristics. Finally, I find that differences in time-invariant labour market characteristics of peers explain around 12 percent of the gender wage gap and 10 to 15 percent of the immigrant wage gap.

References

Abowd, J. M., R. H. Creecy, and F. Kramarz (2002, April). Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data. Center for Economic Studies, U.S. Census Bureau, Technical paper No. TP-2002-06.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251 – 333.

Altonji, J. G., C.-I. Huang, and C. R. Taber (2010). Estimating the Cream Skimming Effect of School Choice. NBER Working Papers: 16579.

Anastasia, B., L. Bertazzon, V. Fincati, M. Gambuzza, M. Rasera, and G. Savini (2009). Immigrazione straniera in Veneto - Rapporto 2009. Technical report, Regione del Veneto e Veneto Lavoro.

Arcidiacono, P., G. Foster, N. Goodpaster, and J. Kinsler (2012). Estimating Spillovers using Panel Data, with an Application to the Classroom. *Quantitative Economics (forthcoming)*.

Bagger, J. and R. Lentz (2008). An Empirical Model of Wage Dispersion with Sorting. University of Wisconsin-Madison Working Paper.

Bagger, J., K. L. Srensen, and R. Vejlin (2013). Wage sorting trends. *Economics Letters 118*(1), 63–67.

Bandiera, O., I. Barankay, and I. Rasul (2009). Social Connections and Incentives in the Workplace: Evidence from Personnel Data. *Econometrica 77*(4), 1047 – 1094.

Bartolucci, C. and F. Devicienti (2012). Better Workers Move to Better Firms: A Simple Test to Identify Sorting. Carlo Alberto Notebooks, No.259.

Battu, H., C. R. Belfield, and P. J. Sloane (2003). Human Capital Spillovers within the Workplace: Evidence for Great Britain. *Oxford Bulletin of Economics and Statistics 65*(5), 575 – 594.

Becker, B. E. and M. A. Huselid (1992). The Incentive Effects of Tournament Compensation Systems. *Administrative Science Quarterly 37*(2), 336–350.

Boning, B., C. Ichniowski, and K. Shaw (2007). Opportunity Counts: Teams and the Effectiveness of Production Incentives. *Journal of Labor Economics 25*(4), 613 – 650.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *American Economic Review 77*(4), 531 – 553.

Bramoulle, Y., H. Djebbari, and B. Fortin (2009). Identification of Peer Effects through Social Networks. *Journal of Econometrics 150*(1), 41 – 55.

Brock, W. A. and S. N. Durlauf (2001). Discrete Choice with Social Interactions. *Review of Economic Studies 68*(2), 235 – 260.

Brock, W. A. and S. N. Durlauf (2003). Multinomial Choice with Social Interactions. National Bureau of Economic Research, Inc, NBER Technical Working Paper: 288.

Card, D., F. Devicienti, and A. Maida (2010). Rent-sharing, Holdup, and Wages: Evidence from Matched Panel Data. National Bureau of Economic Research, Inc, NBER Working Papers: 16192.

Card, D., J. Heining, and P. Kline (2012, August). Workplace Heterogeneity and the Rise of German Wage Inequality. Mimeo.

Chan, T. Y., J. Li, and L. Pierce (2012). Compensation and Peer Effects in Competing Sales Teams. SSRN Working Paper Series.

Cingano, F. (2003). Returns to Specific Skills in Industrial Districts. *Labour Economics 10*(2), 149 – 164.

Cingano, F. and A. Rosolia (2012). People I Know: Job Search and Social Networks. *Journal of Labor Economics 30*(2), 291 – 332.

Colombo, A. and G. Sciortino (2004). Italian immigration: the origins, nature and evolution of Italy's migratory systems. *Journal of Modern Italian Studies 9*(1), 49 – 70.

Davis, S. J. and J. Haltiwanger (1991). Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86. *Brookings Papers on Economic Activity*, 115 – 180.

Dittrich, M., A. Knabe, and K. Leipold (2011). Spillover Effects of Minimum Wages: Theory and Experimental Evidence. CESifo Group Munich, CESifo Working Paper Series: 3576.

Dunne, T., J. Haltiwanger, and L. Foster (2000). Wage and Productivity Dispersion in U.S. Manufacturing: The Role of Computer Investment. National Bureau of Economic Research, Inc, NBER Working Papers: 7465.

Edin, P.-A., B. Holmlund, and O. N. Skans (2008). Wage dispersion between and within plants: Sweden 1985-2000. NBER Working Paper 13021.

Eeckhout, J. and P. Kircher (2009). Identifying Sorting - In Theory. Penn Institute for Economic Research, Department of Economics, University of Pennsylvania, PIER Working Paper Archive.

Erickson, C. and A. Ichino (1994). Wage differentials in Italy: market forces, institutions, and inflation. NBER Working Paper 4922.

Falk, A. and A. Ichino (2006). Clean Evidence on Peer Effects. *Journal of Labor Economics 24*(1), 39 – 57.

Gruetter, M. and R. Lalive (2009). The Importance of Firms in Wage Determination. *Labour Economics 16*(2), 149 – 160.

Guryan, J., K. Kroft, and M. J. Notowidigdo (2009). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *American Economic Journal: Applied Economics 1*(4), 34 – 68.

Hamilton, B. H., J. A. Nickerson, and H. Owan (2003). Team Incentives and Worker Heterogeneity: An Empirical Analysis of the Impact of Teams on Productivity and Participation. *Journal of Political Economy 111*(3), 465 – 497.

Harbring, C. and B. Irlenbusch (2003). An Experimental Study on Tournament Design. *Labour Economics 10*(4), 443 – 464.

Hellerstein, J. K. and D. Neumark (2008). Workplace Segregation in the United States: Race, Ethnicity, and Skill. *Review of Economics and Statistics 90*(3), 459 – 477.

Ichino, A. and G. Maggi (2000). Work Environment and Individual Background: Explaining Regional Shirking Differentials in a Large Italian Firm. *Quarterly Journal of Economics 115*(3), 1057 – 1090.

Istat (2010). Natalità e fecondità della popolazione residente: caratteristiche e tendenze recenti. Available online from http://www.istat.it/it/archivio/38402.

Istat (2011). Tavole Regionali. http://www.istat.it/it/archivio/12973, Last accessed on October 21, 2011.

Kramarz, F., S. Lollivier, and L.-P. Pele (1996). Wage Inequalities and Firm-Specific Compensation Policies in France. *Annales d'Economie et de Statistique* (41-42), 369 – 386.

Kremer, M. (1993). The O-Ring Theory of Economic Development. *Quarterly Journal of Economics 108*(3), 551 – 575.

Kremer, M. and E. Maskin (1996). Wage Inequality and Segregation by Skill. NBER Working Paper 5718.

Kronenberg, K. and T. Kronenberg (2011, March). Keeping up with the Joneses by finding a better-paid job - The effect of relative income on job mobility. MPRA Paper No. 29426, posted 08. March 2011 / 13:22.

Kurtulus, F. A. (2011). What Types of Diversity Benefit Workers? Empirical Evidence on the Effects of Co-worker Dissimilarity on the Performance of Employees. *Industrial Relations 50*(4), 678 – 712.

Lazear, E. P. and S. Rosen (1981). Rank-Order Tournaments as Optimum Labor Contracts. *Journal of Political Economy 89*(5), 841 – 864.

Lazear, E. P. and K. L. Shaw (2008). *Wage Structure, Raises, and Mobility: An Introduction to International Comparisons of the Structure of Wages within and across Firms.*, Chapter 1, pp. 1 – 57. Stanford U: A National Bureau of Economic Research Conference Report. Chicago and London: University of Chicago Press.

Lengermann, P. (2002, June). Is it Who You Are, Where You Work, or With Whom You Work? Reassessing the Relationship Between Skill Segregation and Wage Inequality. U.S. Census Bureau, LEHD Project Technical paper No. TP-2002-10.

Lopes de Melo, R. (2009a). Estado de uma Nação. chapter Emparelhamento no Mercado de Trabalho Brasileiro: Evidência e uma Explicação. Ipea.

Lopes de Melo, R. (2009b). Sorting in the labor market: Theory and measurement.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies 60*(3), p531 – 542.

Marshall, A. (1890). *Principles of Economics.* New York: Macmillan.

Mas, A. and E. Moretti (2009). Peers at Work. *American Economic Review 99*(1), 112 – 145.

Mendes, R., G. J. van den Berg, and M. Lindeboom (2010). An Empirical Assessment of Assortative Matching in the Labor Market. *Labour Economics 17*(6), 919 – 929.

Moretti, E. (2004). Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions. *American Economic Review 94*(3), 656 – 690.

Navon, G. (2010). Human Capital Spillovers in the Workplace: Labor Diversity and Productivity. *Israel Economic Review 8*(1), 69 – 90.

Occari, F. and S. Pitingaro (1997). Demografia di impresa e mobilità del lavoro:una stima della componente spuria sulla base degli archivi Inps. Consiglio Nazionale delle Ricerche, Working Paper, Occupazione e livelli di attività in Italia.

Ouazad, A. (2007). Program for the Estimation of Two-Way Fixed Effects. available at http://personal.lse.ac.uk/ouazad/.

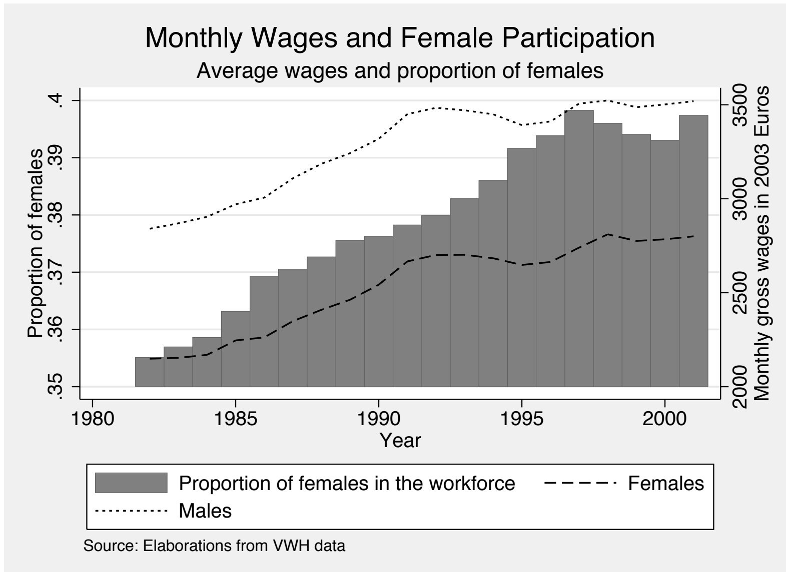
Shimer, R. and L. Smith (2000). Assortative Matching and Search. *Econometrica 68*(2), 343 – 369.

Shvydko, T. (2007, November). Interactions at the Workplace: Peer Effects in Earnings. Department of Economics, University of North Carolina, Mimeo, available from http://www.unc.edu/ tshvydko/.

Tattara, G. and M. Valentini (2010). Turnover and Excess Worker Reallocation: The Veneto Labour Market between 1982-1996. *Labour 24*(4), 474 – 500.

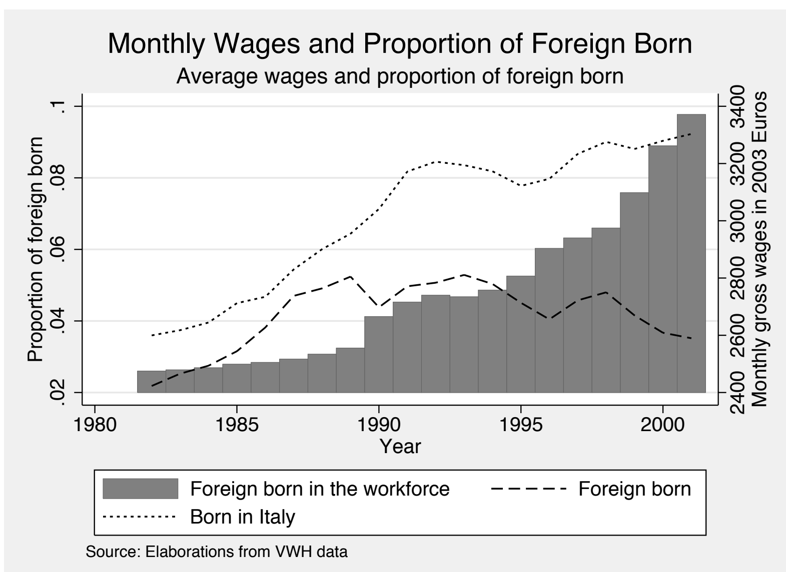
Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Figures and Tables



Source: Author's calculations from the Veneto Worker History Dataset.

Figure 1: Average monthly wages by gender and proportion of females

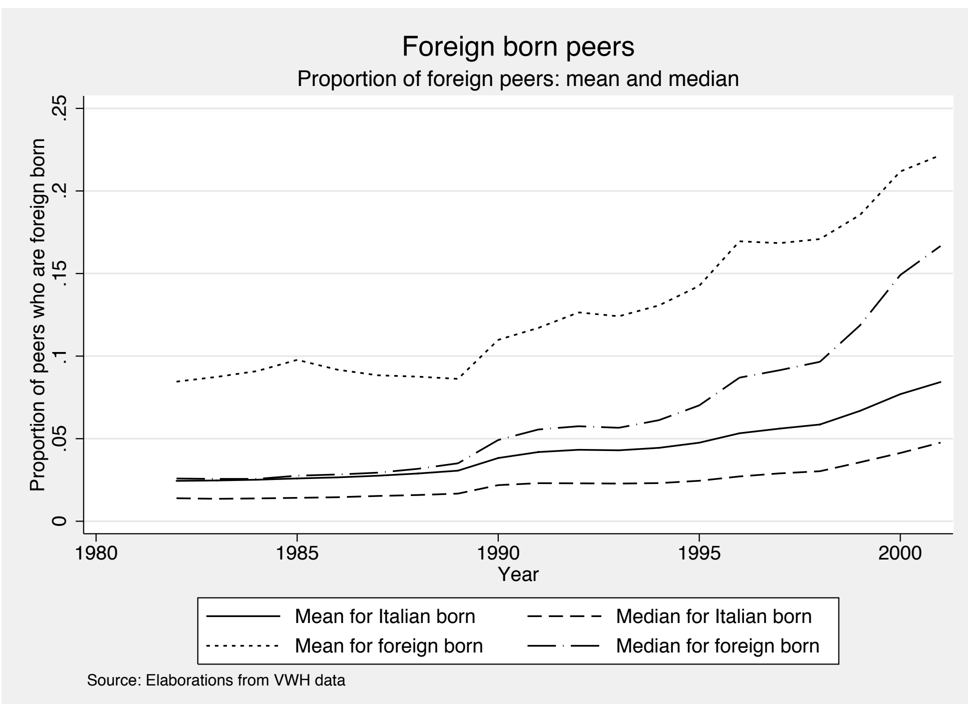


Source: Author's calculations from the Veneto Worker History Dataset.

Figure 2: Average monthly wages by foreign born status and proportion of foreign born

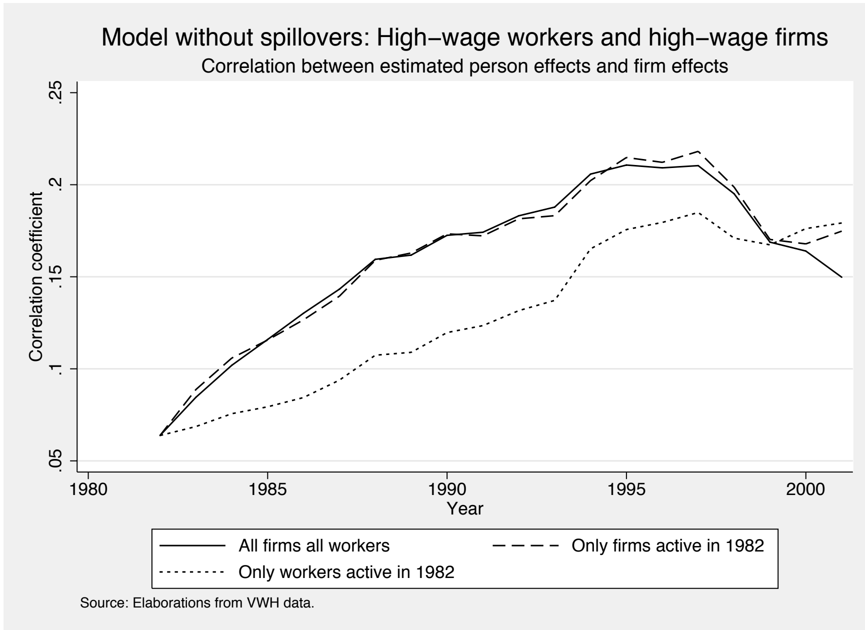
Source: Author's calculations from the Veneto Worker History Dataset.

Figure 3: Standard deviation of log monthly wages over time



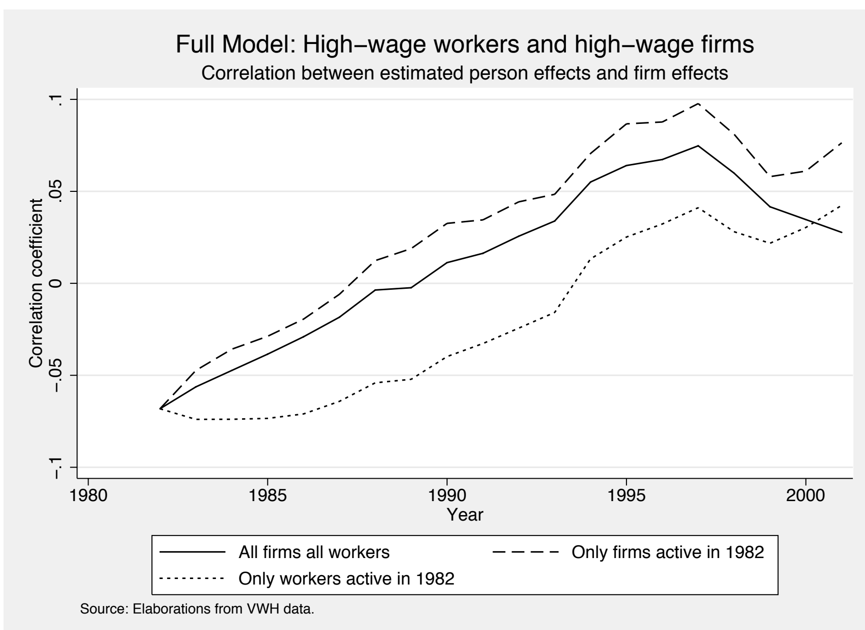
Source: Author's calculations from the Veneto Worker History Dataset.

Figure 4: Average proportion of peers that are foreign born



Source: Author's calculations from the Veneto Worker History Dataset.

Figure 5: Correlation between person effects and firm effects over time, for AKM model



Source: Author's calculations from the Veneto Worker History Dataset.

Figure 6: Correlation between person effects and firm effects over time, for full model

Source: Author's calculations from the Veneto Worker History Dataset.

Figure 7: Decomposition of the gap between the wage of foreign born and Italian born

Table 1: Firm sector

Economic sector of the firm	Frequency	Percentage of all firms
Commerce, bars and hotels	64,825	28.04
Transport and communications	8,196	3.55
Banking and insurances	13,586	5.88
Public administration and other services	23,448	10.14
Extraction of solid fuels	650	0.28
Coal industry	16	0.01
Oil and gas extraction	43	0.02
Oil industry	85	0.04
Production and distribution of electricity and natural gas	147	0.06
Water industries	76	0.03
Other extractive industries	153	0.07
Extraction and processing of metal minerals	24	0.01
Production and first transformation of metals	1,094	0.47
Extraction of non-metal, non-energy minerals	656	0.28
Non-metal material processing	3,739	1.62
Chemical industries	1,808	0.78
Production of artificial fibers	41	0.02
Other metal manufacturing	346	0.15
Construction of metal products	16,569	7.17
Construction and installation of machinery	4,877	2.11
Construction, installation and repairs of office equipment	1,651	0.71
Construction and installation of equipment	4,308	1.86
Construction and assembly of vehicles	582	0.25
Construction of transportation machinery	730	0.32
Construction of clocks and other precision machinery	1,015	0.44
Food industry	4,562	1.97
Sugar. alcohol and tobacco industries	1,604	0.69
Textile industry	3,963	1.71
Leather industry	1,458	0.63
Shoes and clothing industries	9,573	4.14
Wood and wood furniture industries	6,406	2.77
Paper and print industries	2,627	1.14
Rubber and plastic industries	2,659	1.15
Other manufacturing	3,121	1.35
Construction	46,557	20.14

Source: VWH data. Sectors coded using the 3 digit Ateco 81 coding system.

Table 2: Main regression results

Dependent variable: $ln(w_{ijt})$			
	Models		
Variables	(1)	(2)	(3)
Estimated coefficients of covariates			
Experience		0.013	0.018
		(0.000)	(0.000)
		[773]	[631]
Experience^2		-0.001	-0.001
		(0.000)	(0.000)
		[-960]	[-729]
Firm size/1,000		0.013	0.013
		(0.000)	(0.000)
		[526]	[541]
co-worker 'Quality' $\bar{\theta}$			0.358
			(0.0000)
			[11,074]
Fixed effects			
Standard deviation of the person effect: σ_θ	0.383	0.413	0.389
Standard deviation of the firm effect: σ_ψ	0.230	0.215	0.205
Standard deviation of the time effect: σ_τ	0.170	0.201	0.200
Pseudo R^2	0.716	0.720	0.722
Standard deviations of $\bar{\theta}$			
$\sigma_{\bar{\theta}}$ (overall s.d.)			0.218
$\sigma_{\bar{\theta},1982}$ (cross sectional s.d. for 1982)			0.221
$\sigma_{\bar{\theta},1991}$ (cross sectional s.d. for 1991)			0.201
$\sigma_{\bar{\theta},2001}$ (cross sectional s.d. for 2001)			0.199
$\frac{1}{N}\sum_{i=1}^{N}\sigma_{\bar{\theta},i}$ (average of within-person s.d.)			0.104
$\frac{1}{NT}\sum_{m=1}^{NJ}\sigma_{\bar{\theta},m}$ (average of within-firm s.d.)			0.090
$\frac{1}{J}\sum_{j=1}^{J}\sigma_{\bar{\theta},j}$ (average of within-firm s.d.)			0.190
Variance decomposition			
Person effect θ	0.462	0.491	0.469
Firm effect ψ	0.201	0.181	0.134
Time effect τ	0.054	0.058	0.058
Experience		0.056	0.082
Experience^2		-0.077	-0.080
Firm size		0.010	0.010
Spillover effect η			0.049
Unexplained ϵ_{ijt}	0.284	0.280	0.278
Wage Sorting			
$Corr(\theta, \psi)$	0.154	0.160	0.012
$Corr(\theta, \bar{\theta})$			0.420
N_{obs} = 28,115,529, $N_{workers}$ = 3,180,714, N_{firms} = 231,195			

Approximate robust standard errors in brackets, t-stats in squared brackets

Source: Veneto Worker History Dataset.

Table 3: Standardised wage, θ and ψ gaps for different groups

Populations	log(wage)	Person effect θ	Spillover effect $\overline{\theta}$	Firm effect ψ
Full sample mean	7.88	4.46	4.46	1.78
Full sample standard deviation	0.57	0.39	0.22	0.21
Gender gap	0.25	0.21	0.08	0.01
Foreign-born gap	0.13	0.15	0.09	0.02

Source: Veneto Worker History Dataset.

Table 4: The contribution of gender and immigration status to the person effect

Dependent variable: θ_i

	(1)	(2)	(3)
Dummy for Female	-0.180***		-0.193***
	(0.001)		(0.001)
Dummy for Foreign born		-0.192***	-0.244***
		(0.001)	(0.001)
Interaction: Female * Foreign born			0.108***
			(0.002)
Constant	4.412***	4.354***	4.434***
	(0.000)	(0.000)	(0.000)
Observations	3180714	3180714	3180714
R^2	0.032	0.011	0.046

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Veneto Worker History Dataset.

Table 5: Gender and labour market quality of peers

Dependent variable: $\frac{1}{N_{ijt}} \sum_{p \in \mathcal{N}_{ijt}} \theta_p$

	(1)	(2)	(3)	(4)	(5)
Dummy for female	-0.082***	-0.030***	0.037***	0.032***	0.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual unobserved heterogeneity θ_i		0.247***	0.238***	0.222***	0.221***
		(0.000)	(0.000)	(0.000)	(0.000)
Proportion of females in peer group			-0.240***	-0.234***	-0.234***
			(0.000)	(0.000)	(0.000)
Experience				0.003***	0.003***
				(0.000)	(0.000)
Experience^2				-0.000***	-0.000***
				(0.000)	(0.000)
Firm size/1,000				0.026***	0.026***
				(0.000)	(0.000)
Firm heterogeneity ψ					-0.017***
					(0.001)
Observations	28115529	28115529	28115529	28115529	28115529
R^2	0.033	0.214	0.285	0.339	0.339

Heteroskedasticity-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Veneto Worker History Dataset.

Table 6: Birth place and labour market quality of peers

Dependent variable: $\frac{1}{N_{ijt}} \sum_{p \in \mathcal{N}_{ijt}} \theta_p$

	(1)	(2)	(3)	(4)	(5)
Dummy for foreign born	-0.094***	-0.056***	-0.014***	-0.014***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual unobserved heterogeneity θ		0.254***	0.244***	0.226***	0.226***
		(0.000)	(0.000)	(0.000)	(0.000)
Proportion of foreign born in peer group			-0.410***	-0.374***	-0.377***
			(0.001)	(0.001)	(0.001)
Experience				0.003***	0.004***
				(0.000)	(0.000)
Experience^2				-0.000***	-0.000***
				(0.000)	(0.000)
Firm size/1,000				0.025***	0.025***
				(0.000)	(0.000)
Firm heterogeneity ψ					-0.023***
					(0.001)
Observations	28115529	28115529	28115529	28115529	28115529
R^2	0.009	0.213	0.240	0.291	0.292

Heteroskedasticity-robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Veneto Worker History Dataset.

Appendices

A Details on the Iterative Procedure

For notational convenience I define the variable y_{ijt}, which denotes the dependent variable of my model net of all fixed effects and covariates that are not a function of the current θ:

$$y_{ijt} \equiv w_{ijt} - \mathbf{X_{it}}\beta - F_{jt}\kappa - \psi_j - \tau_t \tag{A.1}$$

where all notation corresponds to that of equation (1). As shown below, the key for the estimation is to derive the First Order Conditions of (2) with respect to the worker effect θ_i after having substituted in using equation (A.1):

$$\sum_t \left\{ \left[y_{ijt} - \theta_i - \eta \frac{1}{N_{ijt\sim i}} \left(\sum_{p \in \mathcal{N}_{ijt\sim i}} \theta_p \right) \right] + \sum_{p \in \mathcal{N}_{ijt\sim i}} \eta \frac{1}{N_{ijt\sim i}} \left[y_{ijt} - \theta_p - \left(\eta \frac{1}{N_{ijt\sim p}} \sum_{k \in \mathcal{N}_{ijt\sim p}} \theta_k \right) \right] \right\} = 0$$

In order to make this implicit equation for θ_i operational, I solve the equation above for θ_i moving all of the terms including θ_i to the left-hand side of the equation and then solving for θ_i:

$$\theta_i = \frac{\sum_t \left\{ y_{ijt} - \eta \frac{1}{N_{ijt\sim i}} \left(\sum_{p \in \mathcal{N}_{ijt\sim i}} \theta_p \right) + \sum_{p \in \mathcal{N}_{ijt\sim i}} \eta \frac{1}{N_{ijt\sim i}} \left[y_{ijt} - \theta_p - \left(\eta \frac{1}{N_{ijt\sim p}} \sum_{k \in \mathcal{N}_{ijt\sim p}} \theta_k \right) \right] \right\}}{\sum_t \left(1 + \eta^2 \frac{1}{N_{ijt\sim i}} \right)} \tag{A.2}$$

The person fixed effects that are on the right-hand side of the equation above are those of the previous iteration, and get updated after each θ_i is updated using equation (A.2). As a consequence, even though my model includes different and additional fixed effects, Theorem 2 in Arcidiacono et al. (2012) applies here, since the additional estimated coefficients do not depend on theta and thus can be viewed as part of the dependent variable at each iteration. Theorem 2 shows that equation (A.2) is a contraction mapping, guaranteeing convergence of the estimated parameters to their NLS counterparts, for any initial vector θ_0 if $\eta < 0.4$.[48] In particular, unlike similar two-step

[48] The result in Arcidiacono et al. (2012) is not a bivariate relationship, so that the result may hold for values larger than 0.4 as well, depending on the size of peer groups.

procedures such as that developed in Mas and Moretti (2009), in the procedure of Arcidiacono et al. (2012) measurement error in the covariates does not lead to an attenuation bias of the regression coefficients. This is due to the fact that the indirect effect of ability on outcomes through the peer effects is directly accounted for in the estimation procedure.

Arcidiacono et al. (2012) derive this result by stacking the First Order Condition from the optimization problems for each θ and checking the conditions for the function from one guess at the vector of individual effects of θ to the next $f : \theta \to \theta'$ to be a contraction mapping, which is equivalent to checking the conditions for $\rho(f(\theta), f(\theta') < \beta\rho(\theta, \theta')$ for some $\beta < 1$ and where ρ is a valid distance function. In each step of the iterative procedure, after having updated each member of the vector θ using (A.2) the procedure updates the firm fixed effect and the year by sector fixed effect averaging the residuals for each observation over the relevant set of observations, excluding the fixed effect of interest. After having updated the vector f individual fixed effects, I can now update the vector of firm effects and time effects:

$$\psi_j = \frac{\sum_{i \in \mathcal{N}_j} \left[w_{ijt} - \mathbf{X_{it}}\beta - F_{jt}\kappa - \theta_i - \eta \frac{1}{N_{ijt}} \left(\sum_{p \in \mathcal{N}_{ijt}} \theta_p \right) - \tau_t \right]}{\sum_{i \in \mathcal{N}_j} 1} \tag{A.3}$$

$$\tau_t = \frac{\sum_{t \in \mathcal{N}_t} \left[w_{ijt} - \mathbf{X_{it}}\beta - F_{jt}\kappa - \theta_i - \eta \frac{1}{N_{ijt}} \left(\sum_{p \in \mathcal{N}_{ijt}} \theta_p \right) - \psi_j \right]}{\sum_{i \in \mathcal{N}_t} 1} \tag{A.4}$$

For updating θ_i in iteration α I use a modified version of equation (A.2) for computational convenience, using the result in Lemma 2 of Theorem 1 of Arcidiacono et al. (2012):

$$\theta_i^{\alpha} = \frac{\sum_t \left\{ \eta \frac{1}{N_{ijt}} \left(\sum_{j \in \mathcal{N}_{ijt}} e_{jt}^{\alpha-1} - e_{it}^{\alpha-1} \right) + e_{it}^{\alpha-1} + \left(1 + \eta^2 \frac{1}{N_{ijt}} \right) \theta_i^{\alpha-1} \right\}}{\sum_t \left(1 + \eta^2 \frac{1}{N_{ijt}} \right)} \tag{A.5}$$

where e_{it} denotes the regression residual from the OLS regression estimates of step 1. Equation (A.5) is obtained from equation (A.2) by identifying regression residuals and then substituting them in, isolating the terms that include $\theta_i^{\alpha-1}$. Sum of squared residuals fall after each iteration, and can be performed until a predetermined criterion for convergence is reached.[49]

[49] In the case of my estimation, that criterion is that the sum of squared residuals differ by less than 10^{-7} between two consecutive iterations.

B Structure of the VWH Dataset

The VWH dataset is composed of a worker archive, a firm archive and a job archive. I link the job archive to the worker archive using the worker identifier they share, and the firm archive to the dataset using the firm identifier. The worker archive includes a person identifier, and very limited individual information: gender, birth date, birth place,[50] and residential address.[51] The VWH dataset includes no information on the workers' education. This is not crucial for my estimation however, because all of the time-invariant individual characteristics are captured by the person effect, and could not be separately included even if available. The firm archive includes a firm identifier, firm's name, activity, address, sector,[52] establishment date, cessation date, number of initial employees, area code and postal code of the headquarter. The job archive includes a worker identifier, a firm identifier, duration of the employment relationship (in days), place of work, total yearly real wages in 2003 Euros for each job in each time period, qualification, contract level.

For the analysis in this paper it is crucial to have a correct identification of firms, in a cross sectional as well as dynamic sense. The VWH dataset has been the product of a careful identification of firms as economic entities and not simply as legal entities. The variable has been constructed using the same technique as in Occari and Pitingaro (1997). When a majority share of workers of a large firm moves to another firm the mobility is considered spurious. For small firms the logarithm also requires that location remains unchanged. When mobility is considered spurious, the two firms are recognised as the same firm.[53]

[50]From which I have manually constructed a country of birth variable for foreign born from the place of birth.

[51]This is often different from the current address since there are virtually no incentives for people to change it and so the change may be delayed by many years.

[52]Employers are classified according to the three-digit Ateco 1981 standard classification. The author would like to thank Prof. Giuseppe Tattara for sending all of the information necessary for translating the Ateco 1981 coding into meaningful industry codes.

[53]Additional information on the dataset and in particular on the construction of the two different firm identifiers are available from Tattara and Valentini (2010).

C Sample Restrictions

As discussed above, from the raw VWH data I construct a regression dataset with at most one observation for each worker in each year, and therefore I eliminate additional observations of each worker/year. Apart from cases with missing values in the variables used in the regression, the vast majority of these case are cases in which there are two different records for the same worker in the same firm, which is the result of the fact that the data is based upon a firm identifier that does not take mergers and acquisitions into account. For all cases in which a worker is observed more than once in the same firm in the same year I construct a new relationship that incorporates these different relationships and drops duplicates. For the cases in which there are still multiple observations per worker/year I identify a dominant job keeping the employment relationship with the higher number of days paid.

My main regression model includes a measure of firm size. The VWH does not include firm size, so I construct it from the data, counting all employees employes in a certain firm for each year. This measure may underestimate actual firm size since a firm's workforce may include undocumented workers, or may hire professionals that I cannot observe because it is not part of my dataset.

I also construct a variable for labour market experience: within the period of my data, I can see the employment history of all workers and so I can use the total number of months worked to construct a measure of actual labour market experience. However, for a portion of workers in my sample I cannot observe the start of their labour market careers. For this purpose, I divide workers into two categories, depending on whether I can assume that I observe them from the beginning of their careers. I assume that I see their whole careers if they have no job in the first three years of my dataset and if they are at most 18 years old in 1985, the first year I have since I ignore the first three. For the workers for whom I assume that I am observing their whole labour market career, experience will be equal to observed experience, given by the sum of months in full time employment up to (not including) year t. For workers that I do not see from the start of their careers, experience is given by observed experience up to year t plus the average months of experience accumulated by workers of the same category and gender from their average minimum age of employment up to the first time I see them in my dataset. I divide workers into white collar and blue collar workers based on their occupation, in order to control for the different age of entry in the labour force of white collar workers. Each year, male workers work on average around 10 full-time months if they are white collar workers, around 9.5 months if they are blue collar workers. Female workers work around 9 full-time months if they are white collar and around 8.5 months if they are blue collar workers. Average age of entry in the labour force is very similar for male workers and females workers, at around 22 for white collars, 19 for blue collars.

D Robustness Check: Small Firms and Large Firms

Table 7 below reports estimates of equation (1) on two different sub samples of my population, that of workers of very small firms and of very large firms. Guven that organisational structure and type of interactions are likely to be very different between small and large firms, running separate regression can investigate whether the overall results are driven by firms of a certain size.

In the estimates both from small and large firms I find smaller peer effects and lower proportion of the overall wage variance that is explained by spillover effects. This suggests that my main estimates are not driven by very small firms of very large firms alone. The second column of Table 7 is estimated using the sample of firms that have less than ten employees at a given point in time. For this subpopulation of firms, person and firm effects are important while spillover effects explain around 2.2 percent of all wage variation. A one standard deviation increase in the average labour market skills of peers is associated with a wage gain of 6.8 percent. Using the average within-firm standard deviation, the equivalent figure is 2.9 percent.

The third column of Table 7 shows estimates for the same model for a sample of the largest firms only. Compared to the full sample, peer effects are smaller in terms of average wage effects: while a unitary change in the overall standard deviation is associated with a wage increase of 6.2 percent, the estimate using average firm-level standard deviation in "Peer 'quality' " is of 1.9 percent. They are also relatively unimportant in terms of proportion of the overall variation that is explained by them, i.e. 2.4 percent. The fact that I find smaller effects for larger firms is comforting since for larger firms the entire set of co-worker represents a noisier proxy for the unobserved actual peer group.

Table 7: Regression on different samples

Dependent variable: $ln(w_{ijt})$			
	Models		
	Full	Small firms	Large firms
Number of employees		< 10	$> 1,000$
Estimated coefficients of covariates			
Experience	0.018	0.023	0.018
Experience^2	-0.001	-0.001	-0.001
Firm size	0.000	0.004	-0.000
co-worker 'Quality' $\bar{\theta}$	0.358	0.184	0.340
Fixed effects			
σ_θ	0.389	0.467	0.443
σ_ψ	0.205	0.372	0.280
σ_τ	0.200	0.171	0.237
$Corr(\theta, \psi)$	0.014	-0.373	-0.009
Variance decomposition			
Person effect θ	0.469	0.506	0.551
Firm effect ψ	0.134	0.191	0.188
Time effect τ	0.058	0.072	0.044
Polynomial in experience	0.002	0.023	0.005
Firm size	0.010	-0.000	-0.002
Spillover effect η	0.049	0.022	0.024
Unexplained ϵ_{ijt}	0.278	0.187	0.190
Pseudo R^2	0.722	0.813	0.810
Standard deviations of $\bar{\theta}$			
$\sigma_{\bar{\theta}}$ (overall s.d.)	0.218	0.372	0.181
$\sigma_{\bar{\theta},1982}$ (cross sectional s.d. for 1982)	0.221	0.405	0.163
$\sigma_{\bar{\theta},1991}$ (cross sectional s.d. for 1991)	0.201	0.360	0.147
$\sigma_{\bar{\theta},2001}$ (cross sectional s.d. for 2001)	0.199	0.382	0.190
$\frac{1}{N_t J_t} \sum_{j=1}^{J} N_{jt} \sigma_{\bar{\theta},j}$ (weighted average of within-firm s.d.)	0.089	0.158	0.056
N_{obs}	28,115,529	3,933,459	4,224,592
$N_{workers}$	3,180,714	1,026,651	683,624
N_{firms}	231,195	203,543	178
Note 1: for small firms and large firms, my converge criterion is 10^{-4}			
Note 2: Samples are restricted to observations in the main connected group			

Source: Veneto Worker History Dataset.

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