High Wage Workers and High Wage Peers

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Abstract

This paper investigates the effect of coworker characteristics on wages. I use the average person effect of the set of current coworkers of each worker as a summary measure of relevant peer characteristics. This measure captures the average labor market value of the portable component of coworkers' observed and unobserved characteristics. The effect of interest is identified from within-firm changes in workforce composition over time, controlling for person effects, firm effects, and sector-specific time trends.

My estimates are based on the Veneto Worker History (VWH) dataset. The VWH is a linked employer employee dataset of all workers and firms from the Italian region of Veneto for the years

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1982-2001. The dataset has been constructed by researchers of the University of Venice from Social Security records of the Italian institute for social security ("Istituto Nazionale della Previdenza Sociale", or INPS). The VWH datasets is a very rich dataset and it is ideal for the research question of this paper because of its length (20 years) and its size (my final regression sample has over 28 million observations). Therefore, I observe sufficient mobility of workers from firm to firm to be able to use the variation of the workforce of a firm over time to separately identify person effects, firm effects and spillover effects.

I find that a 10-percent increase in peer quality is associated with a 3.6-percent average wage premium. This means that one standard deviation increase in the average labour market value of coworkers' skills is associated with a wage gain of 4-8 percent, depending on the thought experiment used to construct the distribution of peer quality. In addition, I find that around one fourth of the wage variation previously explained by unobserved firm heterogeneity is actually due to variation in coworker skills: a substantial portion of the contribution of firms to wages is the result of the characteristics of the workers these firms hire. Once I control for spillover effects, the proportion of overall wage variation that is explained by firm effects decreases from 18 percent to 13 percent. This has novel policy implications for sorting and for the role of skill segregation on wage inequality.

Finally, in an empirical application of my model I find that between 10 and 15 percent of the immigrant wage gap is explained by the quality of workers' peers. I find that this gap is primarily driven by the existence of immigrant enclaves but a significant proportion of the gap survives controlling for the tendency of immigrants to work in firms with many other immigrants. This suggest wages of immigrants may be negatively affected by the nature of sorting in the labour market.

Keywords: Spillover effects; Linked Employer-Employee Dataset; Skill segregation.
JEL codes: J31, J79

1 Introduction

It has long been hypothesized that spillover effects may play an important role in the workplace (for example, externalities across coworkers are discussed in Marshall, 1890, p. 12). Understanding spillovers 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, even holding individual characteristics constant. 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 partially explain 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, previous research is based on specialized datasets and specific sectors and tasks, and focuses on the effect of peers operating through effort.[1] These studies typically find evidence of positive spillover effects: 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 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 have similar characteristics and because they are part of the same environment ('correlated effects', Manski, 1993). This suggests that spillover effects ought to be estimated from changes in workforce composition within firms. Secondly, the characteristics of coworkers affecting own outcomes may be unobserved to the econometrician. Excluding them generates a downward bias in the total effects of peers.

Until recently, virtually all observational data on the labour market were individual or household surveys or censuses, making it impossible to link firm's characteristics and characteristics of

[1] 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.

coworkers to any specific worker. Recently, the advent of linked employer-employee data, which include information on many workers inside the same firm and follow the same workers over time, have made it possible to investigate spillover interactions inside firms and to account for the role of unobservables.

In this paper I estimate the effects of coworkers' skills on wages. 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 both have substantial methodological limitations relative to this paper.[2] Shvydko (2007) specifies the peer effect via coworkers' wages, which raises concerns about endogeneity.[3] Lengermann (2002) estimates spillover effects operating through observable and unobservable coworker characteristics, similar to this paper. He finds that a one standard deviation increase in an index of coworker skill is associated with wage increases of 3 to 5 percent. However, Lengermann (2002) uses a different estimator than the one considered in this paper, and his estimator's statistical properties are unknown.

I estimate a log-linear wage regression that extends 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, fixed firm effects that allow for unobserved firm-level heterogeneity, and year by sector effects to control for sector-specific macroeconomic trends. I measure peer characteristics by the average person fixed effect of coworkers. In particular, I control for the average person effect of workers working in the same firm in the same time period. This measures the labour market value of coworkers' "portable" skills (i.e., the returns to characteristics that are person-specific and employer-invariant). I estimate the spillover effect arising from coworkers' observable and unobservable time-invariant characteristics simultaneously with the other parameters, using an estimator based on Arcidiacono et al. (2011). The spillover effect is identified from within-firm changes in the composition of the workforce net of time-invariant unobserved firm heterogeneity, sector-specific effects, and firm size.

I estimate the model using data from the longitudinal Veneto Worker History (VWH) panel,

[2] Battu et al. (2003) measure spillover effects in the UK operating through the level of education of coworkers, 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.

[3] All unexplained within-firm wage variation that is common across coworkers is used to identify spillovers.

which covers the population of private-sector workers of the Italian administrative region of Veneto for the years 1982-2001.[4] I find that spillover effects are an important determinant of wage variation. A one standard deviation increase in 'quality' (i.e. labour market value of portable skills) of a worker's peers is associated with a real wage between 4 and 8 percent higher. 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 10 to 15 percent of the immigrant wage gap is due to the labour market characteristics of peers. In the case of foreign born workers, I find that differences in peer characteristics are not entirely due to ethnic enclaves.

2 Theoretical Background

The theoretical literature has identified a number of means through which the quality of coworkers could affect a worker's wage. However, because there are possibly many forces at work at the same time and we often cannot test the empirical importance of each against each other, it is hard to predict sign and magnitude of spillover effects in the labour market theoretically. New empirical evidence can generate future theoretical work and inform about the relative importance of the mechanisms I outline below in practice.

First, there may be spillover effects in productivity across workers: a worker's production function may depend on the characteristics of her coworkers. One channel that has received particular attention is the possible effect of human capital heterogeneity at the firm level on productivity, as 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 indeed affect spillovers. In a related contribution, Moretti (2004) tests for the existence of human capital spillover effects

[4] 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.

across firms within cities and finds productivity spillovers to be positive and significant for hi-tech plants in the US.

Even for tasks that are individual in nature, the characteristics of peers might play a role in wage determination. Two recent papers examine the role of peer pressure in the workplace using laboratory and field data for individualised tasks. Falk and Ichino (2006) use a lab experiment to investigate social pressure spillovers, and find that productivity is higher and less dispersed when subjects work in pairs rather than individually. 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 quality of coworkers 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 coworkers, and may be willing to accept a lower wage for that because of compensating differentials, 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. In addition, the literature on the effect of minimum wages across the wage distribution[5] suggests that reference points may be important for wage determination. If the wage structure within the firm provides a reference point for all workers, wages of lower-ability workers will be affected by the skill composition inside the firm. Kronenberg and Kronenberg (2011),[6] for example find that workers are more likely to leave a firm as wage inequality in the firm increases. If firms internalised this effect, wages of low-skill workers would be a positive function of the average level of skills in the firm.

Coworkers' skills may also affect wages through bargaining dynamics, independent of productivity. 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, then a worker's wage will be higher when she has higher skill coworkers. Conversely, if highly-skilled workers are able to extract a larger share of the a surplus in a context where wages are a fixed share of total revenues, spillover effects would be negative due to negative bargaining externalities.

[5]See Dittrich et al. (2011) for an overview of that literature.

[6]Despite not referring to it, this papers seems related to the fair wage model of Akerlof and Yellen (1990).

Incentive schemes within the firm can also generate interactions between wages and peer characteristics. In tournament models[7] effort (and thus wages) are a function of the characteristics of all workers in the firm. However, the relationship between quality of coworkers 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.[8] In addition, the expected level of cooperation among workers (and thus total output and individual wages) may also depend on the distribution of types. In order to assess the relative importance of these different channels, the existence and magnitude of the spillover effect should be investigated empirically first, which is what I turn to in the next section.

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.[9] 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 coworkers, or current peer group. A worker i at time t has the set of coworkers $\mathcal{N}_{ijt}$ at time t, with cardinality N_{ijt} (in each period there are $N_{ijt}+1$ workers at firm j including worker i). One of worker i's coworkers is denoted by p. My main regression model is

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

where the outcome of interest is worker i's log monthly 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, its average among peers[10] by $\frac{1}{N_{ijt}}\sum_{p\in\mathcal{N}_{ijt}}\theta_p$, firm effects by ψ_j and industry-specific year

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

[8] 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.

[9] Since the estimation follow workers over time, a more precise notation defines the firm where worker i is employed at the t as $J(i,t)$, but I simply use j since all cases are unambiguous.

[10] Sometimes I refer to this measure as peer 'quality'. The reader should be cautions with its interpretation however. Since I observe wages and not productivity, θ will capture all of the characteristics that make a worker more productive (more able to produce) and the return to those characteristics as well as the characteristics that will make him/her

effects by τ_t. The $b \times 1$ column vector[11] 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 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 two potential issues concerning the identification of peer effects in a linear in means model: it is hard to distinguish social effects from correlated effects. This paper provides solid grounds on which to rule out much of the possible role for correlated effects. Individual covariates $\mathbf{X_{it}}$ are included because individual characteristics that have an effect on wages might also be correlated with the average quality of a worker's peer group. In addition, I include F_{jt} measuring the wage effect of the number of employees of the firm at a given point in time. The goal of including firm size is to make sure that my estimates of peer effects are not simply driven by growth and decline in the number of employees of a firm, which could be a source of bias for example if firms paid higher wages but attracted lower-ability workers when they grew in size. Because I am able to calculate wages per unit of time worked, I can also make sure the effect of demand shocks that might result in higher labour supply for the same employees is not going to drive my results. There may also be common-environment effects ('correlated effects', Manski 1993): some firms might 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, time trends in the average ability of peers and in the outcome variable could affect my estimates of spillover effects. For example, during a year in which macroeconomic conditions are positive firms may pay higher wages but may also see the average ability of their workforce decrease, which would be the case if marginal workers have below-average skills. I therefore control for time trends. In order to allow for time trends to be different in different sectors of the economy,[12] I include industry-specific year trends, denoted by τ_t in equation (1).

more able to extract rents (holding productivity constant). In other words, θ captures 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.

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

[12]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.

The individual fixed effect θ_i captures the effects of all individual time-invariant characteristics that affect wages, i.e. 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 average value of θ among people working with worker i at time t. Equation (1) is written under an implicit assumption on the characteristics included in θ_i. Arcidiacono et al. (2011) and Altonji et al. (2010) refer to this assumption as the 'proportionality assumption'. It 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. (2011). The key assumption of Theorem 1 require residual across any two observations to be uncorrelated: net of person effects, firm effects and time effects, correlations in outcomes across individuals in the same peer group are assumed to be captured by the peer effects entirely. In my case, 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 for different sector. However, all of the remaining intertemporal changes in peer 'quality' within a firm, controlling for all of the other covariates, are used to estimate the peer effect coefficient η, and so need to be assumed orthogonal to the error term ϵ_{ijt}. This is equivalent to assuming that there are no time-varying unobservables systematically driving changes in the composition of the peer group of worker i while at the same time affecting worker i's wage in the same direction. Thereom 1 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.[13]

[13]See Arcidiacono et al. (2011) page 7 for details on these assumptions

For notational convenience I define $\bar{\theta}_{ijt} \equiv \frac{1}{N_{ijt\sim i}} \sum_{p \in \mathcal{N}_{ijt}} \theta_p$. The nonlinear least squares problem derived from equation (1) is then

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

Under the assumptions stated above, the nonlinear least squares solution $\hat{\eta}_{NLS}$ is a consistent and asymptotically normal estimator of the true η as the number of individuals goes to infinity for a fixed number of time periods. The key elements that allow Arcidiacono et al. (2011) 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. (2011) 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 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 heterogeneities 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 minimise equation (2) iteratively, updating one parameter at a time and using previously estimated values for all the other parameters until convergence.[17] The specific iterative procedure described

[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) and Brock and Durlauf (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.

[17]Estimating equation (2) in one step is not computationally feasible with a large dataset.

below builds upon that of Arcidiacono et al. (2011) adapting it to the labour market context and in particular to the inclusion of firm effects.

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.[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 an Ordinary Least Squares procedure that has the outcome variable w_{ijt} net of all fixed effects as the dependent variable;
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 (B.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 (B.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 (B.4).

4 Data and Institutional Background

The empirical investigation below uses the longitudinal Veneto Worker History (VWH) dataset.[20] The dataset includes all workers of the administrative region of Veneto in the North East of Italy[21] except state and local government employees, farm workers and some category of professionals (such as doctors, lawyers, notaries and journalists), who have alternative social security funds. 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.[22] VWH includes register-based information on all establishments and employees that have been hired by those establishments 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 VWH dataset has

[18]The inclusion of additional covariates compared to Arcidiacono et al. (2011) 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.

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

[20]This panel dataset is built at the department of Economics of the University of Venice using the Social Secuity administrative data of the *Istituto Nazionale per la Previdenza Sociale* (INPS), which is the main public institute of social security in Italy.

[21]Additional information on the dataset available in Card et al. (2010) and in Tattara and Valentini (2010)

[22]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.

several attractive features for the estimation of spillover effects in the firm: it is a very large dataset, with the unselected sample containing around 3.6 million workers and 46 million observations at the job by year level, and spans a time period of 20 years.[24]

The region of Veneto is the third Italian region by GDP (Istat, 2011) and has a population of around 5 million, around 8 percent of the country's total. Its economy is characterised by small and very small manufacturing businesses which are organized on a regional basis by specialisation and with local integration.[25] The region underwent fundamental changes in its economic history in the last few decades. Until after World War II, the economy of Veneto was largely based upon farming and saw large out-migration to Germany, Switzerland, the US, Canada and Australia. The 1960s and 1970s were characterized by intense economic development, and Veneto is now one of the richest and most industrialised regions of Italy, and a large net receiver of international migrants. Immigrants currently represent around 10 percent of the population of Veneto, which is well above the Italian average.[26] 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.[27] The equivalent figures for 1991 are 25,000 in absolute number, around one percent of the total population.

Italy is often viewed as a country where collective bargaining is the main mechanism for wage determination. The reality is more complex, and especially for small firms as those that dominate the labour market of Veneto there are many potential sources of wage differentials. National regulations are typically silent about specific compensation levels. Trade union contracts specify non-binding minimum wages at the industry level. Although these are relevant for bargaining inside

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

[25] In particular, the region is has been often studied as a model for industrial districts, characterised by highly specialised small firms, which tend to be geographically very concentrated. Engineering, textile and clothing and furniture being some of the prominent industries. Some of these small firms have experienced remarkable growth such as Benetton and Luxottica.

[26] 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).

[27] 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).

the firm, they simply represent an industry-specific floor for total compensation. Because minimum wages are occupation and rank-specific, promotions can affect the relevance of the contractual minimum wages. Individual bargaining and firm-level agreements are also important, and wage premia are highly heterogeneous across firms (Erickson and Ichino, 1993), and usually higher for small firms, where individual bargaining plays a larger role (Cingano, 2003).

5 Data Selection

From the full dataset, my model dictates a few data selections. First, 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.[28] I choose to construct a dataset where there is at most one observation for each worker in each year.[29] I create a wage variable that measures average monthly wages for full time employment, so that my estimates of wages are driven by variation in compensation per unit of time rather than by labour supply variation. The main regressor of interest in my dataset is a measure of ability of a worker's coworkers, which can be constructed only if the firm has at least two coworkers.[30]

Separately identifying fixed 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 identify connected groups of observations using the algorithm "a2group" written by Ouazad (2007).[31] 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

[28] 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.

[29] 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.

[30] 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.

[31] In turn, "a2group" is derived 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.

all observations that are not part of my main connected sample before estimating my model.[32]

6 Summary Statistics

My regression sample has 28,115,529 yearly observations in total, which have observation from 231,195 different firms and from 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.[33] Figure 1 plots average monthly wages (in 2003 Euros) for full time employment by gender and the gender distribution over time. The proportion of females increases from 35.5 percent in 1982 to around 40 percent from 1997 onwards. 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.

Figure 2 compares workers born in Italy with workers born abroad. The proportion of foreign-born workers increases dramatically, from 2.6 percent in 1982 to 9.8 percent in 2001.[34] 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 primarily by falling average wages of foreign born.[35] While in 1982-1989 average yearly growth rates of gross real wages are 1.70

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

[33] 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.

[34] Up to 1989, foreign born are between 2 and 4 percent of the total. For the most part reflects foreign born with Italian parents returning from Switzerland, Germany and Latin America.

[35] 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.

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 negative 0.33 percent for foreign born.

Looking at wage dispersion, 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.[36] Apart from the year-to-year variation due to business cycle fluctuations, there is a clear upward trend for both measures. Wage dispersion within firms (dashed line on the chart) 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.

During the period of my dataset the average size of firms in my sample did not see any major changes. The average number of employees of a firm[37] 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. Table 1 shows that the largest economic sectors in terms total of 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).

7 Regression Results

The main estimates of equation (1) are presented in Table 2. I report heteroskedasticity-robust standard errors and t-statistics for my coefficients.[38] Column 1 estimates a model with a firm fixed

[36]I calculate the average of the within-firm standard deviation and the standard deviation of the average wage of each firm. Figure 3 is constructed from a dataset that has one observation for each worker in each, so that I can take account of firm size. If I had one observation per firm the statistics on the chart would be entirely driven by small firms.

[37]As I mentioned above because I need to exclude firms that only have one employee from my sample, this average is higher than the average for the population of firms in Veneto during the same period.

[38]Arcidiacono et al. (2011) 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 their size and the size of my dataset, improved standard errors are very unlikely to make any difference for my inference.

effect, a worker fixed effect and a year by industry effect only. Column 2 adds firm size and a polynomial in labour market experience. Controlling for firm effects, the effect of firm size and experience[39] on wages is very small.[40] In Column 3 I add a the average person effect of peers. The relative estimated effect is 0.358: 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, using the overall standard deviation of $\bar{\theta}$, which is 0.218, which is a mix of cross sectional variation (across firms) and variation across time. 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. Using this alternative reference distribution a one standard deviation increase in peer characteristics is associated with a 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. My estimates of 3.7 and 7.9 percent effects may be seen as lower and upper bounds.[41]

8 Post-estimation Analysis

8.1 A simple variance decomposition

From equation (1) I decompose the variance of log monthly wages w_{ijt} as follows:

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

[39] 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.

[40] 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.

[41] In the Appendix, I include robustness checks running the same regression on a subsample of my population.

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

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

The bottom section of Table 2 shows that 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,[42] 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 quality of peers explain around 5 percent of the overall wage variation.[43] The R^2 of column 3 is very similar to that of column 2: the additional 5 percent of the variance of log wages explained by peer quality is associated with a similar decrease in the proportion of the variance explained by the firm effect. A large portion of what our usual firm effects pick up is not about the firm per se, it is about the level of skills of that firm's labour force.

The main regression analysis discussed above includes the estimate of the correlation between the person effect and the firm effect. 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. When I do not include peer effects in my model, I find large positive estimates: high-wage workers tend to work in high-wage firms.[44] Once I include peer effects in the model, I estimate a correlation between θ and ψ of 0.014. High-wage workers do work in slightly higher-wage firms. However, most of the correlation between θ and ψ found in column 3 is driven by high-wage workers having high-wage peers.

Figure 4 expands on these findings investigating the correlation between worker quality and

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

[43] 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' ability.

[44] Note that the comparison is highly imperfect because I use wages per unit of time while the literature typically uses total annual compensation.

firm quality by year for the period 1982-2001. The solid line in Figure 4 shows that the overall correlation between the firm effect and the person effect varies greatly within the sample period. It is negative between 1982 and 1989 and positive afterwards, peaking at 0.074 in 1997. The change in this correlation over time is driven both by mobility of existing workers, and by new firms and new workers entering the dataset. In order to investigate whether the change in the correlation between person effects and firm effects comes from mobility across existing firms of from firm births and deaths, I include in Figure 4 correlations calculated only for the firms that are active in 1982. The dashed line follows the same pattern as the solid line, and exhibits slightly higher correlation coefficients: using a constant pool of firms, the increase in assortative matching across the sample period is stronger, which is consistent with the results in Mendes et al. (2010) of stronger assortative matching among long-lived firms using data from Portugal. Figure 4 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 line while following a very similar trend is lower than the other two lines: among workers that have been around for long, the movement towards assortative matching is slower. Summarizing, the movement towards assortive matching is driven by "old" firms more than "new" ones, but by "new" workers more than by "old" ones.

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 coworkers because of possible non-monotonicities between the firm effect and a firm's prodctivity.[45] I compute the correlation between θ and $\bar{\theta}$ for each year of my dataset and find it to be between 0.36 and 0.45 depending on the year I use.[46] 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 operates primarily through similar workers being grouped together in the same firms, rather than by the matching of certain kinds of workers with certain kinds of firms.

[45]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.

[46]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).

8.2 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', 8 percent lower average peer θ and work in slightly lower-wage firms. On the other hand, on average a foreign born worker has a wage that is 13 percent below that of a native worker; θs is 15 percent lower for foreign born, $\bar{\theta}$ is 9 percent lower, ψ is 2 percent lower. As discussed earlier in this work, 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 theta. In order to partially address this concern, I regress θ on gender and immigration status in Table **??** and 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. Below, I investigate the extent to which the gaps in access to high-wage peers of female and foreign-borb workers affects their labour market outcomes.

8.3 Gender wage gap and peer 'quality'

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 the wages of male and female workers. Consider the following simple decomposition based on my estimates of equation (1):

$$\begin{aligned} E(w^M_{ijt} - w^F_{ijt}) = \; & E(\mathbf{X^M_{it}}\beta - \mathbf{X^F_{it}}\beta) + E(F^M_{jt}\kappa - F^F_{jt}\kappa) + E(\theta^M_i - \theta^F_i) + E(\bar{\theta}^M_{ijt}\eta - \bar{\theta}^F_{ijt}\eta) \\ & + E(\psi^M_j - \psi^F_j) + E(\tau^M_t - \tau^F_t) + E(\epsilon^M_{ijt} - \epsilon^F_{ijt}) \end{aligned} \tag{4}$$

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.[47] Differences in peer 'quality' explain 12 percent of the overall gap: one eighth of the gender wage

[47] 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.

gap is due to the fact that females have on average peers of lower 'quality'. On the other hand, 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:

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

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 coworkers 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 4 presents the estimates from equation (5). Column 3 shows that once I control for the proportion of females among peers, female workers have conditionally higher-θ peers compared to males.[48]

8.4 The immigrant wage gap

Figure 2 and Table 3 documented a large and growing wage gap between foreign born and native workers.[49] Figure 5 shows that foreign born and native workers are also segregated across firms: looking at 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 6 shows a simplified graphical representation of the same decomposition as 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. Across 1982-2001, the majority of this gap is driven by differences in θ. Average peer characteristics explains between 10.4 percent in

[48]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.

[49]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.

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 are more likely to work in low-paying firms.

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 5 displays the estimates for equation (6). Even controlling for 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 due to the characteristics of their peers. These results suggests that the wage gap between Italian born and Italian born that depends on peers cannot be address focusing on immigrant level of segregation across firms only.

9 Concluding Remarks

I estimate the effect of coworkers' labour market skills on wages. I address the main sources of possible bias dues to group selection 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 one-standard deviation increase in peer 'quality' is associated with a rise in real monthly wages of 4-8 percent. In addition, I find that after controlling for peer quality the effect of firms' unobservables on wages decrease by around 26 percent. Next 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. I also find that even after controlling for own time-invariant unobservables, and percentage of foreign born among peers, foreign born workers have peers that have significantly lower labour market 'skills'.

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Appendix

A Figures and Tables

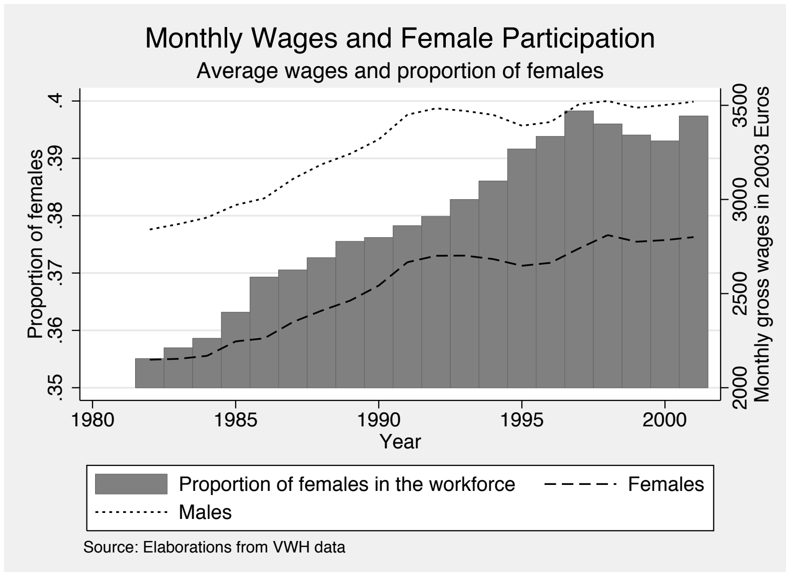

Figure 1: Average monthly wages by gender and proportion of females

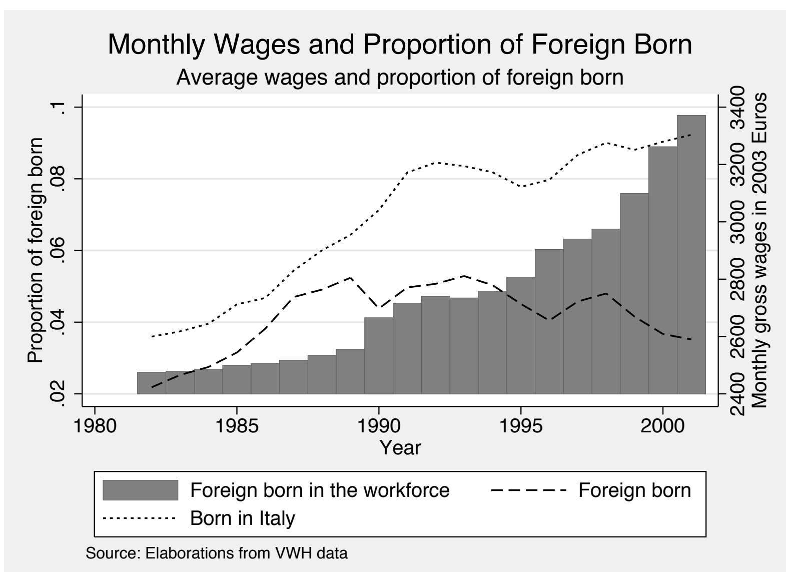

Figure 2: Average monthly wages by foreign born status and proportion of foreign born

Figure 3: Standard deviation of log monthly wages over time

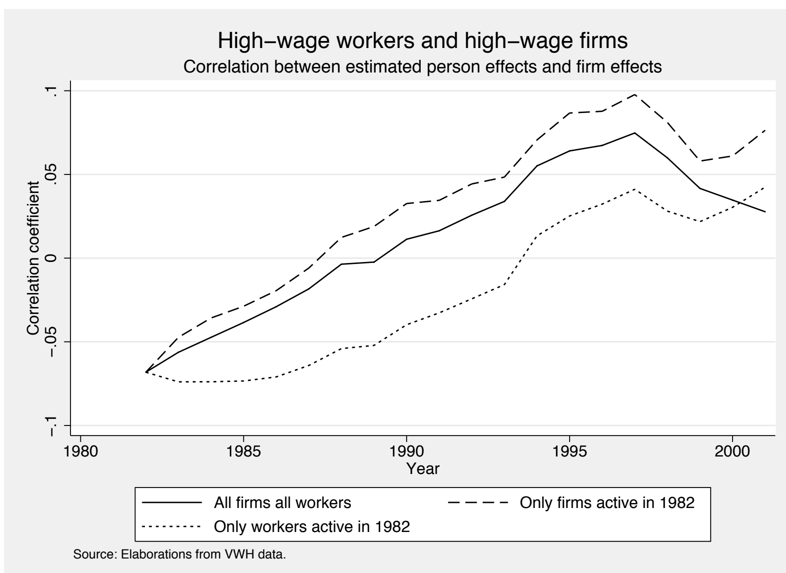

Figure 4: Correlation between person effects and firm effects over time

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: $ln(w_{ijt})$

Variables	Models (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]
Peers θ			0.358
			(0.0000)
			[11,074]
Fixed effects			
σ_θ	0.383	0.413	0.389
σ_ψ	0.230	0.215	0.205
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
$Corr(\theta,\psi)$	0.154	0.164	0.014
Variance decomposition			
θ	0.462	0.491	0.469
ψ	0.201	0.181	0.134
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
ϵ_{ijt}	0.284	0.280	0.278

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

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

Populations	log(wage)	θ	$\bar{\theta}$	ψ
Full sample mean	7.88	4.46	4.46	1.78
Full sample standard deviation	0.57	0.39	0.22	0.21
Differences for females and foreign born				
Gender gap (female vs. male workers)	0.25	0.21	0.08	0.01
Foreign-born gaps (foreign born vs. native born workers)	0.13	0.15	0.09	0.02

Table 4: Gender and 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)
θ		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)
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

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

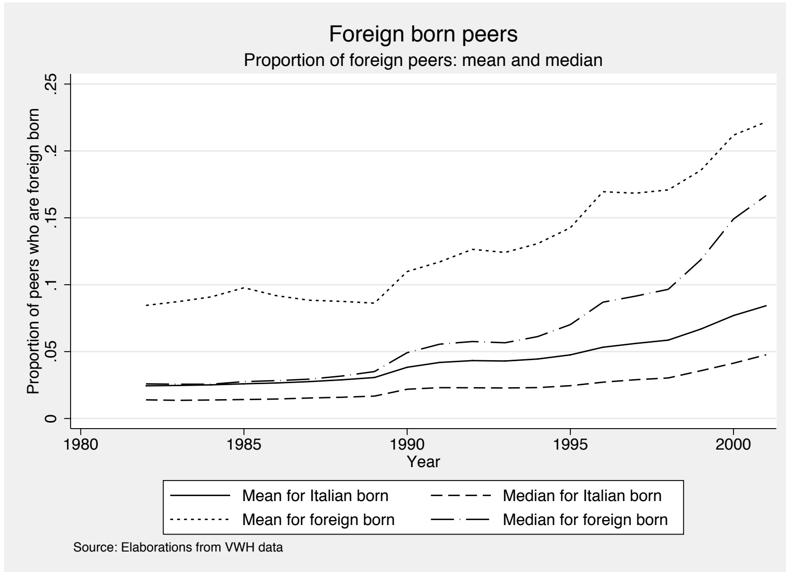

Figure 5: Average proportion of peers that are foreign born

Table 5: Birth place and 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)
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)
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

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

Figure 6: Decomposition of the gap between the wage of foreign born and Italian born

B 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:

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

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 (B.1):

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

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:

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

As discussed below, 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 (B.2). As a consequence, even though my model includes different and additional fixed effects, Theorem 2 in Arcidiacono et al. (2011) 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 (B.2) is a contraction mapping, guaranteeing convergence of the estimated parameters to their NLS counterparts, for any initial vector θ_0 if $\eta < 0.4$[50]. In particular, unlike similar two-step procedures such as that developed in Mas and Moretti (2009), in the procedure of Arcidiacono et al. (2011) 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

[50] The result in Arcidiacono et al. (2011) 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.

through the peer effects is directly accounted for in the estimation procedure.

Arcidiacono et al. (2011) 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 (B.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

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

and that of time effects:

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

For updating θ_i in iteration α I use a modified version of equation (B.2) for computational convenience, using the result in Lemma 2 of Theorem 1 of Arcidiacono et al. (2011):

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

where e_{it} denotes the regression residual from the OLS regression estimates of step 1. Equation (B.5) is obtained from equation (B.2) by rearranging terms so as to identify regression residuals and then substituting them in isolating the terms that include $\theta_i^{\alpha-1}$. The procedure described above lower the sum of squared residuals in each iteration, and can therefore be performed until a predetermined criterion for convergence is reached[51].

[51] 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.

C Structure of the VWH dataset

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 in order to be even more conservative Occari and Pitingaro (1997) also require that location does not change. When mobility is considered spurious, the two firms are recognised as the same firm. Additional information on the dataset and in particular on the construction of the two different firm identifiers are available from Tattara and Valentini (2010).

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:[52] gender, birth date, birth place,[53] and residential address.[54] Not uncommonly for Italian administrative datasets, it has 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 is richer and includes a firm identifier, firm's name, activity, address, sector,[55] 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, time of work (year, month, week, day), duration of the employment relationship, place of work, total yearly real wages in 2003 Euros for each job in each time period, qualification, contract, level including information on whether the contract part-time and/or fixed term.

[52]Unfortunately this is common for administrative datasets of this kind.

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

[54]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.

[55]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.

D Data selection

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 drop 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. I need to use the naive firm identifier for merging the worker, job and firm archives because that is the variable that links them together. After merging and for the remainder of the paper I use the firm identifier that does not treat changes in the firm's ownership as deaths and births of a new firm.

My main regression model includes a measure of firm size. The VWH does not include firm size, so I construct it from the data. This measure is not perfect since I construct it from the dataset, and thus if a firm hired a worker that is not part of my dataset, I would underestimate firm size. For example, a firm may have undocumented workers, or may hire professionals that I cannot observe because it is not covered by Inps, such as a lawyer.

The VWH does not include an experience variable per se, and so I need to construct it: 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 very accurate 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. Finally, in the construction of my experience measure I ignore the possible effect unemployment may have on the depreciation of labour market skills of workers.

E Robustness check: small firms and large firms

In Table 6 I reports estimates of equation (1) on two different subsamples of my population, that of workers of very small firms and of very large firms. In these estimates 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 6 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 6 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.

Table 6: 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
Peers θ	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			
θ	0.469	0.506	0.551
ψ	0.134	0.191	0.188
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
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