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Birthplace diversity of the workforce and productivity spill-overs in firms*

René Böheim[†] Thomas Horvath[‡] Karin Mayr[§]

Abstract

We analyze the effect of workforce composition by birthplace in Austrian firms on workers' wages. In our model, each worker's productivity may depend on whether the coworkers are of the same or of a different birthplace and wages depend therefore both on the relative size of workers' groups as well as on the production structure of firms. We derive empirically testable hypotheses about the effect of coworker birthplace on wages using a stylized model of intra-firm spill-overs across worker groups. We find evidence for complementarities between workers of different birthplace in line with our model that persist (but become smaller in size) after we control for observable productivity characteristics such as occupation and work experience.

Keywords: Immigration, Labor force composition, Labor productivity

JEL classification: J31, J82, J24

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1 Introduction

Immigrant workers are generally more likely to work with other immigrants, in particular with immigrants from their own origin country, than would be predicted by a random allocation of workers to firms—even after accounting for sorting according to region of residence, industry, or education (Carrington and Troske (1998*a*,*b*), Bayard, Hellerstein, Neumark and Troske (1999), Hellerstein and Neumark (2008), Aslund and Skans (2010)). This segregation in the labor market has raised concerns about potential negative effects on labor market outcomes, e.g., wages.[1] However, segregation could be the result of an efficient allocation of workers, if there are positive productivity spill-overs across worker types.[2] In this case, more workplace heterogeneity will lead to higher, not lower, wages, reflecting these spill-overs.

We develop a model to explore the effect of workforce heterogeneity on wages. In our model, wages depend on the relative sizes of the groups whenever there are productivity spill-overs between workers of different birthplace. Workforce composition has been shown to matter for individual labor market outcomes, but the existing empirical evidence is non-conclusive. For example, Carrington and Troske (1998*b*) analyze the distribution of black and white workers across large manufacturing firms in the U.S. and find that the wages of black workers are decreasing but the wages of white workers are increasing in the share of their black coworkers. Using the same data set, Carrington and Troske (1998*a*) find that sex segregation accounts for a substantial fraction of the male-female wage gap in the U.S. manufacturing industry and that women's wages decrease in the share of their female coworkers. More recently, several European studies have looked at the wage effect of workforce composition by birthplace. Elliott and Lindley (2008) show that occupational segregation contributes to immigrant-native wage gaps in the UK. Aslund and Skans (2010) find that immigrants (and natives) earn less when the share of immigrant coworkers is greater. In contrast, Dustmann, Glitz and Schönberg (2011) find that immigrants with a greater share of immigrant coworkers earn more in a sample of four metropolitan areas in West Germany during 1980-2001.

We argue that the diversity of empirical results in the literature might be due to the heterogeneity of spill-overs on the productivity of firms, as the effect of workforce composition on wages depends how firms organize their production. In consequence, there exists an optimal size for each type of

[1] Bayard et al. (1999), for example, find that large parts of the wage gap between whites and non-whites in the U.S. can be attributed to labor market segregation.

[2] For example, immigrants can exert positive spill-overs on the productivity of other immigrants, if they share a common language or social norms (Lazear (1999)). In fact, Hellerstein and Neumark (2008) find that a large fraction of ethnic segregation in the U.S. can be attributed to differences in English-language proficiency.

worker and any wage effect of an increase of its share depends on how that share compares to the optimal share. The wage effect can therefore be expected to positive, if the (immigrant) worker group size at the firm is below the optimal size and negative, if it is above it.[3]

In our empirical analyses, we construct an index of fractionalization by birthplace at the firm-level to estimate spill-overs due to workforce heterogeneity. This index, which has been used as a measure of ethnic fractionalization in, for example, Alesina, Devleeschauwer, Easterly, Kurlat and Wacziarg (2003), reflects the probability that two randomly selected workers from a firm are from a different birthplace.

We expect that wages increase in this index whenever there are positive spill-overs between workers of different birthplace, for example, because there are complementarities between workers of different skills and skill is correlated with birthplace. Conversely, we expect wages to decrease in this index, if there are positive spill-overs between workers of the same birthplace, for example in the form of common language or customs. Of course, it is possible that spill-overs of both kinds exist at the same time and the resulting wage depends on the dominating effect. Our model predicts that, if productivity spill-overs across workers with different birthplace in the firm are positive (negative), the sign of the wage effect of a worker's own group size is negative (positive).

We estimate the predictions from our model using an instrumental variable approach to avoid biases from endogenous sorting of workers into firms. Our data are from Austrian tax files from 1994 to 2005, which provide us with detailed information on the universe of employees. Austria is an ideal country to study wage effects of workforce composition by birthplace because immigrants represent a large share of the workforce and differ considerably in birthplace. Our estimating sample consists of approximately 900,000 observations for 140,000 workers. We find a positive effect of workforce heterogeneity and a negative effect of a worker's group size on wages, which is consistent with productivity spill-overs in our model.

We estimate several alternative specifications to investigate the robustness of our results. For example, we separate the sample into blue-collar and white-collar workers. Spill-overs are perhaps more relevant in non-standard tasks and could, therefore, lead to stronger wage effects for white-collar workers. This is what we find in the data.

Our estimated effect of workforce fractionalization allows us to infer the type of production structure in our sample. The significant positive effect of fractionalization on wages suggests that pro-

[3] It is plausible that firms are more likely to be constrained in their endowment of worker types from above than from below.

duction predominantly exhibits complementarities between workers of different birthplace. Moreover, we can determine the effect of fractionalization by birthplace that remains when successively controlling for potential sources of positive spill-overs across workers of different birthplace, i.e. occupation or work experience. This is a novel approach to test for complementarities between immigrant and native workers with similar observable characteristics. We find that positive wage effects of fractionalization by birthplace become smaller but persist when controlling for occupation and work experience, suggesting that workers of different birthplace that are similar with respect to these characteristics are imperfect substitutes.

Our paper is related to the theoretical literature on job assignment according to which wages do not only depend on worker characteristics but also on workforce composition and the production structure of firms. First, there can be complementarities between workers of the same type. This is the case, for example, in the Kremer (1993) O-ring production function. In Saint-Paul's (2001) model, worker productivity increases in average productivity in the firm, for example, because ideas are spread within the firm. Both models lead to a segregation of groups with wages depending on average group-specific skill. Second, there can be complementarities between workers of a different type. Kremer and Maskin (1996) show that complementarities between workers of the same and of a different type, and the relative size of these complementarities, depend on the difference between types, when the firms have production functions where different tasks within the firm are complementary. More recently, for example, Ottaviano and Peri (2012) stress the need to combine own-group effects with cross-group effects in order to obtain the total wage effects for each native group.[4]

Futhermore, our paper contributes to the literature on the effects of workforce composition, in particular by immigrant and native workers, on economic outcomes such as wages and at the composition (described above). Of those studies, none to the best of our knowledge have explicitly studied the role of productivity spill-overs.

The paper is structured as follows. In Section 2, we derive an expression for optimal wages in the presence of intra-firm spill-overs using a general production function that relates output to the degree of workforce heterogeneity in the firm. Section 3 describes the corresponding empirical model that we use to test for the effect of workforce composition on wages as well as the data and presents our empirical results. Section 4 concludes.

[4]They estimate that native and immigrant workers are imperfect substitutes even if they have the same education and experience levels.

2 The Model

In the following, we develop a model of intra-firm spill-overs to analyse the effect of workforce composition, which is to be determined endogenously in the model, on wages. We use a model based on Saint-Paul (2001), where firms' output can be described as a function of an aggregate index for the workforce only. In our case, this aggregate index is workforce composition by birthplace.[5] This will allow us to consider the wage effects of potential productivity spill-overs within firms in a very general way and derive testable hypotheses on the wage effects of different types of co-workers, as described in the following.

2.1 Intra-Firm Spill-Overs

We consider an economy with a given total number of workers of type n, s_n, $n \in \{0, 1, ..., N\}$, who are distributed across firms that each employ a total number of workers normalized to 1, and free market entry.[6] [7] In each firm, workers of type n have a given skill $y_n \geq 0$ (with, possibly, $y_n = y_m$)[8] and group size g_n that is chosen optimally by firms. Each worker type's productivity is given by the sum of his skill y_n and a spill-over effect that depends on the type composition of his co-workers. This spill-over effect is a function of workforce heterogeneity, $f(F)$, where F is equal to the probability of being matched with a different type $m \neq n$. Total output is given by $a = \sum_n g_n (y_n + f(F))$, with $\sum_n g_n = 1$. We assume that $f(F)$ is continuous and twice differentiable.

To measure worker heterogeneity, we use an index of fractionalization (Alesina et al. 2003) equal to 1 minus the Herfindahl index of worker group shares by type, g_n:

$$F = 1 - \sum_{n=0}^{N} g_n^2. \tag{1}$$

This index reflects the probability that two randomly selected workers from a firm belong to different types. In particular, it increases in the share of a minority group (with a group share smaller than the average group share) and decreases in the share of a majority group (with a group share greater than the average group share). This can be seen when rewriting (1) as a function of

[5]In Saint-Paul (2001) a firm's total output is a function of the average skill level of its workers.

[6]The assumption of a fixed number of workers per firm allows for an equilibrium to exist despite the possibility of increasing returns in production. It is common in models of optimal worker assignment in the presence of spill-overs across workers, see for example Kremer (1993) or Saint-Paul (2001).

[7]Therefore, there will be a total number $\sum_n s_n$ of firms in equilibrium.

[8]We assume worker skill y to be independent of the firm for simplicity. Results would not change if y was allowed to be firm-specific.

the statistical variance of group shares v:

$$F = 1 - \left[\frac{1}{N} + Nv\right], \text{where} \quad v = \frac{\sum_{n=0}^{N}\left(g_n - \frac{1}{N}\right)^2}{N} \tag{2}$$

and deriving

$$\frac{\partial F}{\partial g_n} = -2\left(g_n - \frac{1}{N}\right) \tag{3}$$

which is negative (positive), if g_n is greater (smaller) than $1/N$.

The spill-over function $f(F)$ measures the effect of workforce composition on worker productivity. It can be increasing or decreasing, depending on the nature of spill-overs across worker types. For example, workers of the same type may exert positive spill-overs on each other because they work in teams (Kremer, 1993), or because they share the same language (Lazear (1999), den Butter et al. (2004)). Or they may exert negative spill-overs on each other because they are competing for a complementary fixed factor in the firm (for example, capital or workers of complementary skill types such as administrative and manual workers). In the presence of complementarities between workers of different (the same) type, each worker's productivity depends positively (negatively) on the degree of fractionalization, and $f(F)$ will be increasing (decreasing). In the absence of spill-overs, we assume $f(F) = 0$ such that firm output is just equal to the sum of individual worker productivities $\sum_n g_n y_n$.

A firm's total output is then a function of the group size of worker types:

$$a = \sum_n g_n y_n + f(F(g_n)).$$

Note that this output function exhibits constant returns to group size g_n, if there are no spill-overs and $f(F) = 0$. However, it can also exhibit increasing or decreasing returns, depending on whether (i) there are positive or negative spill-overs across workers of the same type and (ii) an increase in group size g_n serves to increase or decrease workforce heterogeneity.

Proposition 1. *The equilibrium wage of workers employed in a firm with a given workforce composition F and number of employed worker types N is such that*

$$w_n(g_n) = y_n + f(F) - f'(F)2\left(g_n - \frac{1}{N}\right).$$

Wages depend not only on individual worker characteristics as described by y_n but also on how one's own characteristics compare with those of one's co-workers. If there are positive spill-overs from working with workers of the same type, then the wage decreases in own group size. If the spill-overs from working with workers of the same type are negative, then the wage increases in own group size.

Proof. Firms decide on how large a group share of each type, g_n, to hire to maximize profits. The optimal employment structure of a firm k is then the solution to the following maximization problem:

$$\max_{g_n} \sum_n g_n y_n + f(F(g_n)) - \sum_n g_n w_n,$$

subject to

$$g_n \geq 0 \quad \forall n \in \{0, 1, ..., N\}$$

and

$$\sum_n g_n = 1. \tag{4}$$

Firms therefore decide how many workers of each type to hire, g_n, subject to the constraint that the total size of the workforce is given (such that firms cannot increase output by merely changing workforce size but only by hiring a different mix of worker types). If $g_n = 0$, then that type is not employed in the firm. Using (3), the maximization problem results in the following first-order condition:

$$y_n - f'(F)2\left(g_n - \frac{1}{N}\right) - w_n - \lambda \leq 0, \tag{5}$$

where λ is the Lagrange multiplier from (4), which can be interpreted as the opportunity cost of an increase of group size g_n that comes at the expense of a decrease in the size of other groups g_m, $m \neq n$. It can be derived from the condition that $y_n - f'(F)2\left(g_n - \frac{1}{N}\right) - w_n$ be the same for all groups n in the firm in optimum (i.e. firm profits cannot be increased by a marginal replacement of one group by another group). Summing up (5) over all g_n and taking into account the zero-profit condition $\sum_n w_n g_n = \sum_n y_n g_n + f(F)$ shows that λ is equal to the average spill-over $f(F)$.[9] (5) holds with equality if $g_n > 0$.

The first term in (5) is the marginal benefit of an increase in g_n equal to the skill of a worker of

[9] Note that the average effect of an increase in group size on workforce heterogeneity is zero: $\sum_{n=1}^{N} -2\left(g_n - \frac{1}{N}\right) = -2\left(\sum_{n=1}^{N} g_n - 1\right) = 0$.

type n. The second term is the marginal benefit equal to the increase in the productivity of all workers due to the change in workforce heterogeneity F caused by an increase in group size g_n. The third term is the marginal cost of employment of a worker of group n.

It follows that equilibrium group- and firm-specific wages are

$$w_n = y_n + f(F) - f'(F)2\left(g_n - \frac{1}{N}\right). \tag{6}$$

■

Wages of workers of type n are equal to type-n skill plus a wage component that depends on their group size relative to the average group size. This component can be positive or negative depending on whether workers exert a positive or a negative spill-over on their co-workers via a change in workforce heterogeneity.[10] On average, spill-overs in the firm must be zero, since the sum of wages equals total output according to the zero profit condition.[11]

2.2 Workforce composition and wages in equilibrium

The wages of workers of type n as derived above depend on the decision of firms on how many workers of each type to employ. In the following, we characterize the assignment of workers to firms and firms' workforce heterogeneity F in equilibrium as defined below.

Equilibrium. *An equilibrium is a mapping of workers to firms such that (i) firms maximize profits, (ii) no potential entrant firm could make strictly positive profits and (iii) all workers are assigned.*

In equilibrium, existing firms make zero profits and potential entrants cannot make positive profits due to free entry. The overall demand for workers of type n as implied by the number of firms and the size of worker groups n employed in each firm needs to be equal to the overall supply of workers of type n, for all n.

[10] Notice that wages can be negative, if the negative spill-over of a worker dominates his skill. In turn, wages can be positive even if individual skill is zero, if there is a positive spill-over.

[11] We have assumed above that firm size is fixed. Alternatively, we could assume firm size to be variable and generalize the respective constraint (4) accordingly to $\sum_n g_n = s$. Then the wage expression would be $w_n = y_n + f(F)/s - f'(F)2\left(g_n - \frac{1}{N}\right)$. Note, however, that in the present set-up there will be no interior solution to an endogenous firm size s, as the (marginal) cost of firm size is zero. This could be changed easily with the introduction of a set-up or investment cost that increases in firm size.

Proposition 2. *The equilibrium distribution of worker types across firms can be characterized as follows.*

i. For any firm k there exists a range ρ of worker group shares such that the group share of all workers of firm k is from within that range. Firms that employ group shares from within a given range exhibit the same average group share, $\frac{1}{N_\rho}$, and workforce heterogeneity, F_ρ.

ii. Firms with a smaller average group share (employing a greater number of worker types) exhibit a greater (smaller) degree of workforce heterogeneity, if f(F) is increasing (decreasing).

iii. The supply of workers of a given type n, s_n, equals demand: $s_n = \sum_k g_{nk} \, \forall \, n \in \{0, 1...N\}$.

Proof. Consider two existing firms, k and l, with a different number of worker types employed, $N_k < N_l$. Then, workers of type n who are employed in firm k (with a group share of g_{nk}) must earn more than if they were employed in firm l:

$$y_n + f(F_k) - f'(F_k)2\left(g_{nk} - \frac{1}{N_k}\right) \geq y_n + f(F_l) - f'(F_l)2\left(g_{nk} - \frac{1}{N_l}\right) \tag{7}$$

and, vice versa,

$$y_n + f(F_l) - f'(F_l)2\left(g_{nl} - \frac{1}{N_l}\right) \geq y_n + f(F_k) - f'(F_k)2\left(g_{nl} - \frac{1}{N_k}\right). \tag{8}$$

Comparing the difference between the left-hand side of (7) and the right-hand side of (8) with the difference between the right-hand side of (7) and the left-hand side of (8), we find that

$$\left[f'(F_l) - f'(F_k)\right](g_{nk} - g_{nl}) \geq 0. \tag{9}$$

Furthermore, workers of type n and an average group share in firm k, $g_{nk} = 1/N_k$, must earn more than in firm l:

$$y_n + f(F_k) \geq y_n + f(F_l) - 2f'(F_l)\left(\frac{1}{N_k} - \frac{1}{N_l}\right) \tag{10}$$

$$y_n + f(F_l) \geq y_n + f(F_k) - 2f'(F_k)\left(\frac{1}{N_l} - \frac{1}{N_k}\right) \tag{11}$$

which implies that

$$f'(F_l) \geq \frac{f(F_l) - f(F_k)}{2\left(\frac{1}{N_k} - \frac{1}{N_l}\right)} \geq f'(F_k). \tag{12}$$

From (9)-(12) it follows that, if $\frac{1}{N_k} < \frac{1}{N_l}$, firm k employs smaller shares of worker types than firm l, $g_{nk} \geq g_{nl}$, and exhibits a greater (smaller) degree of workforce heterogeneity, $F_k > F_l$ ($F_k < F_l$), if $f(F)$ is increasing (decreasing). If firms k and l employ the same number of worker types, $\frac{1}{N_k} = \frac{1}{N_l}$, then they exhibit the same degree of workforce heterogeneity, $F_k = F_l$. This proves i-ii. iii is the condition for the labor market equilibrium for all types of workers.

■

Corollary 1. *The equilibrium wage of a worker of type n who belongs to a firm-specific worker group of size g_n can be characterized as follows.*

i. The wage of a worker of type n in firm k is linear in the respective worker group size within a given range ρ, $w_{nk}(g_{nk}) = y_n + \phi_\rho - \psi_\rho g_{nk}$.

ii. For any firm k within a given range, the wage function w_{nk} is tangent to the productivity function $y_n + f(F)$ of a worker who belongs to an average-size group $g_{nk} = 1/N_k$:

$$\phi_\rho = f(F_k) + f'(F_k)2\frac{1}{N_k}$$

$$\psi_\rho = -f'(F_k)2$$

such that $w_{nk}\left(\frac{1}{N_k}\right) = y_n + f(F_k)$.

iii. The wage function is convex in workforce heterogeneity.

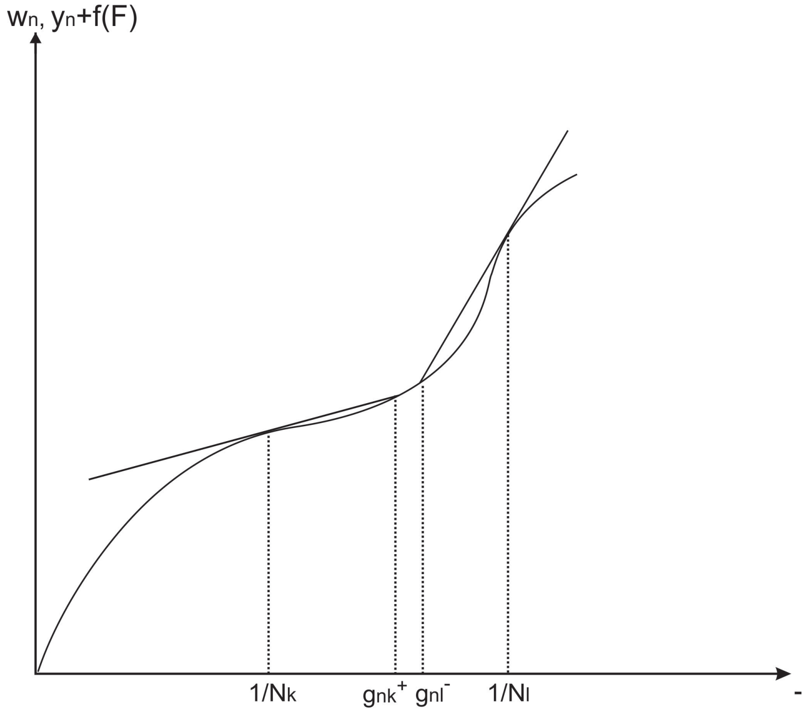
iv. Wages $w_n \geq y_n + f(F)$ for all g_n.

Proof. i-iii follow from (9)-(12). iv must hold due to free entry. If it was violated for some g_{nj}, then an entrant hiring N_j worker types of equal group size $g_{nj} = \frac{1}{N_j}$ would make strictly positive profits.

■

Figure 1 shows how firms are organized in equilibrium depending on the shape of the spill-over function f(F). As stated in proposition 2, firms can be grouped into clusters that hire the same number of worker types, exhibit the same degree of workforce heterogeneity and offer the same wage schedule $w_{nk}(g_{nk})$. Firms in different clusters have a different number of worker types, a different degree of workforce heterogeneity and a different wage schedule. Note that it is possible

Figure 1: Workforce composition and wages in equilibrium.



NOTE: This graph shows an example for an equilibrium composition of the workforce and associated wages of workers of type n in two clusters of firms. Firms in cluster k employ N_k different types of workers (i.e. the average worker group size in the firm is $\frac{1}{N_k}$) in different group sizes with a maximum group size of g_{nk}^{+}. Firms in cluster l employ a greater number of N_l different types of workers in different group sizes with a minimum group size of g_{nl}^{-}. Since the group size of all workers is smaller in cluster l compared to k, workforce heterogeneity is greater in l than in k. Therefore, since the spill-over function $f(F)$ is increasing in workforce heterogeneity F in this example, wages are greater in cluster l than in k. Wages are also increasing with decreasing group size within firms: with decreasing group size, the marginal effect of group size on aggregate workforce heterogeneity and, therefore, on the positive productivity spill-overs within the firm increases. The total number of clusters, and firms within clusters, is determined by labor market clearing.

for a firm j to employ workers in only one group size $g_{nj} = \frac{1}{N_j}$ - that is, to employ a number N_j of worker types in equal shares. In this case, wages are $w_{nj} = y_{nj} + f(F_j)$, which follows from part iv of corollary 1. An example for this is shown in Figure 1 for $g_{nk}^{+} < g_{nj} < g_{nl}^{-}$.[12] In the figure, the spill-over function f(F) is increasing in workforce heterogeneity F and the wage function $w_n(g_n)$ becomes increasingly steep with increasing values of F.[13] For given F, wages are increasing with decreasing worker group size.[14] At a group size equal to the average group size at the firm, the wage is equal to worker productivity $w_n = y_n + f(F)$.

[12]We denote the size of the smallest group in firm k with g_{nk}^{+} and the size of the largest group in firm l with g_{nl}^{-}.

[13]Note that it is also possible that f(F) is decreasing. Then, the wage function would become increasingly flat with increasing values of F and results would run analogously.

[14]Note that for the wage function to be continuous, the distribution of group sizes has to have full support.

The function f(F) can have convex parts, with local increasing returns to fractionalization. This generates an agglomeration of worker groups of similar size into firms, which decreases the variance of group size in firms and, therefore, increases fractionalization. In the ultimate case, firms employ workers in equal group shares. f(F) can also have concave parts, with local decreasing returns to fractionalization generating an agglomeration of worker groups of different size in firms. Note that if f(F) is concave throughout, firms will employ the full range of worker group sizes, and wages will be linear over this range.

The number of clusters and the number of firms per cluster is determined by the shape of the function f(F) and the supply of workers of type n, s_n, and the number of worker types N in the economy. In sum, it must be that $\sum_k g_{nk} = s_n \, \forall \, n$, such that all workers are employed.

3 Empirical Evidence

We started out by noting that the productivity of a worker may depend not only on his own characteristics but also on the characteristics of his co-workers, for example, because they work in teams. In particular, there might be positive spill-overs on productivity, if workers are complements in production. However, there may also be negative effects of working with similar co-workers, for example, because workers of the same type compete for a complementary fixed factor in the firm. In this case, workers of the same type are substitutes in production.

We describe the potential effects of working with co-workers by a productivity spill-over function $f(F)$. In our model, we predict the wage effects of co-workers who belong to the same type, without imposing a specific functional form on the spill-over function. If workers of the same type are complements (i.e., $f(F)$ is decreasing in the share of similar co-workers), wages are increasing in the size of this group, and vice versa. (See proposition 1.)

In the following, we test this prediction using comprehensive matched employer-employee data for workers in Austrian firms. We first present the empirical specification and then describe the data and the results, which we find to support the predictions of our model.

3.1 Specification

We estimate the following empirical specification of wages to test our model:

$$w_{ijt} = \alpha + \beta F_{jt} + \gamma_1 S_{ijt}^{own} + X_{ijt}' \delta + \upsilon_{ijt}, \tag{13}$$

where w_{ijt} are log wages of worker i in firm j at time t, F_{jt} describes the workforce heterogeneity in firm j at time t according to equation (2). S^{own}_{ijt} is the share of coworkers in the firm with the same country of origin as worker i. X_{ijt} captures worker-, firm- and time-specific characteristics. We include age and age squared, tenure at the firm, and overall labor market experience as workers' characteristics. We also control for the size of the firm, the share of blue collar workers, and the share of women in the firm.

The error term takes the form $\upsilon_{ijt} = \pi_i + \phi_j + \epsilon_{ijt}$, the sum of a worker fixed-effect, π_i, a firm fixed-effect, ϕ_j, and a white noise residual ϵ_{ijt}.[15] Firm- and time-fixed effects serve to control for the return to heterogeneity, $f'(F)$, which is likely to vary across firms and time (depending, for example, on unobserved manager characteristics) but is likely to be the same for workers at a given firm and year, ceteris paribus. Region-specific characteristics that are correlated with both immigrants in a region and with economic outcomes could lead to the estimation of a correlation between a region's share of immigrants and labor market outcomes, even in the absence of a causal effect of immigration on productivity. For example, areas with higher population densities may have higher wages and lower unemployment rates and attract more immigrants than rural areas. We therefore include region fixed-effects.

Estimating equation (13) with OLS will yield biased results, if the share of immigrant workers in a firm is the result of endogenous sorting. This could happen, for example, if migrants locate in regions with strong labor demand due to unobserved factors not controlled for by firm- and time-fixed effects. To avoid a potential endogeneity bias, we use an instrumental variable approach where we instrument the firms' worker shares with the previous year's share of immigrants in the region-sector cell, $S^{own}_{rs,t-1}$. To control for potential endogeneity in the index of fractionalization—which is a function of the share of each worker's own group within the firm—we instrument the firm's fractionalization with last year's fractionalization in the region-sector cell, $F_{rs,t-1}$:

$$w_{ijt} = \alpha + \beta F_{jt} + \gamma S^{own}_{ijt} + X'_{ijt}\delta + \upsilon_{ijt}, \tag{14}$$

[15]Due to the large number of workers and firms in our sample the estimation of firm and worker effects is computationally intensive. We therefore apply an algorithm developed by Abowd, Kramarz and Margolis (1999) using a Stata module by Ouazad (2008). Standard errors are derived by bootstrapping.

and the first-stage regression are specified as:

$$
\begin{aligned}
F_{jt} &= \pi_{10} + \pi_{11} F_{j,rs(t-1)} + \pi_{12} S^{own}_{ij,rs(t-1)} + X'_{ijt}\pi_{13} + \nu^{1}_{ijt}, \\
S^{own}_{ijt} &= \pi_{20} + \pi_{21} F_{j,rs(t-1)} + \pi_{22} S^{own}_{ij,rs(t-1)} + X'_{ijt}\pi_{23} + \nu^{2}_{ijt},
\end{aligned}
\tag{15}
$$

where $S^{own}_{rs,t-1}$ is last year's share of workers with the same birthplace in industry s and region r and $F_{rs,t-1}$ is last year's fractionalization in region r and sector s.

The identifying assumption of our instrumental variable approach is that the location choice of worker types in a region-industry cell is uncorrelated with future changes in labor demand in these region-sector cells. Such an approach has been used by, for example, (Card, 2001). Lagged values of our instruments ensure that they are determined prior to the instrumented variables, but it is worth noting that regional labor market conditions could be correlated over time. Then, past conditions could affect current location choices, and our instruments would be invalid (Borjas, 2003). Therefore, we use region-industry values that provide additional variation and should help identify the causal relationship.

3.2 Data

Our data are from Austrian tax records that cover the entire population of private sector employees in Austria, for the years 1994 to 2005. Austrian employers are required by law to file a tax statement for each employee at the end of the year. The statements detail the gross earnings, bonuses and other voluntary wage components, the number of days employed, and other information, e.g., the place of residence. We combine these tax records with data from the Austrian Social Security Database (ASSD).[16] From the ASSD, we obtain detailed information on the workers' employment histories, in particular, their work experience, tenures in firms, and the number of previous jobs, unemployment spells, and sick leave episodes. We construct firm-level information, such as the firm size or the firm's composition of the workforce, in addition to available indicators for industry classification (NACE) and location. We obtain the workers' country of origin from the Austrian Public Employment Service (AMS) and their Labor Market Database ("Arbeitsmarktdatenbank"), which we match to our data. For each firm, we calculate the fractionalization index F_{jt}.

Our dependent variable, log daily wages, is derived from gross wages as well as the number of days

[16] See Zweimüller, Winter-Ebmer, Lalive, Kuhn, Wuellrich, Ruf and Buchi (2009) for details on these data.

employed at each firm. Since we do not observe the number of hours worked, we restrict the sample to men as women are more likely to work part-time than men.[17] We exclude workers from seasonal industries (tourism, construction, and farming) and drop firms with fewer than 10 employees. We draw a 15 percent random sample of all male private employees, aged 20 to 60 between 1994 and 2005. The final sample consists of approximately 130,000 workers in about 19,000 firms. In total, this makes more than 840,000 observations.

We use the country of birth rather than citizenship as the indicator for an immigrant worker, because ethnic background may be more relevant for productivity spill-overs than citizenship. Table 1 compares the distribution of the countries of origin in our sample with official census data and demonstrates that our data capture well the distribution of the overall population. The table also shows that while there are differences between citizenship and country of birth, these differences tend to be minor. Citizenship matters for the employment of workers, because employment regulations differ for workers from EU member states and other immigrants. Workers from the EU are free to settle and work in Austria, while workers from non-EU member states are required to hold an explicit work permission. However, changes in citizenship occurred rarely during our sample period.

We find that the employment of foreign workers is concentrated in few firms, about 50 percent of firms employ less than 15 percent of foreign workers and 10 percent of firms employ more than 50 percent of immigrant workers. Less than one percent of firms employ only immigrant workers. Figure 2 shows the distribution of immigrant workers over firms for the year 2000. According to the graph, most immigrant workers work in firms with a low share of other immigrant workers. However, there is considerable variation in the share of immigrant workers over firms.

Table 2 shows descriptive statistics for native Austrians and four groups of immigrant workers. These groups are the three largest groups of immigrants, Germans, workers from former Jugoslavia, and Turks, and a residual group consisting of all other immigrant workers. Average wages are greatest for Austrian and Germans, and about a third less for the other groups.

Fractionalization and the relative sizes of different groups are calculated for the entire firm, i.e., also including workers who are not sampled, in particular, women. The average fractionalization index is about 0.17 for natives and on average about 0.47 for immigrants. We observe that Germans have a relatively low value of 0.29 compared to workers from Turkey, who have a fractionalization

[17] In 1994, about 1.4 percent of male and 26 percent of female employees worked part-time (Statistik Austria, 2011). These numbers increased steadily over time, reaching 4.8 percent and 37.8 percent, respectively, in 2004.

index of 0.50, and workers from ex-Jugoslavia, with a value of 0.43. These values indicate that immigrants are more likely than natives to work with other immigrant workers.

The share of immigrant workers in the firm, which is on average about 12 percent for Austrians, almost 21 percent for Germans, about 36 percent for workers from ex-Jugoslavia and about 41 percent for Turkish workers, confirms this evidence. Workers in the residual group of "other" work in firms where the share of foreigners in on average 33 percent.

Natives and immigrants differ along other characteristics, too. On average, Austrians have characteristics that are often associated with relatively higher wages, such as working in larger firms than immigrants: the average firm size is about 900 for Austrians compared to 430 for immigrants; tenures for Austrians are about 10 years in comparison to about 6.5 years for immigrants; their labor market experience in Austria is with about 19 years almost twice as long as those of immigrants. Austrians, and Germans, are less likely to be blue-collar workers than immigrants.

There are also characteristics where we observe only minor differences between Austrians and immigrants. These characteristics are age, which is on average about 40 years across all groups, and the share of women in the firm, on average about 25%.

Table 3 compares firms with below and above average fractionalization. Firms with a low fractionalization index pay on average higher wages, some €98 per day, compared to those with a more homogeneous workforce, which pay on average €83 per day. Low-fractionalization firms employ a lower share of immigrant workers than firms with a high fractionalization index. They have a lower share of blue-collar workers than low-fractionalization firms, 44 vs. 68 percent, but a greater share of female workers, 33 vs. 26. Low fractionalization firms are smaller and they are slightly less dynamic, as about 15 percent of low-fractionalization firms did not change the number of their workforce over the previous year. This compares to some 12 percent for high-fractionalization firms.

These descriptive statistics provide a picture of the heterogeneity of workforces across firms, but also the heterogeneity across immigrants from different countries of origin. Table 4 tabulates the average share of coworkers with whom workers of different countries work. The pattern stresses again that workers of the same country of origin tend to work together and that immigrant workers are more likely than natives to work with immigrant workers. The workforce in which Austrians work consists of 90 percent Austrians on average, less than 1 percent of German workers, some 5 percent workers from ex-Jugoslavia, and about 2.4 percent Turkish and workers from other countries. In contrast, the average workforce of a Turkish worker consists only to about 58 percent of Austrians and some 23 percent of Turkish workers; the share of German workers is comparable to that for the typical Austrian worker, around 1 percent; and the share of workers from ex-Jugoslavia is greater at 13 percent.

3.3 Results

Table 5 presents our main estimation results from estimating the effect of workforce heterogeneity on workers' wages, where we instrument the fractionalization index and the share of workers with the same birthplace as described above. In these estimations, we control for age and age squared, experience, firm size, tenure and tenure squared, the share of foreign workers, and year-fixed effects.

The first specification is a specification similar to those used by other researchers in their analyzes of wage effects of own group size. The estimate suggests that there are positive effects arising from the size of a worker's own group, which could be interpreted as positive network effects (e.g., Dustmann et al., 2011), but is also consistent with theories of discrimination (Becker, 1957). However, if there are productivity spillovers stemming from the heterogeneity of workers, this result suffers from omitted variable bias. Specification 2 uses both our index of fractionalization and the share of workers from the same country of origin as explanatory variables, without controlling for firm or person fixed-effects. The results from this specification indicate that there are positive returns to workforce heterogeneity and from group size. Controlling for firm fixed-effects, but not for person fixed-effects, yields results, tabulated in column 3, which are similar to those from our specification 2 where do not control for firm-fixed effects.[18] These estimates suggest that a change in the fractionalization index of 0.2 (about one standard deviation) leads to about 5.8% higher wages.

Because our data provide only few personal characteristics, it is important to control for unobserved person fixed-effects in order to obtain unbiased estimates.[19] In our fourth specification, we control for person fixed-effects but not for firm fixed-effects. We estimate a large and positive coefficient for our measure of workforce heterogeneity, and a corresponding negative coefficient for *share own*, as predicted by our model. This estimate is robust to the inclusion of firm fixed-effects, and column 5 presents the results from this preferred specification. The estimates point towards a strong positive effect of fractionalization on wages and a strong negative impact of a worker's own group size on wages. In other words, we estimate that there are large and positive returns to workforce

[18] Differences exist for coefficients on other controls which are not shown in Table 5. Results are available on request.

[19] For example, we do not have information on education or occupation. As education or occupation is typically fixed for adult employees, a person fixed-effect is an appropriate way to control for such heterogeneity.

heterogeneity and slightly negative returns to the number of workers who are from the same country of origin.[20] On average, an increase of the fractionalization index by one standard deviation is estimated to lead to about 22% higher wages. Note that an increase by one standard deviation implies doubling the average fractionalization in firms.[21]

3.4 Robustness

We provide several robustness checks to gauge the robustness of our results. Our main concern is the validity of our instrument, which is valid if it successfully controls for endogenous sorting of immigrant workers into firms. If the positive effect of fractionalization on wages is due to endogenous sorting of immigrants into firms where they earn higher wages, we should observe the positive consequences of fractionalization rather for immigrant than for native workers. We therefore estimate the wage regressions for native and immigrant workers separately. The results in columns (2) and (3) of Table 6 show that native workers benefit more from workforce heterogeneity than immigrant workers. It is therefore unlikely that endogeneity of workforce heterogeneity with respect to wages is driving our results.

Our results indicate that a more heterogenous workforce leads to higher wages. If this effect stems from complementarities in the performed tasks, the effects of fractionalization should be smaller for workers who perform more homogeneous tasks. We test this prediction by separating the sample into blue-collar and white-collar workers, under the assumption that the tasks of white-collar workers are more heterogenous than those of blue-collar workers. Results reveal that white-collar workers' wages react more strongly to workforce heterogeneity than blue-collar workers' wages, suggesting that the complementarity of workers with different birthplaces is smaller for blue-collar workers than for white-collar workers.

Workers who have short tenures might benefit more from productivity spill-overs than workers with long tenures, because workforce heterogeneity might lead to faster accumulation of firm-specific human capital. Estimation results in columns (5) and (6) of Table 6 provide evidence for this conjecture. We estimate effects separately for workers who had tenures of up to 500 days or more than 500 days and find that workers with shorter tenure benefit more from complementarities by birthplace compared to workers with longer tenure.

[20]The results from the first stage regressions are tabulated in Table A.3. The estimated correlations are robust across specifications and provide large F-statistics.

[21]For comparison, we tabulate the results from OLS estimates in Table A.1. Compare these results with the corresponding IV-estimates, we see that the estimates from the OLS are attenuated.

These findings provide insights into the nature of the substitutability in production between workers of different birthplace. This is an issue that is greatly contested in the empirical literature on the labor market effects of immigration, since the elasticities of substitution between (subgroups of) immigrants and natives are mainly responsible for the presence or absence of an impact of immigration on native wages. In this literature, increasingly refined estimates based on the nested CES production function introduced by Borjas (2003) have strived to pinpoint the degree to which immigrant and native workers are substitutes or complements to each other. (See, for example, Borjas (2003), Aydemir and Borjas (2007), Card (2009), Borjas, Grogger and Hanson (2012) and Ottaviano and Peri (2012).) So far, the debate has not come to a conclusion yet. We contribute to this literature by deriving the nature of productivity spill-overs between immigrants and natives directly from our estimates of the wage effects of workforce heterogeneity. This way, we can assess the wage effects of workers from a different birthplace without committing to a specific functional form of the production function. Our estimated positive effect of fractionalization in the workforce suggests that—controlling for the measures of productivity that we can observe (status, age, tenure, labor market experience)—workers with a different birthplace are imperfect substitutes. This reflects with previous findings in, for example, Ottaviano and Peri (2012), who find that native and immigrant workers are imperfect substitutes even within cells of education, experience and occupation. They also find that the elasticity of substitution is much smaller among low educated workers than among workers overall. Disaggregating workers into subsamples, we find that the degree of complementarity is smaller for blue-collar workers than for white-collar workers. In contrast, Ottaviano and Peri (2012) find that the degree of complementarity is greater for low educated than for higher educated workers. They argue that this could be the case, because immigrants specialize in different tasks than natives in particular among the low educated, but not so much among the high educated. According to our data, this does not seem to be the case at the firm level: here, workers who differ by birthplace appear to be more substitutable among blue-collar workers than among white-collar workers.

4 Conclusion

The workforce composition in many industrialized countries is changing in the course of large and increasing inflows of immigrant workers. As of 2000, the overall stock of migrant workers in OECD countries represented 12 per cent of the total labor force.[22] In Austria, 15 per cent of the labor force

[22] Martin (2005).

in 2001 were immigrants from a variety of source countries with the largest shares coming from Former Yugoslavia, Turkey and Germany. Workforce composition has been shown to matter for wages. Existing empirical findings are, however, ambiguous regarding the sign of effects: increases in the share of immigrant coworkers decrease immigrant (and native) wages in some studies (e.g. Aslund and Skans (2010)) but increase wages in other studies (e.g. Dustmann, Glitz and Schönberg (2011)).

We provide a potential explanation for the variety of existing empirical findings based on the theory of optimal job assignment in firms (Kremer (1993), Kremer and Maskin (1996)). According to this theory, optimal workforce composition depends on the production structure of firms and, in particular, on the existence of complementarities between workers of the same (or different) type. We show that a greater share of immigrant coworkers can increase or decrease immigrant and native wages. The effect depends on both the nature of complementarities between worker types and the size of worker group shares. In particular, if there are complementarities between workers of different birthplace, we expect wages to increase in the group size for workers who belong to a minority group, but to decrease for workers who belong to a majority group in the firm, and vice versa.

We find these predictions confirmed in our data. We provide evidence for complementarities between workers of different birthplace in Austrian firms. Our findings suggest that there is an effect of immigrant coworkers on wages via a link between workforce heterogeneity and productivity. We consistently find that workforce heterogeneity leads to higher wages, presumably because teams of mixed background are more productive. Apart from effects on productivity, the literature stresses two other explanations for a wage effect of immigrant coworkers: discrimination and ethnic networks used in the job finding process. Our wage effect, however, seems to exist independently of those other possible effects. We find that it is weaker for immigrants than for natives. In contrast, discrimination or ethnic networks should lead to greater wage effects for immigrants workers.

We may conclude from our findings that worker segregation need not necessarily have a negative effect on wages. Instead, our theory predicts that an increase in the likelihood of working with a coworker from the same group can have a positive wage effect, depending on the nature of productivity spill-overs in firms. In fact, we find evidence for such a positive effect linked to complementarities in production for workers of different birthplace. The same could be true, in principle, for workers of a different gender or ethnicity, which might be interesting for future research.

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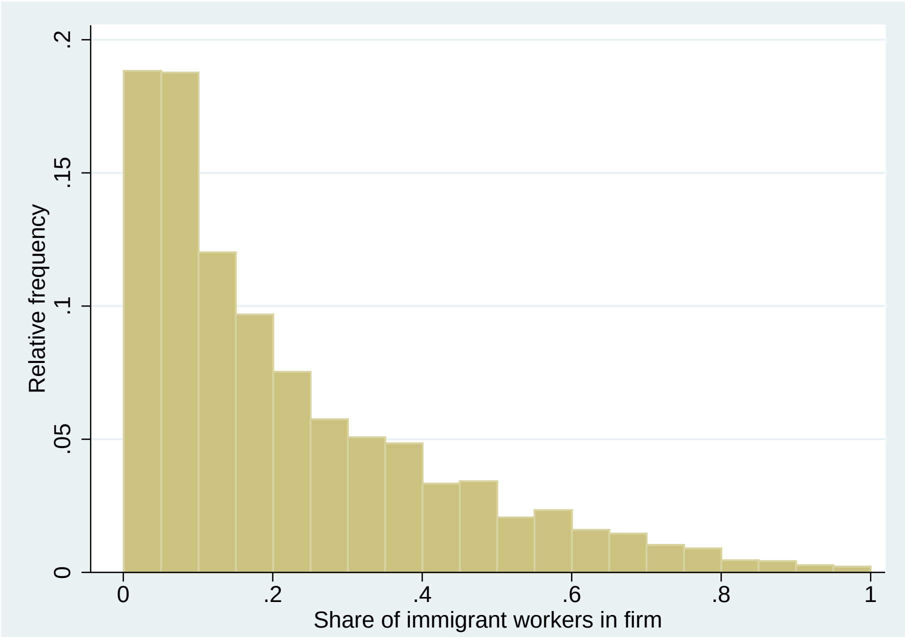
5 Graphs and Tables

Figure 2: Distribution of immigrant workers over firms.



NOTES: Shares of immigrant workers in Austrian firms in 2000. Firms with less than 10 employees excluded. N=79,944 firms.

Table 1: Workers' migration background (% of working population).

	Official statistics		Sample
	citizenship	country of birth	
Native	89.69	85.41	85.61
Immigrant	10.31	14.59	14.39
Europe:	9.36	12.79	13.13
former Yugoslavia	4.71	5.43	6.05
EU-27-States:	2.86	4.96	4.34
Germany	1.01	1.70	1.32
Poland	0.37	0.68	0.63
former Czechoslovakia	0.27	0.62	0.56
Hungary	0.22	0.40	0.56
Turkey	1.61	2.07	2.40
America	0.16	0.28	0.18
Africa:	0.21	0.42	0.31
Nigeria	0.04	0.05	0.04
Oceania	0.02	0.03	0.02

NOTES: Working population by citizenship/country of birth in 2001. Census 2001 data, Statistics Austria, selected countries.

Table 2: Descriptive statistics, by workers' country of birth.

	Overall	Austria	Germany	Jugoslavia	Turkey	Other
Wage	99.1	102.2	129.5	69.4	68.0	78.0
	(52.7)	(53.5)	(76.8)	(21.9)	(20.1)	(45.4)
Fractionalization	0.20	0.167	0.292	0.438	0.498	0.425
	(0.19)	(0.17)	(0.2)	(0.17)	(0.16)	(0.21)
Share foreign	0.15	0.117	0.207	0.356	0.414	0.327
	(0.17)	(0.13)	(0.19)	(0.21)	(0.2)	(0.23)
Share own	0.81	0.895	0.071	0.227	0.230	0.108
	(0.27)	(0.13)	(0.13)	(0.17)	(0.17)	(0.15)
Age	39.6	39.6	40.5	40.5	37.3	40.6
	(9.6)	(9.93)	(9.3)	(9.5)	(9.35)	(8.32)
Experience	18.1	18.9	10.6	12.8	12.6	9.1
	(8.2)	(7.85)	(8.31)	(7.99)	(7.16)	(5.18)
Tenure	9.34	9.79	7.05	6.02	6.22	5.45
	(7.81)	(7.98)	(6.53)	(6.04)	(5.95)	(4.54)
Share blue	0.557	0.537	0.465	0.754	0.738	0.669
	(0.32)	(0.32)	(0.33)	(0.19)	(0.18)	(0.28)
Share female	0.248	0.252	0.292	0.202	0.210	0.244
	(0.21)	(0.21)	(0.2)	(0.2)	(0.19)	(0.21)
Firmsize						
<25	13.3	13.0	10.4	16.8	13.5	18.5
25-50	11.9	11.4	11.0	16.3	12.4	16.5
50-100	13.1	12.6	13.6	16.7	15.6	16.2
100-200	14.4	14.1	14.3	17.0	16.4	14.0
>200	47.3	48.9	50.8	33.2	42.2	34.7
Observations	841531	740896	9472	47934	23656	19573

NOTES: Mean values for the year 2000. Standard deviation in parentheses.

Table 3: Firm characteristics, by low and high fractionalization.

	Fractionalization	
	Low	High
Wages	98.223	82.686
	(55.3)	(44.99)
Share female	0.333	0.257
	(0.24)	(0.22)
Share blue	0.446	0.685
	(0.36)	(0.27)
Share native	0.963	0.590
	(0.11)	(0.36)
Firmsize	71.4	97.8
	(248.6)	(469.2)
Firmsize increased	0.427	0.436
Firmsize decreased	0.423	0.444
Obs	53697	75058

NOTES: Mean values for the year 2000. Standard errors in parentheses. Wages are daily wages in €. "Firmsize increased (decreased)" is a binary indicator set to 1 if the firm's workforce increased (decreased) over the last year.

Table 4: Share of coworkers of same or different birthplace (in %).

	Natives	German	Jugoslavia	Turkish	Other	Fractionalization
Natives	89.53	0.83	4.79	2.39	2.46	0.167
German	79.27	7.13	5.49	3.96	4.15	0.292
Jugoslavia	64.45	1.06	22.75	7.09	4.66	0.437
Turkish	58.61	1.16	12.80	22.96	4.47	0.498
Other	67.33	1.28	9.46	5.49	16.45	0.425

NOTES: Workers' background in Austrian firms in 2000. Firms with less than 10 employees excluded. N=79,944 firms.

Table 5: Effect of workforce heterogeneity on workers' wages (IV-estimates).

	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Fractionalization	—	0.228***	0.289***	0.608***	1.104***
	—	(0.054)	(0.087)	(0.028)	(0.218)
Share own	0.008***	0.111***	0.170***	-0.022***	-0.029***
	(0.002)	(0.009)	(0.002)	(0.002)	(0.007)
Person fixed-effects	yes	no	no	yes	yes
Firm fixed-effects	yes	no	yes	no	yes

NOTES: Estimation results for a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005, N=841,531. (Bootstrapped standard errors in parentheses based on 10 replications, clustered on firm.) Seasonal employment is excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. Frationalization and share of own group are instrumented; instruments are the lagged region × sector-specific values. ***, **, and * indicate significance at the 1, 5, and 10% level. Other controls are experience, tenure, tenure^2, age, age^2, and year fixed-effects. Controls at the firm level are firmsize, the share of female workers, the share of blue collar workers, average employers' age and tenure.

Table 6: Effect of workforce heterogeneity—results from sub-samples (IV-estimates).

	All	Birthplace		Status		Tenure (days)	
		natives	immigrants	blue collar	white collar	1–500	500+
Fractionalization	1.104***	1.220***	0.283**	0.676***	1.474***	1.215***	0.918***
	(0.218)	(0.122)	(0.113)	(0.094)	(0.337)	(0.264)	(0.201)
Share own	-0.029***	-0.032***	-0.117***	-0.022***	-0.032***	-0.044***	-0.016**
	(0.007)	(0.006)	(0.042)	(0.003)	(0.012)	(0.011)	(0.008)
Observations	841,531	740,896	100,635	450,493	391,038	384,426	457,105

NOTES: Estimation results for a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005. Seasonal employments excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. (Bootstrapped standard errors in parentheses based on 10 replications, clustered on firm.) Seasonal employment is excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. With the exception of the first specification, fractionalization and size of own group are calculated for the estimated subgroup only, but including workers who were not sampled. Frationalization and share of own group are instrumented; instruments are the lagged region $\times$ sector-specific values. ***, ** and * indicate significance at the 1, 5 and 10% level. All estimates control for person fixed-effects and firm-fixed effects. Other controls are experience, tenure, tenure^2, age, age^2, and year fixed-effects. Controls at the firm level are firm size, the share of female workers, the share of blue collar workers, average employers' age and tenure.

A Appendix

Table A.1: OLS estimates of the effect of birthplace heterogeneity and own group size on wages.

	(1)	(2)	(3)	(4)	(5)
Fractionalization	—	-0.055***	-0.029***	0.006*	0.045***
	—	(0.019)	(0.009)	(0.003)	(0.008)
Share own	0.008***	0.079***	0.129***	0.008***	0.007***
	(0.002)	(0.007)	(0.002)	(0.001)	(0.002)
Person fixed-effects	yes	no	no	yes	yes
Firm fixed-effects	yes	no	yes	no	yes
Rsquared	0.938	0.334	0.178	0.413	0.938

NOTES: N=841,531 observations for workers from a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005. Seasonal employments excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. (Robust standard errors in parentheses, clustered on firm.) ***, **, and * indicate significance at the 1, 5, and 10% level. Other controls are experience, tenure, tenure^2, age, age^2 and year fixed-effects. Controls at the firm level are firmsize, the share of female workers, the share of blue collar workers, average employers' age and tenure.

Table A.2: OLS estimates of the effect of birthplace heterogeneity and own group size on wages for different subsamples.

	All	Birthplace		Status		Tenure (days)	
		natives	immigrants	blue collar	white collar	short	long
Fractionalization	0.045***	0.048***	0.031**	0.033***	0.058***	0.032***	0.042***
	(0.008)	(0.013)	(0.015)	(0.006)	(0.013)	(0.008)	(0.015)
Share own	0.007***	0.007***	0.008	0.006*	0.006***	0.004*	0.007*
	(0.002)	(0.003)	(0.019)	(0.003)	(0.002)	(0.002)	(0.004)
Observations	841,531	740,896	100,635	450,493	391,038	384,426	457,105
Rsquared	0.938	0.937	0.927	0.913	0.940	0.938	0.945

NOTES: Estimation results for all workers from a 15% random sample of all male non-selfemployed private sector workers between 1994 to 2005. Seasonal employments excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. (Clustered robust standard errors in parentheses.) ***, ** and * indicate significance at the 1, 5 and 10% level. All estimates control for person fixed-effects and firm-fixed effects. Other controls are experience, tenure, age, age^2 and year fixed effects. Controls at the firm level are firmsize, the share of female workers, the share of blue collar workers, average employers' age and tenure.

Table A.3: First stage results, main estimates.

	(1)	(2)	(3)	(4)	(5)
$A: Fractionalization_{rs,t-1}$	—	0.523***	0.243***	0.194***	0.167***
SE	—	(0.019)	(0.007)	(0.036)	(0.023)
F-Stat	—	[396.4]	[619.7]	[56.15]	[57.93]
B: $Share\ own_{rs,t-1}$	1.066***	0.977***	1.059***	0.925***	1.067***
SE	(0.003)	(0.003)	(0.001)	(0.005)	(0.003)
F-Stat	[62.12]	[7607]	[62160]	[1707]	[60.16]
Person fixed effect	yes	no	yes	no	yes
Firm fixed effect	yes	no	no	yes	yes

NOTES: Estimation results for all workers of a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005. Seasonal employments excluded. Dependent variable in panel A is the fractionalization index and in panel B the share of the workers with the same country of origin in the firm. (Robust standard errors in parentheses, clustered on firm.) [F-statistics in brackets.] Frationalization and share of own group are instrumented; instruments are the lagged (region $\times$ sector)-specific values. ***, **, and * indicate significance at the 1, 5, and 10% level. All estimates control for person fixed-effects and firm-fixed effects. Other controls are experience, tenure, age, age^2, and year fixed effects. Controls at the firm level are firmsize, the share of female workers, the share of blue collar workers, average employers' age and tenure.

Table A.4: First stage results, subsamples.

	All	Birthplace		Status		Tenure (days)	
		natives	immigrants	blue collar	white collar	short	long
$A.1$: $Fractionalization_{rs,t-1}$	0.167***	0.166***	0.240***	0.204***	0.132***	0.155***	0.165***
SE	(0.023)	(0.025)	(0.036)	(0.042)	(0.018)	(0.038)	(0.017)
F-Stat	[58.20]	[72.43]	[42.65]	[74.98]	[74.79]	[56.13]	[87.37]
$B.2 : Share\ own_{rs,t-1}$	1.067***	1.067***	1.225***	1.078***	1.058***	1.082***	1.058***
SE	(0.003)	(0.002)	(0.131)	(0.003)	(0.003)	(0.002)	(0.003)
F-Stat	[62.54]	[62.73]	[49.97]	[57.87]	[62.65]	[40.91]	[69.33]

NOTES: Estimation results for workers from a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005. Seasonal employments excluded. Dependent variable in panels A.1 and B.1 is the fractionalization index and in panels A.2 and B.2 the share of the workers with the same country of origin in the firm. (Robust standard errors in parentheses, clustered on firm.) [F-statistics in brackets.] Instruments are the sector-specific shares of workers with the same birthplace. Fractionalization is instrumented by its five-year lag. ***, **, and * indicate significance at the 1, 5, and 10% level. All estimates control for person fixed-effects and firm-fixed effects. Other controls are experience, tenure, age, age^2, and year fixed effects. Controls at the firm level are firmsize, the share of female workers, the share of blue collar workers, average employers' age and tenure.

B Additional Tables

These Tables provide additional material for the editors and referees. They can be made available on request or in an online appendix, they are not intended for an eventual printed copy of our contribution.

Table B.1: IV-estimation results, Table 6, Panel A.

	All		Birthplace		Status		Tenure (days)	
			natives	immigrants	blue collar	white collar	short	long
Share own	-0.029***	-0.030***	-0.032***	-0.117***	-0.022***	-0.032***	-0.044***	-0.016**
	(0.007)	(0.006)	(0.006)	(0.042)	(0.003)	(0.012)	(0.011)	(0.008)
Fracationalization 1.104***	1.141***	1.220***	0.283**	0.676***	1.474***	1.215***	0.918***	
	(0.218)	(0.150)	(0.122)	(0.113)	(0.094)	(0.337)	(0.264)	(0.201)
Share foreign		-0.149***						
		(0.020)						
Share female	0.050***	0.047***	0.060***	-0.037	-0.007	0.077***	0.014	0.075***
	(0.016)	(0.015)	(0.010)	(0.028)	(0.017)	(0.016)	(0.019)	(0.017)
Share blue	-0.056***	-0.054***	-0.059***	0.016	-0.022**	-0.082***	-0.068***	-0.034**
	(0.010)	(0.010)	(0.017)	(0.020)	(0.010)	(0.028)	(0.018)	(0.016)
average age	-0.004***	-0.004***	-0.004***	-0.001	-0.003***	-0.005***	-0.004***	-0.003***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
average tenure	-0.001	-0.001	-0.001	-0.005***	-0.002***	0.000	-0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
tenure	0.009***	0.009***	0.008***	0.014***	0.009***	0.009***	0.051***	0.006***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
tenure^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.006***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
experience	0.052***	0.052***	0.054***	0.035***	0.032***	0.057***	0.058***	0.039***
	(0.003)	(0.006)	(0.004)	(0.005)	(0.004)	(0.008)	(0.003)	(0.009)
age	0.050***	0.050***	0.051***	0.030***	0.046***	0.055***	0.051***	0.035***
	(0.009)	(0.010)	(0.007)	(0.002)	(0.012)	(0.012)	(0.004)	(0.005)
age^2	-0.046***	-0.046***	-0.048***	-0.020***	-0.025***	-0.069***	-0.050***	-0.040***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
number of employees	-0.012**	-0.012***	-0.018***	0.018**	-0.005	-0.016**	-0.007	-0.015***
	(0.005)	(0.003)	(0.004)	(0.008)	(0.003)	(0.008)	(0.004)	(0.003)
Observations	841,531	841,531	740,896	100,635	450,493	391,038	384,426	457,105
Fstat	[67.51]	[67.51]	[66.95]	[37.07]	[42.39]	[63.84]	[37.53]	[73.96]

NOTES: Estimation results for all workers of a 15% random sample of all male non-selfemployed private sector worker between 1994 to 2005. Seasonal employments excluded. Dependent variable is the logarithm of daily wages, deflated to 2000 prices. (Robust standard errors in parentheses, clustered on firm.) [F-statistics in brackets.] Frationalization and share of own group are instrumented; instruments are the lagged (region × sector)-specific values. ***, **, and * indicate significance at the 1, 5, and 10% level. All estimates control for person fixed-effects and firm-fixed effects. Year fixed effects included in all specifications.