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Understanding the Native-Immigrant Wage Gap Using Matched Employer-Employee Data. Evidence from Germany*

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Abstract

Hellerstein and Neumark (1999) developed a straightforward method to detect wage discrimination using matched employer-employee data. In this paper a new method to measure wage discrimination is proposed, that builds on the ideas first developed by Hellerstein and Neumark. It has four main advantages: it is robust to labor market segregation, it does not impose linearity on the wage setting equation, it avoids the problematic estimation of production functions, and it is not only a test for discrimination but also produces measures of discrimination. Using matched employer-employee data from Germany, I find that immigrants are being discriminated against. They receive wages which are 13 percent lower than native workers in the same firm.

JEL Code: J71, J64

KEYWORDS: Labor market discrimination, immigration, matched employer-employee data.

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1 Introduction

In the Altonji and Blank's handbook chapter (1999), labor market discrimination is defined as a situation in which persons who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity or gender.

The most widely-used approach to test for labor market discrimination takes the unexplained gap in Mincer-type wage regressions as evidence of discrimination. This method, also known as the residual method, estimates Mincer-equations for both groups and then decomposes the difference in mean wages into "explained" and "unexplained" components. The fraction of the gap that cannot be explained by differences in observable characteristics is considered to be discrimination. In spirit of Altonji and Blank's definition, the residual approach may be understood as a comparison of wages and productivity where the latter is approximated by a function of observable characteristics. However, if there are unobservable characteristics that correlate with migration status and that are also correlated with productivity[1], this discrimination measure may be biased.

The availability of matched employer-employee data allows a response to this potential weakness of the residual approach. In the absence of good enough worker level data to control for differences in productivity, a smart idea is to directly estimate the productivity gap using output measures at the firm level. Whenever perfect competition holds in the labor market any difference in wages that is not driven by a difference in productivity may be considered discrimination. Hellerstein and Neumark (1999); and Hellerstein, Neumark and Troske (1999); proposed a method that builds on that intuition. It uses firm-level data to estimate the relative marginal products of various types of workers, which are then compared with their relative wages. The productivity of each type of worker is estimated in terms of the proportion of workers of each type in the

[1]We typically think of environmental variables, tastes, education quality and language skills.

firm. Given that its implementation and the interpretation of its results are extremely simple, this approach has been significantly popular in the last ten years. An important number of papers have applied this method to different countries, including the already mentioned Hellerstein and Neumark (1999) paper with Israeli data, and the Hellerstein, Neumark and Troske (1999) article using U.S. data, in addition to Verner (1999) using data from Ghana, Crepon, Deniau and Pérez-Duarte (2002) with French data, Lopez-Acevedo et al (2005) with data from Mexico, Zhang and Dong (2009) and Rickne (2010) with Chinese data, Van Biesebroeck, (2009) with data from three Sub-Saharan countries and Campos-Vazquez (2009) with German data.

This paper proposes a method to test for labor market discrimination that builds on the Hellerstein and Neumark (1999) idea of directly using productivity data to measure discrimination. I take advantage of a matched employer-employee panel data set to estimate a reduced form wage setting equation at the firm level that tests; controlling for productivity and firm's fixed characteristics; whether the proportion of immigrants is significant. This approach exploits the within-firm variation of the native-immigrant composition across time to identify different wage policies toward those groups.

This approach adds to the existing test of wage discrimination in three main dimensions: firstly it provides quantitative measures of wage discrimination. Comparing relative wages and relative productivity is only informative on the existence of wage discrimination. Secondly, it does not impose linearity on the wage setting equation. Comparing relative wages and relative productivity is informative with regard to discrimination whenever the function that links wages and productivity is linear. The strategy proposed in this paper is more flexible allowing the wage-productivity elasticity to be different from one. Finally, and more importantly, it produces measures of discrimination that are robust to labor market segregation. As Altonji and Blank (1999) note, the variation in worker composition is likely to be correlated with heterogeneity in the production technology and may be endogenous to the model. If this is the case, the Hellerstein and Neumark test for discrimination estimated with cross sectional data would not be valid.

There have been two main attempts to control for the worker's composition endogeneity. In a more recent paper, Hellerstein and Neumark (2004) propose to take segregation into account by dealing with omitted plant-specific productivity parameters as in Olley and Pakes (1996). Although this method proposes a potential solution to the estimation of some parameters of the production function, its implications in this context are not totally clear. Firstly, as Mairesse and Griliches (1998) point out, the Olley and Pakes method may not be the best alternative if in the firm-specific productivity term there are mostly fixed components[2]. Secondly, the model presented by Olley and Pakes implies a correlation of the firm labor input with the plant-specific productivity parameter, but does not generate endogeneity in worker composition[3]. Finally, it is not clear how the wage gap should be estimated once we have estimated the productivity gap using this strategy.

The alternative strategy is to control for endogenous composition by following a more typical fixed-effects panel data approach. Exploiting within firm variation, both the wage gap and the productivity gap are well defined but it is problematic to achieve precise estimates of the relative productivity parameter. The lack of precision in the quality parameter estimates is a pervasive problem in Cobb-Douglas production functions with quality adjusted labor input when we only exploit within firm variation[4]. The approach presented in this paper also exploit within firm variation, but it avoids the estimation of production functions, and therefore it may produce precise measures of wage discrimination.

As a spin-off of the main results, the method also allows me to estimate firm-

[2]This is because the firm's capital has already adjusted to the firm specific productivity term, and hence the investment at time t would not depend on the former

[3]This is because Hellerstein and Neumark include worker heterogeneity in a Cobb-Douglas production function with quality linearly-adjusted labor input. This production function imposes perfect substitution between workers' groups: therefore in the context of Olley and Pakes, the rent-maximizing firm only takes into account the total labor input in efficiency units, and the composition of this input should be exogenous

[4]See for example Hellerstein and Neumark (1998); Cahuc, Postel-Vinay and Robin (2006) or Bartolucci (2010).

specific discrimination parameters following the strategy presented by Arellano and Bonhomme (2009). Although these estimates are noisy (I have a small-T panel), the unbiased correlation with other firm variables, such as profit or tenure of immigrants, may be estimated and used to obtain indirect evidence of different discrimination theories, testing some of their implications.

I use a 1996-2005 panel of matched employer-employee data provided by the German Labor Agency, called LIAB.[5] This dataset is especially useful for the current study for two reasons. Firstly, it contains essential data about the workers' nationalities. Secondly, it is a panel that tracks firms as opposed to individuals, which is necessary for obtaining estimates in the wage setting equation that are robust to a correlated firm fixed effect.

The results show that immigrants suffer from wage discrimination. Depending on the measure of productivity and the specification used, the immigrant wage premium ranges between -7 and -17 percent, and is always significantly negative. These findings are different from the conclusions drawn by the traditional and the Hellerstein and Neumark (1999) approaches. The elasticity of wages to productivity is significantly different from one: therefore assuming that wages are a linear function of productivity may not be the best option. As opposed to the fixed-effects estimates, when estimating by OLS the discrimination measure was significantly reduced, which gives evidence of positive segregation of immigrants into good firms. Although the reduced-form wage setting equation is very simple, it has an acceptable fit of the wage-bill data and the main results of the paper are remarkably robust to many specification tests. I find neither significant evidence of immigrants moving to less discriminatory firms, nor significant evidence in favor of a statistical discrimination model: nevertheless, I do find evidence against a taste-based discrimination model.

A significant portion of the empirical literature on discrimination focuses on gender and racial discrimination. Wage differentials between natives and immigrants have generally been understood as an assimilation process that involves

[5]This dataset is subject to strict confidentiality restrictions. It is not directly available; only after the IAB has approved the research project, The Research Data Center (FDZ) can provide on site use or remote access to external researchers.

differences in productivity, such as language skills (e.g. Borjas 1994; Chiswick and Miller 1995; Carnevale et al. 2001; Dustmann and van Soest 2002), differences in education quality (Sweetman 2003) or differential returns to foreign schooling and labor market experience (e.g. Friedberg 2000 and Bratsberg and Ragan 2002). As discrimination has normally been detected through the unexplained gap in wage equations and this approach is not the best option to disentangle differences in productivity and discrimination, there are few papers addressing labor market discrimination against immigrants. Some exceptions, also with matched employer-employee data, are Aydemir and Skuterud (2008) and Aeberhardt and Pouget (2007) where the sources of immigrants wage differentials within and across establishments are explored. There is a new working paper by Campos-Vazquez (2008) that uses the same LIAB data as this paper and replicates the Hellerstein and Neumark (1999) analysis to test for discrimination against German immigrants.

The rest of this paper is organized as follows. In the next section, I briefly describe the immigration phenomena in Germany. In Section 3, I present the model and I formally compare it with the Hellerstein and Neumark (1999) approach. In the fourth section, I present the data-set. Section 5 presents the results and robustness check. In Section 6, I show how this method can be used to distinguish between different discrimination theories and in the last section, I conclude.

2 Background

Germany is a very interesting country through which to study migration, mainly because immigrants represent an important and stable fraction of the population. The proportion of immigrants has experienced very limited change in the last 15 years ranging between 8.2 percent and 8.9 percent, see Figure 1.

The first immigration wave that immediately followed the end of the Second World War started when several millions of refugees from the former East Germany and from Eastern European regions resettled in the Federal Republic of

Germany.

The second immigration wave started in 1955, when Italy and Germany signed a treaty which allowed organized recruitment of Italian workers to meet the needs of the growing German economy. The recruitment of the foreign labor force intensified dramatically reacting to the sharp increase in demand for additional labor force. This policy was expanded to the following countries: Spain and Greece (1960), Turkey (1961), Morocco (1963), Portugal (1964), Tunisia (1965) and Yugoslavia (1968)[6]. These agreements were intended to meet the needs of the German economy by reducing the movement costs of unskilled workers. Foreign workers were recruited to Germany on a temporary basis.

The practice of foreign labor recruitment stopped in 1973, following the oil crisis and a sharp decrease in labor demand. The end of the labor recruitment and new barriers for foreign workers to settling in Germany minimized the short-term immigration and started a new tendency toward permanent settlement among those who entered Germany as temporary workers. This was the start of the next period of immigration to Germany, the one based on family reunifications of guest workers who arrived earlier. The Turkish population was the main nationality which took advantage of this possibility and in spite of the halt placed on recruitment in 1973, it continued to rise and now forms the largest foreign minority in Germany.

Since the late 1980s, the inflow of refugees and asylum seekers has increased and has marked another phase in post-war immigration. The number of asylum applicants rose significantly in the second half of the 1980s and peaked at 440,000 in 1992, partly as a result of the war in the former Yugoslavia. Between 1988 and 1992, 1.1 million asylum-seekers filed applications. As a reaction to this, the German Parliament agreed to the "asylum compromise" in 1993, which made applying for political asylum in Germany considerably more difficult. Hence, the number of applications for asylum has declined steadily and the proportion of immigrants has stabilized, see Figure (1).

The percentage of immigrants in Germany increased from less than 1 per-

[6]See Rudolph (1994) for a good description of this phenomenon.

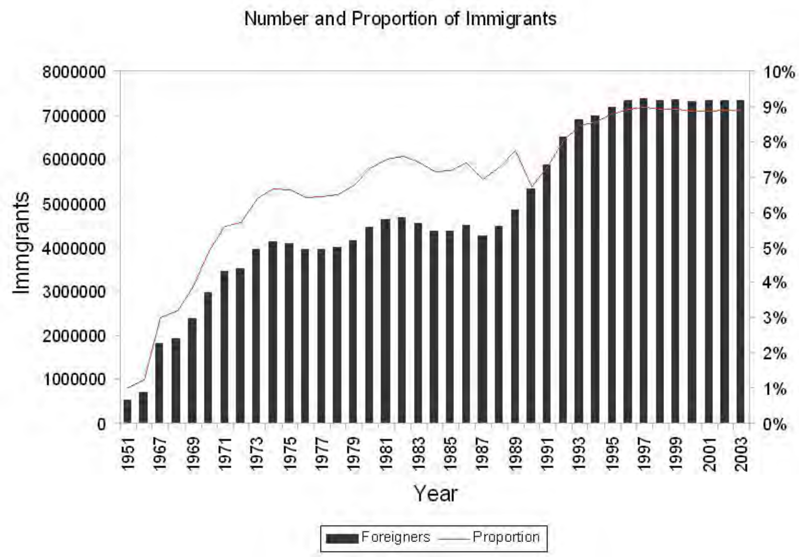

Figure 1: Number and Proportion of Immigrants

cent, 506,000 foreigners in 1955 to 8.2 percent in 2007[7], 6,744,879 registered immigrants[8], see Figure (1). In terms of workers, in my sample the fraction of immigrants is slightly higher and ranges from 9.4 to 10.9 percent between 1996 and 2004. See Section 4 for more details.

3 The Model

As stated in the introduction, Altonji and Blank (1999) define labor market discrimination as a situation in which persons who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity or gender.

Following the handbook's definition of labor market discrimination, individual productivity should be a sufficient statistic to explain wages. Therefore,

[7]Data from the Federal Office for Migration and Refugees.

[8]There are no statistics concerning irregular immigration or immigrants staying in Germany without a permit. Unofficial estimates, which refer to between 500,000 and one million irregular immigrants residing in Germany, are not based on scientific assessment. As the data used in this paper come from social security records I consider only registered immigrants.

discrimination could be detected estimating the following generic wage setting equation:

$$W_{i,j,t} = F(P_{i,j,t}; I_i), \tag{1}$$

where $W_{i,j,t}$ is the wage of individual i, on firm j, at time t, $P_{i,j,t}$ is the individual productivity and I is an indicator function that takes the value 1 if the individual is foreign born. We would be able to test if firms discriminate against immigrants if we could test if $F(P_{ijt}; I_i = 1) \neq F(P_{ijt}; I_i = 0)$

Without making structural assumptions on the labor market model generating the data, the functional form of $F(.,.)$ is unknown. As a baseline, let me consider a log-linear approximation to $F(.,.)$:

$$w_{ijt} = \alpha + \beta p_{ijt} + \gamma I_i + \epsilon_{ijt}, \tag{2}$$

where w_{ijt} is the log-wage of individual i, on firm j, at time t, p_{ijt} is the individual log-productivity and I_i is an immigrant indicator. In this context, I interpret ϵ_{ijt} as an econometric mean-zero residual term due to the imposed log-linearity in the wage setting equation.

Firms may differ in terms of observed characteristics like region, sector or unionization of the workforce but they could also differ in terms unobserved ones as wages policies, risk aversion, technology or managerial quality. It is likely that some of these differences may imply differences in the firm's wage setting equation. To capture firm fixed heterogeneity let α_j be firm specific. In Section 6, I propose a wage setting equation where more heterogeneity is allowed[9].

As discrimination was defined as a situation in which workers who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related with their migration status, in this context, a direct test for discrimination would be to test $\gamma \neq 0$[10].

[9]In Section 6: I allow for heterogeneity in γ. This would imply a difference if $\bar{I}_{jt}$ is correlated with γ_j and then $E(\gamma_j) \neq \gamma$.

[10]In Section 5.2.3, I also allow for different βs according to the migration status.

Although the log-linearity assumption is relaxed in Subsections 5.2.2, 5.2.3 and 5.2.4, it is a convenient specification for the following reasons:

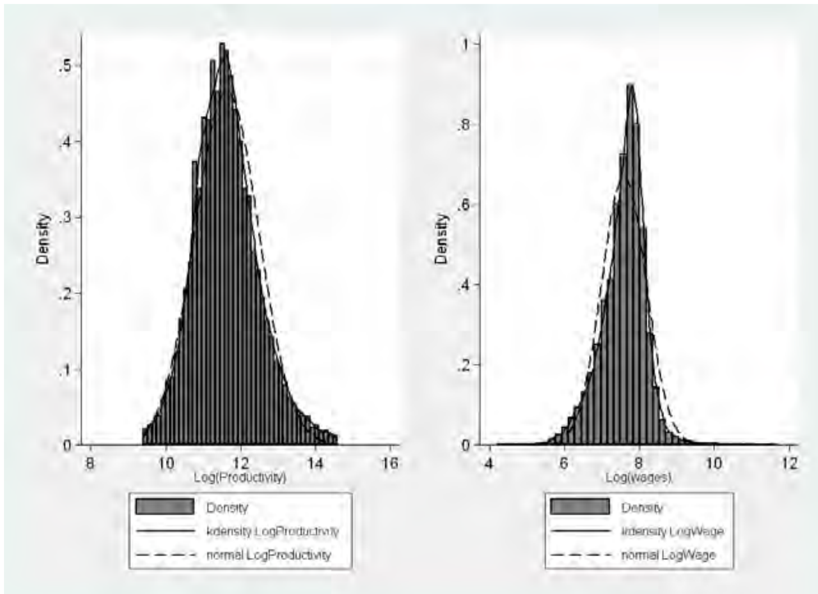

Figure 2: Log(Productivity) and log(Wages)

- It is the natural specification to connect wages and productivity, which, using firm level data, have been found to be approximately log-normally distributed, see figure 2[11].

- It provides a direct connection with the residual approach, where the log-wage equation is a linear combination of workers and firm characteristics, proxying the match productivity.

- The interpretation of the parameters is straightforward, in terms of constant elasticities.

- The log-linear wage equation, at the firm level, has a reasonably good

[11]Figure 3 has being constructed using 24,444 observations. The top 1% and the botton 1% of the distribution of output per worker has been excluded.

performance fitting the data. See Figure 3,[12] and measures of the goodness of fit of the model in the estimations presented in Section 5.

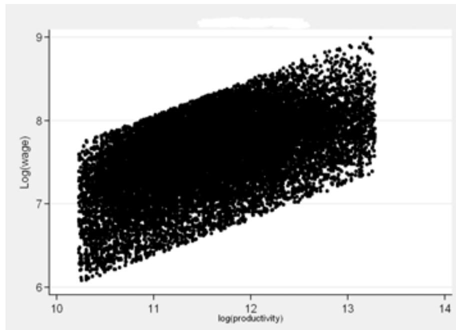

Figure 3: Log-Linear Wage Setting Equation

To directly estimate (2) is not feasible because individual productivity is generally unobserved. There are some cases where individual productivity is more easily measured such as academic positions, see Ferber and Green (1982), or jobs with under-piece contracts, see Milgrom, Petersen and Snartland (2007). Although this kind of study may have measures of individual productivity, they are likely to be weaker in terms of external validity.

3.1 The Hellerstein and Neumark approach

The Hellerstein and Neumark approach has been found to be a very convincing method to detect wage discrimination. Hellerstein and Neumark (1999) and Hellerstein, Neumark and Troske (1999) use matched employer-employee data from Israel and the US to estimate relative marginal products of various types

[12] Due to confidentiality restriction the IAB is not allowed to provide any data which refer to individual observations. Each point in a scatter plot is considered as individual information: therefore scatter plots can only be shown if the point cloud is compact enough to avoid any possible identification of individual information. Figure 3 has been constructed using 20,559 observations (82.4% of the observations of the original sample). I exclude extreme observation (below the fifth percentile, and above the 95^{th} percentile, 2,494 observations) of the distribution of the residual term in a linear regression of the logarithm of mean-wage at each firm, on the logarithm of total output per worker at each firm, I also exclude the extreme observations (below the fifth percentile, and above the 95^{th} percentile, 1,890 observations) of the original distribution of output per worker.

of workers. Then they compare productivity differentials ($\rho = \frac{E(P_{ijt}|I_i=1)}{E(P_{ijt}|I_i=0)}$) with wage differentials ($\lambda = \frac{E(W_{ijt}|I_i=1)}{E(W_{ijt}|I_i=0)}$).

Most of their popularity arose because their idea is very natural. If observable worker characteristics are not a convincing enough proxy of worker productivity, we cannot trust on the residual approach. Therefore, it may be convenient to directly estimate productivity. Assuming that wages are a linear function of productivity, the test is straightforward.

λ is estimated exploiting data on firms' wage bills and differences in gender composition across firms. They estimate by nonlinear least squares the following equation:

$$\ln(\bar{w}_{jt}) = cons + \ln(1 + (\lambda - 1)\frac{L_W}{L}),$$

where $\bar{w}_{jt}$ is the mean wage paid by firm j, L is the total number of workers in the plant j, and L_w is the proportion of women.

ρ is estimated with production functions, assuming a Cobb-Douglas or translogarithmic functional forms with quality adjusted labor input. In their simpler case, they estimate marginal products of women and men by NLLS in the following equation:

$$Ln(Y_{jt}) = aLn(K_{jt}) + bLn(M_{jt}) + cLn(L^Q_{jt}) + g(K_{jt}, M_{jt}, L^Q_{jt}),$$

where K_{jt} is capital, M_{jt} is material, $g(K_{jt}, M_{jt}, L^Q_{jt})$ is the second order term in the production function and L^Q_{jt} is quality of labor aggregate that is defined as:

$$L^Q = L\left\{1 + (\rho - 1)(L^W/L)\right\}$$

where L is the total number of workers in the plant and L^W is the number of women in the plant[13].

The Hellerstein and Neumark strategy may be interpreted within the framework presented in this paper. Whether to estimate (2) is not feasible because individual productivity is not observed, it is possible to aggregate (2) at the

[13] The Hellerstein and Neumark (1999) model is more complicated because they allow for several population groups. See Hellerstein and Neumark (1999) for details.

group level, and then to recover γ. Taking averages of equation (2) across groups (immigrants and natives), we have:

$$\frac{\Sigma(w_{ijt}|I_i=0)}{\Sigma 1(I_i=0)} = \frac{\beta\Sigma(p_{ijt}|I_i=0)+\Sigma(\alpha_j|I_i=0)+\gamma I_i+\Sigma(\epsilon_{ijt}|I_i=0)}{\Sigma 1(I_i=0)}, \quad (3)$$

and:

$$\frac{\Sigma(w_{ijt}|I_i=1)}{\Sigma 1(I_i=1)} = \frac{\beta\Sigma(p_{ijt}|I_i=1)+\Sigma(\alpha_j|I_i=1)+\gamma I_i+\Sigma(\epsilon_{ijt}|I_i=1)}{\Sigma 1(I_i=1)}. \quad (4)$$

Subtracting (4) from (3) and noting that $\Sigma(\epsilon_{ijt}|I_i=1)=0$ and $\Sigma(\epsilon_{ijt}|I_i=0)=0$ [14], we have:

$$\begin{aligned} & \lambda-\rho \qquad (5) \\ \simeq\quad & \gamma+\underbrace{\underbrace{(1-\beta)(1-\rho)}_{\text{Linearity Bias}}+\underbrace{\left[\frac{1}{\Sigma 1(I_i=1)}\Sigma(\alpha_j|I_i=1)-\frac{1}{\Sigma 1(I_i=0)}\Sigma(\alpha_j|I_i=0)\right]}_{\text{Segregation Bias}}}_{\text{Potential Bias}}\end{aligned}$$

where λ represents the ratio between the mean wage of immigrant workers and the mean wage of native workers, and ρ represents the immigrant-native relative productivity. $\lambda-\rho$ is informative on wage discrimination if $\beta=1$ and $cov(\alpha_j, I_i)=0$. Hellerstein and Neumark (1999) make inference about discrimination (i.e.: γ) simply by comparing λ and ρ estimated at the firm level. Although they are very cautious in their interpretation of this difference, arguing that $\hat{\lambda}-\hat{\rho}$ gives evidence in favor of discrimination, if $\beta\neq 1$ or $cov(\alpha_j, I_j)\neq 0$, there is not an *a priori* direction of the bias and hence it is not clear how informative are their findings.

[14]This is easily proved noting that:

$$\begin{aligned} & \overbrace{\left[\frac{1}{\Sigma 1(I_i=1)}\Sigma(w_{ijt}|I_i=1)-\frac{1}{\Sigma 1(I_i=0)}\Sigma(w_{ijt}|I_i=0)\right]}^{\to E(w_{ijt}|I_i=1)-E(w_{ijt}|I_i=0)\simeq\lambda-1}- \\ & \beta\overbrace{\left[\frac{1}{\Sigma 1(I_i=1)}\Sigma(p_{ijt}|I_i=1)-\frac{1}{\Sigma 1(I_i=0)}\Sigma(p_{ijt}|I_i=0)\right]}^{\to E(p_{ijt}|I_i=1)-E(p_{ijt}|I_i=0)\simeq\rho-1} \\ = \quad & \gamma+\left[\frac{1}{\Sigma 1(I_i=1)}\Sigma(\alpha_j|I_i=1)-\frac{1}{\Sigma 1(I_i=0)}\Sigma(\alpha_j|I_i=0)\right], \quad \blacksquare\end{aligned}$$

In order to be clearer in this explanation let me decompose the bias in two components:

Linearity Bias: The first part of the bias addresses the fact that, whenever a change in productivity is not fully transferred to wages, two groups with different productivity may have larger or smaller relative differences in wages that do not imply discrimination. As can be seen in Section 5, β is found to be significantly different from one. Depending on the specification and the measure of productivity used, it ranges between 0.25 and 0.45. To show numerically how important may be this bias, let me consider a very simple example where there are two groups, A and B, where A is 20 percent more productive than B. If there is not discrimination against any group and assuming that $\beta = 0.4$, the wage paid to workers of the A group are supposed to only be 8 percent higher than workers of the B group. The Hellerstein and Neumark (1999) approach would wrongly imply that workers of the A group are being discriminated because the productivity gap is larger than the wage gap.

Segregation Bias: The second part of the bias is relevant if there is labor market segregation. Segregation bias, the last term in (5), is connected to the Altonji and Blank (1999) remark on the early work of Hellerstein and Neumark (1999). They argue that the variation in worker composition is likely to be correlated with heterogeneity in the production technology and may be endogenous to the model. In this context the firm's technology is captured by the firm's fixed effect, α_j. There have been many attempts to deal with segregation:

- Hellerstein and Neumark (1999) firstly tried to control for some of the observed differences between firms by clustering the analysis at different levels. If the firm heterogeneity, or at least its endogenous component, were totally captured by a discrete variable or a combination of discrete variables, this alternative would provide a test for discrimination that is robust to segregation. However, the firm's idiosyncratic component must not necessarily be observable and discrete. Moreover, in Section 5.1, I find evidence of positive correlation between the proportion of immigrant workers in the firm and the unobserved component of the firm fixed effect.

- A second attempt to deal with segregation was proposed in Hellerstein and Neumark (2004), where the production function is estimated following the Olley and Pakes (1996) strategy. This alternative is promising, but some of its implications for this context are still not totally clear. Firstly, when discussing segregation, we think of an association between the workforce composition and the firm's type or its idiosyncratic component, and the Olley and Pakes method may not be the best alternative if in the firm-specific productivity term there are mostly fixed components [15]. Secondly, in the model presented by Olley and Pakes, the rent-maximizing firm chooses the level of inputs according to the plant-specific productivity parameter. This generates endogeneity of productive inputs. But imposing a production function with heterogeneous labor input where different types of workers are perfect substitutes, does not generate endogeneity of worker composition. Finally, it is also not clear how the wage gap should be estimated once we have estimated the productivity gap using this strategy.

- The third alternative strategy is to control for endogenous composition including firm fixed-effects. By exploiting within firm variation, both the wage gap and the productivity gap are well defined but it is problematic to achieve precise estimates of the relative productivity parameter. The lack of precision in the quality parameter estimates is a pervasive problem in the Cobb-Douglas functional form with quality adjusted labor input, when we only exploit within firm variation. See, for example, Hellerstein and Neumark (1999) where, using this strategy, they obtain estimates of the productivity gap that are almost non-informative[16].

[15] This was point out in Mairesse and Griliches (1998) and is because the firm's capital has already adjusted to the firm specific productivity term, and hence the investment at time t would not depend on the former

[16] Among different samples and specifications, when they only exploit within firm variation, the estimated gender ratios of productivity ($ie:\rho$) range between 0.61 and 0.88 and their standard errors range between 0.33 and 0.25, therefore ρ is never significantly different from one, and the null hypotheses of no differences in productivity is never rejected

3.2 Detecting discrimination at the firm-level

Without measures of individual productivity, and having shown that to aggregate at the group level might also be problematic in some cases, a second best would be to aggregate the equation (2) within the firm:

$$\bar{w}_{jt} = \alpha_j + \beta\bar{p}_{jt} + \gamma\bar{I}_{jt} + \bar{\epsilon}_{jt}, \tag{6}$$

where $\bar{w}_{jt}$ is the mean of log-wages in firm j, $\bar{p}_{jt}$ is the mean of individual log-productivity of firm j, and $\bar{I}_{jt}$ is the proportion of immigrants in firm j at time t[17].

The advantage of aggregating equation (2) within the firm is that it is now feasible to estimate equation (6) due to the availability of productivity measures at the firm level. The conceptually relevant measure of productivity should be the marginal productivity of workers in firm j. Assuming the standard Cobb-Douglas with quality adjusted labor input production function:

$$Y_{jt} = A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{\phi_l},$$

where A_j is the firm fixed effect, Y_{jt} is the output of firm j at time t, K_{jt} is its capital, and L_{jt}^{Q} is its quality adjusted labor input. Where I define the labor input in efficiency units like in Hellerstein and Neumark (1999) $L_{jt}^{Q} = L\left\{1 + (\rho - 1)(L^I/L)\right\}$. The marginal productivity of native workers is given by $\phi_l A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{(\phi_l - 1)}$, that equals $\phi_l Y_{jt}/L_{jt}^{Q}$. The marginal productivity of immigrant workers is given by $\rho\phi_l A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{(\phi_l - 1)}$, that equals $\rho\phi_l Y_{jt}/L_{jt}^{Q}$. Therefore the mean marginal productivity (F_l) is:

$$F_l = \phi_l A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{(\phi_l - 1)}(1 - \frac{L_{jt}^{I}}{L_{jt}}) + \rho\phi_l A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{(\phi_l - 1)}\frac{L_{jt}^{I}}{L_{jt}}.$$

Replacing $A_j K_{jt}^{\phi_k}(L_{jt}^{Q})^{\phi_l}$ by Y_{jt}, L_{jt}^{Q} by $L_{jt}\left\{1 + (\rho - 1)(L_{jt}^{I}/L_{jt})\right\}$, and rearranging:

$$F_l = \phi_l Y_{jt}(L_{jt}\left\{1 + (\rho - 1)(L_{jt}^{I}/L_{jt})\right\})^{-1}\left[(1 - \frac{L_{jt}^{I}}{L_{jt}}) + \rho\frac{L_{jt}^{I}}{L_{jt}}\right].$$

[17] The migration status indicator, I_i, is worker specific, but the proportion of immigrant workers is firm and time specific

$$F_l = \phi_l \frac{Y_{jt}}{L_{jt}}$$

Therefore, using the log of output per worker or using the log of mean marginal productivity would only modify the constant term α_j in (6) adding $\beta \log(\phi_l)$ to it.

This specification has the advantage that it does not necessarily imply estimating relative productivity as in Hellerstein and Neumark (1999). The use of group specific productivity measures usually involves the estimation of a production function with quality adjusted labor input. In order to have estimates robust to any correlation of inputs, including labor input composition, with the firm fixed effect, the production function should be estimated by differenced-GMM as in Arellano and Bond (1989), or by SYSTEM-GMM using the set of instruments proposed in Arellano and Bover (1995). When estimating this kind of production function by GMM, I significantly lose precision and the quality-adjustment parameters are almost non-informative. This problem is usual in this production function specification. In the Appendix, I present the Non Linear Least Squares estimates of the production function in levels to compare my results with those obtained with the Hellerstein and Neumark (1999) approach.

4 Data

The data I use for the present study refer to West-German workers[18] contained in the linked employer-employee dataset of the IAB (LIAB) which covers the period 1996-2005. LIAB is created by matching the data from the IAB establishment panel and the process-produced data from the Federal Employment Services (Social security records).

The IAB Establishment Panel is an annual survey of German establishments, which started in Western Germany in 1993 and was extended to Eastern Germany in 1996. The sample of selected establishments is random and stratified

[18] All employees and trainees subject to social security are included, while the self-employed, family workers, a subgroup of civil servants ("Beamte"), students enrolled in higher education and those in marginal employment are excluded

by industries, establishment size and regions. The sample unit is the establishment. The establishments approached to complete in the survey are selected from the parent sample of all German establishments that employ at least one employee covered by social security. Participation of establishments is voluntary, but the response rates are high, they exceed 70 percent[19]. The firm's data gives details of total sales, value added, investment, total wage bill, depreciation, number of workers and sector. I only consider firms with strictly positive output. To ensure a consistent comparison of results across specifications, the data used for each specification exclude observations with missing values for any of the independent variables used in the regressions. Firms in the financial and public sectors are excluded from my subsample, see Table 1 for some descriptive statistics.

Table 1: Firms

Firm's Descriptive Statistics	
Workers	211.86
output*	54.3
depreciated Capital*	1.38
value Added*	23.0
Total Wage Bill*	8.24
Unionized	63.4%
Single Establishment	70.2%
Immigrant's Proportion	7.7%
Imm. Prop within-firm Std. Dev.	2.6%
Observations	20,886

Note: * per annum in millions of euros. Descriptive statistics obtained from the panel of firms.

The distinctive feature of this data is the combination of information about individuals and details concerning the firms in which these people work. The workers' source contains valuable data on age, sex, migration status[20], daily wage (censored at the upper earnings limit for social security contributions),

[19]For a more precise description of this dataset, see Alda et al (2005)

[20]I consider immigrants to these workers who do not have the German nationality. In 1.999 there was a law reform that modified the naturalization criteria. In Section B, I discuss this issue in more depth and show that the main results of the paper are valid independently of the change in this law

schooling/training, occupation based on a 3-digit code and the establishment number.

Table 2: Demographic Differences

	Immigrants	Natives
Sex (%)	25.6	31,2
Age (years)	39.6	40.4
Tenure (years)	10.5	11.1
Experience (years)	15.1	16.7
Unskilled (%)	80.9	52.4
Part-time jobs (%)	9.2	12.8
Agriculture (%)	2.5	3.9
Manufacturing (%)	70.3	59.1
Construction (%)	3.0	3.3
Trade (%)	3.5	6.9
Services (%)	20.6	26.7
Daily Wages (€)	94.7	109.0
Observations	1.185.362	11.832.370

Note: Descriptive statistics estimated from the panel of workers. As wages are censored at the upper earnings limit for social security contributions, mean-wages are obtained by Maximum-Likelihood assuming log-normality.

In Table 2, I present descriptive statistics of both immigrants and natives, estimated from the sample of workers. The proportion of women is significantly higher in the native population. Immigrants are younger and they have less tenure and experience. There are important differences in terms of occupations and sectors. Immigrants are more concentrated in the manufacturing sector and low-skill occupations[21] than natives.

5 Results

In this section, I present results of the estimation of the baseline specification (6) and I examine the robustness of these benchmark estimates.

[21]Following the FDZ's criteria, I have considered the following groups to be unskilled jobs: Agrarian occupations, manual occupations, services and simple commercial or administrative occupations. However, I have considered the following groups to be skilled jobs: engineers, professional or semi-professional occupations, qualified commercial or administrative occupations, and managerial occupations.

To estimate equation (6), I replace $\bar{w}_{jt}$ with the log of the mean-wage in firm j at time t and $\bar{p}_{jt}$ with the log of the output per-worker[22] in firm j at time t. Although the conceptually most convenient measure of productivity is value added, in this data set this measure may have some reliability problems[23]. Assuming that a constant fraction of the output is spent in materials, both measures would be equivalent for my purposes but, as a proof of robustness, I report results with both measures.

Table 3: Wage Setting Equation

$\overline{w}_{jt}$	(1)	(2)	(3)	(4)	(5)	(6)
$\beta_{\overline{output}}$	-	-	0.426	0.486	-	-
	-	-	(0.013)	(0.006)	-	-
$\beta_{\overline{Value-Added}}$	-	-	-	-	0,392	0.233
	-	-	-	-	(0.013)	(0.005)
γ	**-0.181**	**-0.258**	**0.070**	**-0.126**	**0.032**	**-0.168**
	(0.044)	(0.043)	(0.040)	(0.041)	(0.039)	(0.049)
Fixed Effects	no	yes	no	yes	no	yes
obs.	29,943	29,943	29,943	29,943	29,943	29,943
R^2	1.2%	-	37%	-	33%	-
R^2-With.	-	1.4%	-	28%	-	13%
R^2-Betw.	-	0.2%	-	38%	-	35%

Note: Each column represents a single linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions (column 1, 3 and 5) standard errors are calculated clustering by firm.

In Table 3, I present the results. In columns (1) and (2), I report the estimates without including any measure of productivity. The OLS estimate of γ in column (1) is understood to be the unconditional wage gap, only controlling for time effects. This wage gap is obtained from firm-level data and it is not statistically different from the unconditional wage gap obtained from worker-level data[24]. On the other hand, γ estimated by within groups, without further

[22]As in LIAB there are data on total output and total wage bill paid by each firm, to estimate equation (6), I replace the mean of the log with the log of the mean of wages and productivity. This is discussed in greater depth in the Appendix A.

[23]See Adisson, Schank, Schnabel and Wagner (2003) for a thorough discussion on this issue.

[24]The unconditional wage gap obtained from worker-level data is -13.1 percent, see Table 13

controls, refers to the average unconditional wage gap within firms. The difference between the overall wage differential and the within firm wage gap is informative about sorting of immigrants into firms, this issue will be discussed further in the next subsection.

In columns (2) and (3), I report estimates using output per worker as a measure of productivity. In this specification the estimated premium for being an immigrant is 7 percent, marginally significant (p-value = 0.082). However, estimating the same specification by within groups it is noteworthy that the discrimination parameter is -12.6 percent, also significant but now negative, which would imply that immigrants are being discriminated. This finding is surprising if we take into account that, using the same data, both the traditional approach and the Hellerstein and Neumark (1999) approach conclude that immigrants are not receiving significantly lower wages than natives[25].

Estimating equation (6) but including value added per worker as a measure of productivity, $\hat{\beta}$ is lower in both estimations, OLS and WG. I find the same pattern in terms of $\gamma' s$ than in columns (3) and (4). The lower punctual estimate of $\beta_{Value-Added}$, and the lower R^2 may be understood to be evidence of measurement error in value added as pointed out by Addison et al (2003).

It is important to note that β, the elasticity of wages to productivity, is found to be significantly different from one in every specification and, hence, the assumption that wages are equal or a constant fraction of productivity, may be critical. These results suggest that the linearity bias described in Section 3.1 would be relevant in this dataset.

Note that without including any measure of productivity there is obviously a very poor fit of the wage data. However, when including productivity in these regressions, the R^2 becomes acceptable and similar to the standard R^2's obtained with individual level wage regressions.

[25]See Sections D and E in the Appendix

5.1 Segregation

The positive difference $\hat{\gamma}_{OLS} - \hat{\gamma}_{WG}$ may be understood to be evidence in favor of positive segregation of immigrants into firms with higher fixed effect. This positive segregation implies an underestimation of discrimination when the within-firm variation is not isolated.

In the Appendix D, I present discrimination measures estimated with Mincer-Equations and an Oaxaca-Blinder decomposition. I find that the unexplained wage gap is 2 percent which would mean that immigrants have a positive premium, this is also found in the analysis with OLS. My hypothesis is that this positive premium is mainly due to positive segregation.

The concept of segregation aims to capture systematic sorting by workers belonging to different groups. Segregation becomes interesting when this sorting is associated with job characteristics that finally affect wages. Whenever the concentration of workers is higher in some regions or in some sectors, it may reveal self selection of immigrants and its policy implication will be small. On the other hand, a measurement to establish whether immigrants are systematically sorted into worst paying firms, within a region, sector and firm size cell, may provide evidence of more policy relevant structural differences between both groups.

Comparing the wage premium of immigrants, estimated with different sets of controls, I provide indirect evidence of the relative importance of various dimensions of immigrant segregation in generating differences in wages. Results are reported in Table 4.

In order to make the comparison with previous results easier, the first and last columns replicate the results reported in Table 3. In column (2), I report results when only controls for region are included. When I control for region, I observe that the estimated γ is smaller than the one reported in column (1). This finding connects with Borjas (1999), who argues that immigrants are not randomly assigned to regions, presumably they choose areas which provide them with better opportunities. The presence of a lower γ when controlling

Table 4: Segregation

$\overline{w}_{jt}$	(1)	(2)	(3)	(4)	(5)
β_{output}	0.426	0.419	0.446	0.427	0.486
	(0.014)	(0.014)	(0.015)	(0.016)	(0.006)
γ	**0.070**	**0.026**	**0.039**	**-0.066**	**-0.126**
	(0.040)	(0.042)	(0.038)	(0.040)	(0.042)
Region	no	yes	no	yes	-
Sector	no	no	yes	yes	-
Firm Characteristics	no	no	no	yes	-
Firm Fixed Effects	no	no	no	no	yes
obs	24.943	24,943	20,886	23,720	19,663
R^2	0.372	0.372	0.433	0.445	0.369
	(1)	(2)	(3)	(4)	(5)
$\beta_{Value-Added}$	0.392	0.385	0.372	0.355	0.233
	(0.014)	(0.014)	(0.014)	(0.014)	(0.005)
γ	**0.033**	**0.014**	**0.010**	**-0.081**	**-0.168**
	(0.040)	(0.041)	(0.038)	(0.040)	(0.046)
Sector	no	yes	no	yes	-
Region	no	no	yes	yes	-
Firm Characteristics	no	no	no	yes	-
Firm Fixed Effects	no	no	no	no	yes
obs	24,943	24,943	20,886	24,943	19,663
R^2	0.335	0.334	0.369	0.387	0.347

Note: Each column represents a single within-group linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions (column 1,2,3 and 4) standard errors are calculated clustering by firm. R^2 do not take into account the variation in firm fixed effects.

by region is consistent with this assessment, because it indicates that part of the positive premium that immigrants obtain is due to their choice of region. Positive segregation in term of region has also been found in Canada by Aydemir and Skuterud (2008).

Column (3) reports results when controls for Industry have only been included. These controls may be important if we take into account the fact that the sectoral composition is significantly different across migration status, see Table 2. A comparison of γ from columns (1) and (3) is informative about the effect of industrial segregation over wages. The difference in γ is -3.1 percent when using output and -2.3 percent when using value-added.This difference in

γ, which is significantly different from zero, implies positive segregation of immigrants into better industries. There are several studies which aim to measure the proportion of the gender and racial wage gap due to interindustry differences in worker composition. For immigrants this literature is smaller: a good example is again Aydemir and Skuterud (2008) with Canadian matched employer-employee data. They find that immigrants are employed in industries with slightly lower wage effects.

In column (4), I present results when region-effects, sector-effects and other firm characteristics are included. I have considered firm size, an indicator of unionization[26] and an indicator that takes the value one if the firm is a single-establishment. γ is found to be significantly lower than that reported in column (1). This finding suggests that part of the positive wage premium that immigrants were supposed to receive according to the estimates presented in column (1) is a consequence of their choices of sector, region and firm's observable characteristics: once we control for them, immigrants receive wages between 7 percent and 8 percent lower than natives.

It is surprising that there is a great part of the wage differential that is not accounted for by "observable" segregation. Comparing γ from columns (4) and (5), it is noteworthy that once I control for observable and unobservable firm fixed characteristics the wage premium for immigrants is still significantly lower than that reported in column (4). These findings show that immigrants are hired in better firms than natives also within each region, sector and firm's characteristics cell. However, within the firm they receive wages which are between 13 percent and 17 percent lower than natives. This result suggests that clustering the analysis in terms of observable characteristics, would not be sufficient to robustly test for the existence of wage discrimination.

Although this exercise is very simple, these patterns seem to be robust. The same results are found using slightly different specifications, see Subsections 5.2.2, 5.2.3 and 5.2.4.

[26]In the IAB Establishment survey there is an explicit question that ask if the establishment is bound by industry-wide wage agreements, a company agreement concluded by the establishment and trade unions or not bound by collective agreements.

A last issue related to segregation is the difference between segregation among establishment and segregation within establishments. I have referred to segregation meaning segregation among establishments. γ, the measure of discrimination considered in this paper, captures both direct wage discrimination and segregation within establishments. In general firms cannot have explicit differences in wage policies towards different groups but they are allowed to have as many occupations, and wage categories, as they need and hence to concentrate some groups into specific wage categories that is conceptually equivalent to setting discriminatory wages, but harder to prove. In this paper, I skip this debate, and both sources of within-firm wage-differentials are considered to be discrimination.

5.2 Specification and Robustness Tests

To be able to test for wage discrimination, we need to know the functional form of $F(.,.)$ in equation 1. However, without making structural assumptions on the labor market model, the functional form of the wage setting equation is unknown. As a baseline, I have considered a restrictive log-linear approximation to $F(.,.)$, with only two types of workers, where the wage policies only differ across groups in terms of the constant, and the firm heterogeneity is totally captured by a firm fixed effect. In this subsection most of these assumptions are relaxed and are shown to be non critical.

5.2.1 Types of Workers

The empirical strategy proposed in this paper uses firm level data: hence, I cannot include a broad set of variables to characterize workers. This may involve a problem since previous results may capture different wage policies towards other groups that correlate with the migration status. To illustrate this point, let me assume that immigrants are not discriminated against, but women are, as the gender composition is significantly different between natives and immigrants[27]; thus, I would find that immigrants are receiving higher salaries than natives.

[27] See Table 2

In Table 2, it has been shown that migration status is highly correlated with gender and job-qualification[28]. To examine the robustness of my benchmark estimates, I estimate the model controlling for gender and job qualification.

*Gender Composition:*To analyze if previous results are driven by differences in gender composition, I estimate equation (6) but decomposing the workforce into four groups in terms of migration status and gender:

$$\bar{w}_{jt} = \alpha_j + \beta \bar{p}_{jt} + \gamma_{IM} \frac{L_{jt}^{IM}}{L_{jt}} + \gamma_{NW} \frac{L_{jt}^{NW}}{L_{jt}} + \gamma_{IW} \frac{L_{jt}^{IW}}{L_{jt}} + \bar{\epsilon}_{jt}, \tag{7}$$

where L_{jt}^{IM} is the number of male immigrants working in firm j at time t, L_{jt}^{NW} is the number of female natives and L_{jt}^{IW} is the number of female immigrants.

Table 5: Migration and Gender

$\overline{w}_{jt}$	Output	Value-Added
β	0.486	0,233
	(0.006)	(0.005)
γ_{IM}	-0.087	-0,133
	(0.053)	(0.058)
γ_{NW}	-0.078	-0,039
	(0.032)	(0,035)
γ_{IW}	-0.283	-0,271
	(0.071)	(0.077)
Fixed Effects	yes	yes
obs,	24,943	24,943
R^2	0.3829	0.3452

Note: Each column represents a single within-group linear regression using the panel of firms. Male-Natives are the reference group. Time Dummies are included in every specification. Standard errors in Parentheses. R^2 do not take into account the variation in firm fixed effects.

Results are presented in Table 5. We observe that male immigrants receive wages that are between 9 percent and 13 percent lower than male natives. Female immigrants receive wages that are between 20 percent and 23 percent lower than female natives. Women receive lower wages than men. This difference ranges between 4 percent and 8 percent for natives, but it is not always

[28]Note in Table 2 that migration status is also highly correlated with the firms sector, but firms characteristics are captured by the firm fixed effect.

significant. These findings are consistent with results presented in Bartolucci (2010), where estimating a structural model to study gender wage gaps with the same data-set, women are not found to have significantly lower bargaining power in every sector, and the estimated wage gap caused by discrimination is 9 percent.

Skilled-Unskilled Composition: To understand if previous results are driven by job-qualification composition, I estimate equation (6) also decomposing the workforce into four groups in terms of migration status and job-qualification:

$$\bar{w}_{jt} = \alpha_j + \beta \bar{p}_{jt} + \gamma_{IS} \frac{L_{jt}^{IS}}{L_{jt}} + \gamma_{NU} \frac{L_{jt}^{NU}}{L_{jt}} + \gamma_{IU} \frac{L_{jt}^{IU}}{L_{jt}} + \bar{\epsilon}_{jt}, \tag{8}$$

where L_{jt}^{IS} is the number of skilled-immigrant workers in firm j at time t, L_{jt}^{NU} is the number of unskilled-natives and L_{jt}^{IU} is the number of unskilled-immigrants. The reference group are the natives in skilled occupations. Results are presented in Table 6.

Table 6: Migration and Job-Qualification

$\overline{w}_{jt}$	OUTPUT	VALUE-ADDED
β	0.478	0,228
	(0.006)	(0.005)
γ_{IS}	0.266	0,355
	(0.106)	(0.115)
γ_{NU}	0,272	0,453
	(0.032)	(0.035)
γ_{IU}	-0,105	-0,109
	(0.046)	(0.050)
FIXED EFFECT	YES	YES
OBS,	24,943	24,943
R^2	0.3829	0.316

Note: Each column represents a single within-group linear regression using the panel of firms. Skilled-Natives are the reference group. Time dummies are included in every specification. Standard errors in Parentheses. R^2 do not take into account the variation in firm fixed effects..

We observe that immigrants surprisingly receive salaries higher than natives when working in high qualification occupations. Unskilled immigrants receive wages significantly lower than unskilled-natives. It is noteworthy that, although unskilled workers receive wages 40 percent lower than skilled ones[29], once I control for productivity, native-unskilled workers have a positive wage differential, receiving wages that are 35 percent higher that native workers with equivalent productivity, in skilled occupations. This finding is also consistent with Bartolucci (2010), where unskilled workers are found to have higher bargaining power in every sector[30].

5.2.2 Wage Setting Equation non-linear in log-productivity

The wage setting equation was assumed to be linear in log-productivity. In this subsection, I test whether relaxing this assumption modifies the main results of the paper. Let me consider the following wage setting equation:

$$\bar{w}_{jt} = \alpha + G(p_{jt}) + \gamma \bar{I}_{jt} + \bar{\varepsilon}_{jt}$$

where as before, productivity is measured as the log-output per worker and $G(.)$ is a fourth-order polynomial.

Results are presented in Table 7. Although the non-linear component of the effect of productivity is significant[31], the estimated discrimination parameter, γ, is not found to be statistically different from the one estimated using the linear version of the wage setting equation. Moreover, I find exactly the same pattern in term of segregation. Estimating the specification by OLS, see column (1), γ is significantly positive. OLS estimates of γ become insignificant when controlling for firm observable characteristics and negative[32] when it is estimated controlling for firm fixed effects, see column (4).

[29] The conditional mean of wages is 40.7 percent higher for skilled workers than for unskilled ones. See Table (13) in the Appendix.

[30] As in Bartolucci (2010), I cannot conclude that skilled workers are being discriminated against because I am basically comparing different jobs.

[31] The joint test of the tree coefficients equal to zero are: $F(3, 9331) = 163.81$ (p-value=0.00) in column (1), F(3, 9331)=79.93 (p-value=0.00) in column (2), $F(3, 8950) = 113.58$ (p-value=0.00) in column (3) and $F(3, 15598) = 434.04$ (p-value=0.00) in column (4)

[32] In the WG estimation, γ is significant at the 10% level, p-value of 8.8%.

Table 7: Wage Setting Equation Non-Linear on Log-Productivity

$\overline{w}_{jt}$	(1)	(2)	(3)	(4)
Output	0.265	0.311	0.266	0.017
	(0.035)	(0.044)	(0.044)	(0.037)
Output^2	0.290	0.289	0.282	0.046
	(0.025)	(0.027)	(0.030)	(0.011)
Output^3	-0.030	-0.031	-0.029	-0.004
	(0.003)	(0.003)	(0.003)	(0.0001)
Output^4	0.001	0.001	0.001	0.0001
	(8*10^{-5})	(9*10^{-5})	(1*10^{-4})	(2*10^{-5})
γ	**0.083**	**-0.027**	**-0.063**	**-0.069**
	(0.039)	(0.038)	(0.039)	(0.040)
Firm Size	-	0.069	0.052	-
	-	(0.033)	(0.004)	-
Single	-	0.003	0.007	-
	-	(0.003)	(0.003)	-
Union	-	0.018	0.016	-
	-	(0.011)	(0.011)	-
Sector Dummies	NO	NO	YES	-
Region Dummies	NO	NO	YES	-
	NO	NO	NO	YES
obs.	24,943	23,720	19,663	24,943
R^2	42.80%	45.74%	49.71%	39.67%

Note: Each column represents a single linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions (column 1, 2 and 3) standard errors are calculated clustering by firm.

5.2.3 Wage Setting Equation with Group Specific Elasticity to Productivity.

In the baseline specification, I consider that the wage elasticity to productivity is constant across groups. In this subsection, I test whether relaxing this assumption modifies the main results of the paper. Let me consider the following wage setting equation:

$$\bar{w}_{jt} = \alpha + \bar{I}_{jt}\beta_I p_{I,jt} + (1 - \bar{I}_{jt})\beta_N p_{N,jt} + \gamma\bar{I}_{jt} + \bar{\varepsilon}_{jt} \tag{9}$$

Where $p_{I,jt}$ is the log-productivity of immigrants in firm j at time t, $p_{N,jt}$ is the log-productivity of natives in firm j at time t, β_I is the elasticity of wages to immigrants productivity and β_N is the elasticity of wages to natives productivity.

Assuming again a Cobb-Douglas production function with quality adjusted labor input, it has been proved in Section 3.2, that the log of natives' marginal productivity can be written as $p_{N,jt} = \log(\frac{Y_{jt}}{L_{jt}} \frac{\phi_l}{1+(\rho-1)\bar{I}_{jt}})$, and the immigrants' can be written as: $p_{I,jt} = \log(\frac{Y_{jt}}{L_{jt}} \frac{\phi_l \rho}{1+(\rho-1)\bar{I}_{jt}})$, hence:

$$\bar{w}_{jt} = \alpha + \bar{I}_{jt}\beta_I \log(\frac{Y_{jt}}{L_{jt}} \frac{\phi_l \rho}{1+(\rho-1)\bar{I}_{jt}}) + (1-\bar{I}_{jt})\beta_N \log(\frac{Y_{jt}}{L_{jt}} \frac{\phi_l}{1+(\rho-1)\bar{I}_{jt}}) + \gamma \bar{I}_{jt} + \bar{\varepsilon}_{jt} \quad (10)$$

Where, rearranging and noting that as ρ is supposed to be near 1, $\log(1+(\rho-1)\bar{I}_{jt}) \cong (\rho-1)\bar{I}_{jt}$ and $\log(\rho) \cong (\rho-1)$:

$$\begin{aligned} \bar{w}_{jt} &= \alpha + \beta_N \log(\phi_l) + \beta_N \log(\frac{Y_{jt}}{L_{jt}}) + [(\beta_I - \beta_N) log(\rho\phi_l) + \gamma]\, \bar{I}_{jt} \\ &\quad + (\beta_I - \beta_N)\bar{I}_{jt} \log(\frac{Y_{jt}}{L_{jt}}) + (\beta_I - \beta_N)(1-\rho)\bar{I}_{jt}^2 + \bar{\varepsilon}_{jt}. \end{aligned}$$

Therefore, I estimate:

$$\bar{w}_{jt} = A + B\bar{p}_{jt} + C\bar{I}_{jt} + D\bar{I}_{jt}\bar{p}_{jt} + E\bar{I}_{jt}^2 + \bar{\varepsilon}_{jt},$$

where, as before $\bar{p}_{jt} = \log(\frac{Y_{jt}}{L_{jt}})$, and $A = \alpha + \beta_N \log(\phi_l)$, $B = \beta_N$, $C = (\beta_I - \beta_N) log(\rho\psi_l) + \gamma$, $D = \beta_I - \beta_N$ and $E = (1-\rho)(\beta_I - \beta_N)$. Therefore we can recover estimates of the difference $\beta_N - \beta_I$ to be able to evaluate the assumption made on the baseline specification. Note that, without further information, for example, an external estimation of ϕ_l, γ can not be recovered from this exercise. The parameter C, which corresponds to the proportion of immigrants in the firm, can only identify γ when $\beta_N = \beta_I$.

Results are presented in Table 8. The wage elasticity to productivity is not found to be different between natives and immigrants. $(\beta_N - \beta_I)$ is not statistically different from zero and the estimated standard deviation of this difference remains within reasonable bounds and ranges between 0.03 and 0.05.

Table 8: Wage Setting Equation with group specific β

$\bar{\mathrm{W}}_{jt}$	(1)	(2)	(3)
$(\beta_N - \beta_I)log(\rho\phi_l) + \gamma$	0.345	0.135	-0.504
	(0.626)	(0.604)	(0.379)
$(\beta_N - \beta_I)$	0.034	-0.017	0.009
	(0.055)	(0.052)	(0.031)
$(\beta_N - \beta_I)(\rho - 1)$	-1.04	0.025	-0.461
	(0.114)	(0.012)	(0.101)
Sector, Region and Firms Characteristics	no	yes	-
Firm Fixed Effects	no	no	yes
obs.	24,943	20,886	24.943
R^2	37.56%	49.92%	39.18%

Note: Each column represents a single linear regression using the panel of firms. A quartic on productivity and time dummies are included in every specification. Standard errors in parentheses. In OLS regressions (column 1 and 2) standard errors are calculated clustering by firm.

This last result gives additional support to the baseline specification where β has been assumed to be homogeneous across groups.

5.2.4 Wage Setting Equation Linear in Levels.

As discussed in Section 3, there are important advantages to considering the wage setting equation in logs. In this subsection, I recalculate the wage setting equation parameters taking a linear approximation to $F(.,.)$ in (1). I estimate:

$$\bar{W}_{jt} = \alpha_j + \beta \bar{P}_{jt} + \gamma \bar{I}_{jt} + \bar{\epsilon}_{jt} \tag{11}$$

where $\bar{W}_{jt}$ is the wage bill per worker of firm j, $\bar{P}_{jt}$ is the output per worker of firm j, and $\bar{I}_{jt}$ is the proportion of immigrants in firm j at time t. Results are presented in Table 9.

Although results are less precise than the baseline specification, they are qualitatively and quantitatively compatible with results presented above. Taking into account that the mean-wage[33] is 2300.10 euros, the OLS estimate of γ in

[33] I consider mean-wage to be the average of total wage bill per-worker over the distribution of firms in the sample used in columns (1), (3) and (5).

Table 9: Wage Setting Equation in Levels

$\bar{W}_{jt}$	(1)	(2)	(3)	(4)	(4)
Output	0.055	0.060	0.063	0.301	0.124
	(0.001)	(0.001)	(0.002)	(0.023)	(0.023)
Output^2	-	-	-	-1.43e^{-05}	-5.06e^{-07}
	-	-	-	(2.07e^{-06})	(1.95e^{-06})
Output^3	-	-	-	2.99e^{-10}	-8.68e^{-11}
	-	-	-	(6.92e^{-11})	(6.29e^{-11})
Output^4	-	-	-	-2.01e^{-15}	1.58e^{-15}
	-	-	-	(7.58e^{-16})	(6.25e^{-16})
γ	132.54	32.98	-344.64	23.91	-383.08
	(78.21)	(87.85)	(124.54)	(87.04)	(124.24)
Region, Sector and Firm Characteristics	no	yes	-	yes	-
Firm fixed effects	no	no	yes	no	yes
obs.	22,449	18,882	22,449	18,882	22,449
R^2	8.79%	12.92%	8.58%	14.56%	9.78%

Note: Each column represents a single linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions (column 1, 3 and 4) standard errors are calculated clustering by firm.

column (1) implies that immigrants are receiving wages 5.7 percent higher than natives. As before, when including a wider set of controls, γ becomes insignificant, see column (2), and significantly negative when controlling for observable and unobservable firm fixed characteristics, see column (3). The firm fixed effect specification in column (3) suggests that immigrants receive wages that are 15.0 percent lower than natives. When allowing a more flexible specification for output, results do not change significantly, see columns (4) and (5).

Results presented in Table 9 are considering a sample where observations of firms with output below the fifth percentile and above the 95^{th} percentile of the output distribution, have been excluded. When considering the entire sample, the estimated discrimination parameter ranges between -12,957 and 6,071 euros. Taking into account that the gross mean monthly wage in the sample is approximately 2,300 euros, these results are found to have no economic meaning. This sample trimming does modify results obtained with the baseline specification, see Section C in the Appendix.

6 Testing Implications of Discrimination Models

Another interesting feature of this approach is that it allows me to estimate (6) with firm specific γ. Hence, it provides a firm specific measure of wage discrimination against immigrants which is useful when testing some of the implications of different discrimination models.

There are two mains branches in the theoretical discrimination literature: Taste Based Discrimination and Statistical Discrimination. These models emphasize two broad types of discrimination. The first is prejudice, which Gary Becker (1971) formalizes as a "taste" by at least some members of the majority group against interacting with members of the minority group. The second is statistical discrimination by employers in the presence of imperfect information about the skills or behavior of members of the minority group. Even though it is difficult to empirically distinguish between both theoretical hypotheses, some lessons can be drawn from the present exercise.

One of the implications of the model presented in Becker (1971) is that discriminating employers earn lower profits than non-discriminators[34], since the non-discriminators will pay less for their labor by hiring discriminated workers. This implication may be directly tested in this framework. If taste-based discrimination were the true model we should observe a positive correlation between γ_j and firm profits.

The first papers to discuss statistical discrimination were Phelps (1972) and Arrow (1973). The basic premise of this literature is that firms have limited information about the skills and turnover propensity of applicants: hence, they have an incentive to use easily observable characteristics such as race or gender to "statistically discriminate" among workers if these characteristics are correlated with performance[35]. There are two main branches in the statistical discrimination literature.

The first investigates whether biased racial and gender stereotypes might be self confirming when the payoff for hard-to-observe worker investments depends on employer beliefs. Therefore an *a priori* unfounded belief about a group performance may be *a posteriori* confirmed. This issue, that was mainly addressed by Arrow (1973) and Coate and Loury (1993), is not analyzed in this paper because it should be captured controlling for productivity.

The second branch concerns the consequences of group differences in the precision of the information that employers have about individual productivity. It was mainly developed by Aigner and Cain (1977) with subsequent papers by Lundberg and Startz (1983) and Lundberg (1991). If this were the case, as firms continuously acquire more information about their worker productivity, pay would become more dependent on actual productivity and less dependent on easily observed characteristics like migration status. Therefore we should

[34] This is pointed out in several papers: see for example Black (1995) and Bowlus and Eckstein (2002). Both papers analyze employer taste discrimination in a search model which predict profits to be decreasing in the discrimination coefficient.

[35] Although it is illegal to make hiring, pay, or promotion decisions based on predictions about worker performance by gender or migration status, such behavior would be hard to detect in many circumstances.

observe a positive correlation between tenure and γ_j.

Having firm specific discrimination parameters also allow us to have a better understanding of immigrant self selection into less discriminatory employers. If there is self-selection of immigrants into these employers, the expected value of γ_j obtained here should be different from γ obtained in the previous section.

To estimate firm specific discrimination parameters, I follow Arellano and Bonhomme (2010). I estimate equation (6) in two simple steps by firstly obtaining the common parameters as follows: I regress the residual of firm specific regressions of the total wage bill and the variables with constant coefficients, on the proportion of immigrants and a constant term:

$$Q_j \bar{w}_{j,t} = (Q_j \overline{Z}_{j,t})' \delta + Q_j \epsilon_{jt},$$

where $Q_j = (I_{Tj} - X_j (X_j' X_j)^{-1} X_{ji})$, X_j is a $2 \times T_j$ matrix with a column of ones that identifies the firm fixed effect and a column with the firm proportion of immigrants, T_j the individual length of the panel (As my data-set is an unbalanced panel T is firm-specific) and Z_j is a matrix that contains those variables with constant coefficients: that are time dummies, and output per worker or value added per worker depending on the specification.

Once I have estimated δ, γ_j is easily recovered[36]:

$$\begin{pmatrix} \hat{\alpha}_j \\ \hat{\gamma}_j \end{pmatrix} = X_j (X_j' X_j)^{-1} (\bar{w}_{j,t} - Z_j' \delta) = \begin{pmatrix} \alpha_j \\ \gamma_j \end{pmatrix} + X_j (X_j' X_j)^{-1} \epsilon_{jt}.$$

Note that the estimated firm-specific fixed effect as the firm specific discrimination parameter are equal to the true parameters plus a term that is $O(1/T_j^{0.5})$. See Arellano and Bonhomme (2009) for more details.

The sample used in this exercise is the panel of firms. Given that I estimate two firm specific coefficients, only firms with more than two observations have been considered. Firm specific γ_j are only identified in these firms where the proportion of immigrants varies: therefore firms with no, or marginal variation

[36]The MATA code to estimate a linear model with random coefficients is available from the author upon request

Table 10: Wage Setting Equation with Random Coefficients

A

$\overline{w}_{jt}$	(1)	(2)
$\beta_{\overline{output}}$	0,452	-
	(0.009)	-
$\beta_{\overline{Value-Added}}$	-	0.174
	-	(0.006)
$\bar{\gamma}_j$	-0.489	-0.921
	(0.334)	(0.374)
$mean(\bar{\alpha}_j)$	2.45	5.84
	(0.030)	(0.032)

B

Second Stage Regressions	α_j	γ_j	α_j	γ_j
Profits	-7.0e^{-10}	-9.7e^{-8}	-6.9e^{-9}	-1.4e^{-7}
	(3.2e^{-9})	(3.6e^{-8})	(3.5e^{-9})	(4.0e^{-8})
Tenure of Immigrants	3.5e^{-5}	-1.5e^{-4}	4.5e^{-5}	-1.1e^{-4}
	(1.9e^{-5})	(2.1e^{-4})	(2.0e^{-5})	(2.3e^{-4})
Proportion of Immigrants	0.025	1.68	-0.166	3.39
	(0.23)	(2.60)	(0.249)	(2.91)
Unionized Workforce	-0.133	0.749	-0.053	0.267
	(0.081)	(0.909)	(0.087)	(1.02)
Single Establishment	-0.145	0.887	-0,284	0.415
	(0.081)	(0.902)	(0.086)	(1.01)
Constant	2.61	-1.50	5.79	–1.03
	(0.108)	(1.20)	(0.115)	(1.34)
Observations	1,877		1,877	

Note: Each column in panel A represents a single linear regression with fixed effects and firm specific γ using the panel of firms. Time dummies are included in both specification. Each Column in Panel B represents single linear regression of the estimated α_j and γ_j in Panel A on selected firm specific variables. Sector dummies are included. Standard errors, in parentheses in both panels. Standard deviation of $\bar{\alpha_j}$ and $\bar{\gamma_j}$ are corrected following Arellano and Bonhomme (2009).

in the proportion of immigrants have been excluded[37].

Results are presented in Table 10. Given the short time dimension, most of the variation in the firm-specific coefficients is only noise, and hence the second step is mostly imprecise. Firm fixed effects are found to be negatively correlated

[37] In particular, in order to exclude firms with low variation in $\bar{I_j}t$, from the whole sample of firms with positive variation in $\bar{I_j}t$, I exclude every firm where the standard deviation of the proportion of immigrants is below the 10^{th} percentile of the firms distribution of the standard deviations of $\bar{I_j}t$

with the firm profits[38]. As these fixed effects represent wages, given productivity this finding is not surprising. Firms with higher average tenure are found to be better payers. Although the covariance is marginally significant when using output as a measure of productivity, single establishments are in general worse payers. The proportion of immigrants is not found to be significantly correlated with the firm-specific discrimination parameter, which is important for the robustness of the main result of the paper, where γ is assumed to be homogeneous.

In order to test some of the implications of the taste based discrimination and statistical discrimination theories, I finally regress the firm specific discrimination parameter in the firm's mean profits and the firm's mean tenure of immigrants. I find that the mean-tenure of immigrants in the firm is negatively but not significantly associated with the discrimination parameter. On the other hand, profits have a significantly negative correlation with the discrimination parameter: that means that firms with higher profits discriminate more, against what is predicted by the taste-based discrimination literature. This may be understood to be indirect evidence against the taste based discrimination model.

7 Conclusion

The Hellerstein and Neumark strategy has been found to be a very direct and popular method to detect wage discrimination using matched employer-employee data. The purpose of this paper is to develop a test for wage discrimination that completes the Hellerstein and Neumark (1999) approach. The proposed method estimates a wage setting equation at the firm level that exploits changes in productivity and changes in the native-immigrant composition within firm across time in order to have identification of different wage policies toward those groups. This test add to the existing one in four main dimensions: it is robust to labor market segregation, it does not impose linearity in the wage setting equation, it avoids the problematic estimation of production functions,

[38] The covariance between firm fixed effects and profits is only significant when using Value Added.

and it is not only a test for discrimination, but also produces measurements of discrimination.

Using Matching Employer-Employee data from Germany, I find that immigrants are suffering wage discrimination. Depending on which measure of productivity is used, discrimination ranges between 12.8 percent and 16.8 percent. This finding is surprising if we take into account that both the traditional approach and the Hellerstein and Neumark (1999) approach conclude that immigrants do not receive significantly lower wages in Germany.

The elasticity of wages to productivity is significantly different from one and hence assuming wages equal, or a constant fraction of productivity may be dangerous. Although the reduced-form wage setting equation is very simple, it has an acceptable fit of the wage data and without controlling for firm fixed characteristics, I obtain similar results to those that would be obtained with employee-level data. When estimating by OLS, discrimination is found to be significantly lower, which provides evidence of positive segregation of immigrants into good firms. In order to understand the nature of this segregation, I included different sets of controls and I find that most of the segregation is accounted by differences in region, sector and firm size.

I find that female immigrants are more discriminated against than males. They receive wages between 20 and 23 percent lower than female natives while male immigrants receive wages between 9 and 13 percent lower than male natives. Unskilled immigrants receive salaries lower than unskilled natives but immigrants working in high-qualification occupations receive higher wages than their native counterparts.

The basic results of the paper are robust. Estimating a similar specification but considering wages and output instead of log-wages and log-output or allowing a more flexible specification for productivity, I find the same results. Although β has been assumed to be the same between natives and immigrants, I do not find evidence of differences in the wage elasticity to productivity between both groups.

I do not find significant evidence of immigrants moving to those less discriminatory firms nor significant evidence in favor of the statistical discrimination model but I do find evidence against a taste-based discrimination model.

A Mean of log-productivity and log of mean productivity

As it is not possible to recover the mean of log-productivity using output data, I use the log of mean productivity. Assuming that wages and productivity are log-normally distributed, it is possible to correct for the differences between the mean of log-productivity and the log of mean productivity including a measure of the within-firm variance of productivity. Omitting this correction, estimates would be still correct if I assume that this within-firm variance remains constant across time and then these differences become part of the firm fixed effects. The main weakness of this approach is that I have to assume that the firm-specific variance of productivity does not change when composition changes.

For a more robust, and complex, solution to this problem, I can rearrange equation (2):

$$W_{ijt} = e^{\alpha_j}(P_{ijt})^{\beta}(\gamma)^{I_i}e^{\varepsilon_{ijt}},$$

and then, solving for P_{ijt}.

$$P_{ijt} = e^{(\alpha_j/\beta)}(W_{ijt})^{(1/\beta)}(\gamma/\beta)^{I_i}e^{(\varepsilon_{ijt}/\beta)}.$$

Aggregating within firm:

$$\bar{P}_{jt} = e^{(\alpha_j/\beta)}\sum_{i\in j}(W_{ijt})^{(1/\beta)}(\gamma/\beta)^{I_i}e^{(\varepsilon_{ijt}/\beta)}.$$

This can not be estimated directly, because W_{ijt} is endogenous to the model and it is then correlated with the error term ε_{ijt}. However, the wage setting equation provides me proper instruments as $\bar{P}_{jt}$ and I_i to estimate it by GMM. This alternative is one of the main point in the research agenda.

B The 1999 German Reform of the Citizenship and Nationality Law

In May 1999, the German Parliament amended the Citizenship and Nationality Law of 1913. The reform had three main elements:

- changes in the naturalization criteria;
- denial of dual citizenship;
- introduction of birthright citizenship.

Before the new legislation came into force, foreign nationals were granted entitlement to naturalization only after 15 years of residence in Germany. With the new legislation, a foreign national is entitled to naturalization after lawfully residing in Germany for eight years. The only requirements comprise: loyalty to the German Constitution, no need for social security or unemployment benefits, no criminal convictions and an adequate command of the German language. Although anecdotal evidence suggests than dual citizenship was hardly allowed by officials before the reform, the 1999 reform includes an explicit denial of dual citizenship. Before 1999, a child born in Germany would gain German citizenship if at least one of the parents possessed German citizenship at the time of birth. Under the new regime, a child born of foreign parents would gain citizenship at birth if at least one parent had been legally resident in Germany for eight years.

In this paper I use data on nationality to identify immigrants. This law is supposed to have implications for the population of immigrants in which I am interested on. In order to take this point into account, I estimate the baseline specification with two subsamples, before and after 1999. Results are reported in Table 11.

Although the estimates differ among both subsamples, these differences are not significantly different from zero. Moreover, the main findings of the paper are valid for both time periods. Immigrants are found to have lower wages, once

Table 11: The 1999 German Reform

$\overline{w}_{jt}$	Before 1999 REG	Before 1999 WG	After 1999 REG	After 1999 WG
$\beta_{\overline{output}}$	0.405	0.586.	0.431	0.389
	(0.029)	(0.016)	(0.015)	(0.008)
γ	0.135	-0.104	0.045	-0.211
	(0.058)	(0.079)	(0.047)	(0.056)
OBS.	5,660	5,660	19,283	19,283
R^2	36.3%	-	37.0%	-
R^2-With.	-	33.2%	-	18.7%
R^2-Betw.	-	39.8%	-	38.1%

Note: Each column represents a single linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions standard errors are calculated clustering by firm.

we control for observed and unobserved firm fixed characteristics. Based on the differences in γ estimated by OLS and WG, there is evidence suggesting positive segregation of immigrants before and after the 1999 reform of the Citizenship and Nationality Law.

C Sample Selection

As it can be seen in Subsection 5.2.4, when the equations are estimated in levels, not in logs, results are very sensitive to observations in the tails of the distribution of output. In this section, I show that this is not the case for the baseline specification. I estimate again the wage setting equation (6), but with the same sample trimming used in Subsection 5.2.4.

Results are presented in Table 12. The estimates of γ in every specification are found to be equivalent to those estimated with the full sample. This sample selection does not modify the main findings of the paper.

Table 12: Wage Setting Equation - Sample Trimming

$\bar{\mathrm{W}}_{jt}$	(1)	(2)	(3)
Output	0.351	0.364	0.353
	(0.005)	(0.005)	(0.009)
γ	0.070	0.022	-0.094
	(0.024)	(0.025)	(0.039)
Region, Sector and firm Characteristics	no	yes	-
Firm fixed effects	no	no	yes
obs.	22,449	18,882	22,449
R^2	19.58%	12.92%	19.29%

Note: Each column represents a single linear regression using the panel of firms. Time dummies are included in every specification. Standard errors in parentheses. In OLS regressions, columns (1) and (2), standard errors are calculated clustering by firm. The sample used in this estimation exclude observations with output below the fifth percentile and above the 95^{th} percentile of the output distribution.

D Detecting Discrimination - Traditional Approach

In order to compare different strategies to detect wage discrimination, in this section I provide estimates of discrimination using Mincer-type wage equations. As can be seen in Table 13, immigrants have positive wage differentials. Controlling for observed characteristics, they receive wages that are, on average, 7.2 percent higher than natives.

Oaxaca-Blinder Decomposition

Using results presented in Table 13, I perform an Oaxaca-Blinder decomposition which simply decomposes the wage-gap between differences in observable and unobservable characteristics.

The results of the Oaxaca-Blinder decomposition are presented in Table 14. The counterfactual immigrants' mean-wage has to be interpreted as the mean-wage that immigrants would have if they had the natives' distribution of observable characteristics. Therefore the difference between the counterfactual immigrants mean-wage and the observed immigrants mean-wage is the portion of the gap that is due to differences in observable characteristics.

Table 13: Mincer Wage Equations - Censored-Normal Regression. Maximum Likelihood Estimates

	General	Natives	Immigrants
Sex	-0.185	-0.186	-0.150
	(0.0004)	(0.0003)	(0.0009)
Immigrant	0.072	-	-
	(0.0004)	-	-
Age	0.061	0.065	0.035
	(0.0001)	(0.0001)	(0.0003)
Primary Education	0.237	0.241	0.204
	(0.0008)	(0.0004)	(0.0008)
College	-0.246	-0.246	-0.202
(incomplete)	(0.0009)	(0.0009)	(0.0025)
Technical College	0.370	0.376	0.314
(completed)	(0.0007)	(0.0007)	(0.0026)
College	0.583	0.588	0.516
	(0.0008)	(0.0008)	(0.0033)
University Degree	0.709	0.716	0.648
	(0.0007)	(0.0007)	(0.0023)
Tenure	0.020	0.020	0.014
	(0.0001)	(0.0001)	(0.0002)
Experience	0.026	0.025	0.033
	(0.0001)	(0.0001)	(0.0002)
Skilled	0.407	0.411	0.357
	(0.0010)	(0.0010)	(0.0055)
Part-time jobs	-0.696	-0.703	-0.616
	(0.0004)	(0.0004)	(0.0013)
Constant	2.381	2.319	2.894
	(0.0019)	(0.0020)	(0.0031)
Pseudo R2	46.5%	50.8%	46.3%
Observations	13,017,732	11,832,370	1,185,362

Note: Each column represents a single Maximum-Likelihood linear regression using the panel of workers. Standard errors are given in parentheses. Native-men with no formal education in low-qualification occupations are the reference group. Time and Sector Dummies included.

Table 14: Oaxaca-Blinder Decomposition

(a) Observed Natives Mean Daily Wage	(b) Observed Immigrants Mean Daily Wage	(c) Counterfactual Immigrants Mean Daily Wage
109.0 €	94.7 €	111.2 €
Total W-Gap ((b)-(a))/(a)	Explained W-Gap=((b)-(c))/(a)	Unexplained W-Gap=((c)-(a))/(a))
-13.1%	-15.1%	2.0%

The portion of the unconditional wage-gap that is not accounted for by observable characteristics has usually been interpreted as wage discrimination. In this case, immigrants would not be discriminated against. They would be receiving wages that are 2 percent higher than similar natives.

E Detecting Discrimination - Hellerstein and Neumark (1999) Approach

In order to compare my results with results found using the Hellerstein and Neumark (1999) approach, I estimate the firm production function and the firm wage equation. The production function is given by:

$$Ln(Y_{jt}) = const. + \alpha_k Ln(K_{jt}) + \alpha_l Ln(L^Q_{jt}), \tag{12}$$

using firm level data, where Y_{jt} is the value added by firm j at time t, K_{jt} is depreciated capital[39] of firm j at time t, and L^Q_{jt} is the quality adjusted labor input.

$$\begin{aligned} L^Q &= \{L^{mns}_{jt} + \gamma_w L^{wns}_{jt} + \gamma_i L^{mis}_{jt} + \gamma_u L^{mnu}_{jt} + \gamma_i \gamma_w L^{wis}_{jt} \\ &\quad + \gamma_w \gamma_u L^{wnu}_{jt} + \gamma_i \gamma_u L^{miu}_{jt} + \gamma_w \gamma_i \gamma_u L^{wiu}_{jt}\} \end{aligned}$$

[39]The survey gives information about investment made to replace depreciated capital. Assuming that a constant fraction (d) of capital depreciates by unit of time: $K^d_{jt} = d \times K_{jt} \Rightarrow \log(K^d_{jt}) = \log(d) + \log(K_{jt})$. Therefore $\alpha_k \log(d)$ goes to the constant term.

where L_{jt}^{mns} is the number of male, native and skilled workers, L_{jt}^{wns} is the number of female, native and skilled workers, L_{jt}^{mis} is the number of male, immigrant and skilled workers, L_{jt}^{mnu} is the number of male native and unskilled workers, L_{jt}^{wis} is the number of female, immigrants and skilled workers, L_{jt}^{wnu} is the number of female, native and unskilled workers, L_{jt}^{miu} is the number of male, immigrant and unskilled workers, and L_{jt}^{wiu} is the number of female, immigrants and unskilled workers in firm j at time t.

The wage equation is given by:

$$Ln(W_{jt}) = const. + \kappa Ln(L_{jt}^{Q}), \tag{13}$$

where W_{jt} is the total wage bill paid by firm j at time t. In Table 15, I report the results from the estimations of the production function and wage equations using the total wages and salaries reported in the LIAB as paid by the establishment between 1996 and 2004. In column (1) I present parameters estimated from equation (12) by non-linear least squared regressions, In column (2) I report parameters estimated from equation (13) by non-linear least squared, and in column (3) I report p-values from tests of equality between parameters reported in column (1) and (2).

Looking first at the production function estimates in column (1), I find that the coefficient for immigrants indicates that foreign workers are somewhat equally productive to natives with an estimate of γ_i that is 0.99, not significantly different from one. I also find that productivity of women is surprisingly low and that workers in unskilled occupations produce two thirds less than workers in skilled occupations. Looking at the wage equation I find similar patterns in terms of immigrants and women. Workers in unskilled occupations receive salaries that are 53 percent lower than workers in skilled occupations.

Column (3) of Table 15 reports the p-values of tests of equality of the coefficients from the production function (column (1)) and the wage equation (column (2)). The results for immigrants are not conclusive, as the productivity gap and the wage gap are not significantly different from zero. The results

Table 15: Hellerstein et al Approach

	(1) Output	(2) Wage	(3) p-value (1)-(2)
Immigrants	0.99	0.98	54.2%
	(0.09)	(0.03)	-
Women	0.34	0.38	3.7%
	(0.02)	(0.01)	-
Unskilled	0.33	0.47	0.0%
	(0.01)	(0.01)	-
α_k	0.16	-	-
	(0.01)	-	-
α_l	0.89	-	-
	(0.01)	-	-
κ	-	1.05	-
	-	(0.002)	-
constant	9.29	7.47	-
	(0.62)	(0.02)	-
R^2	0.82	0.92	-
Observations	12,259	17,224	-

Note: Columns (1) and (2) represent single non-linear regressions using the panel of firms. Male–Skilled-Natives are the reference group. Time Dummies are included in every specification. Standard errors are given in Parentheses.

for women show that the productivity gap between men and women exceeds the wage gap. The wedge between relative wages and relative productivity is -0.04 (0.34 - 0.038), and the p-value of the test of the equality of relative wages and relative productivity for women is 3.7 percent. This approach would conclude that men are being discriminated against.

References

[1] Aeberhardt R. & Pouget J. (2007) "National Origin Wage Differentials in France" IZA Discussion Paper No. 2779

[2] Alda H., Bender S. & Gartner H. (2005) "The linked employer-employee dataset of the IAB (LIAB)", IAB Discussion Paper No. 6/2005

[3] Altonji J. and Blank R. (1999) "Race and Gender in the Labor Market" in Orley Ashenfelter and David Card, eds., Handbook of Labor Economics. Vol. 3, Amsterdam: North Holland

[4] Arellano, M. and S.R. Bond (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", Review of Economic Studies, 58, pp. 277-297

[5] Arellano, M. and S. Bonhomme (2010) "Identifying Distributional characteristics in Random Coefficient Panel Data Models"CEMFI Working Paper

[6] Arellano, M., and O. Bover (1995), "Another Look at the Instrumental-Variable Estimation of Error-Components Models," Journal of Econometrics, 68, pp. 29-52

[7] Arrow, K. (1973), "The theory of discrimination", in: O.A. Ashenfelter and A. Rees, eds., Discrimination in labor markets (Princeton University Press, Princeton, NJ) pp. 3-33

[8] Aydemir, A. and M. Skuterud (2008). "The immigrant wage differential within and across establishments". Industrial and Labor Relations Review 61(3), pp. 334-352

[9] Aigner, DJ. and G. Cain (1977), "Statistical theories of discrimination in labor markets", Industrial and Labor Relations Review, 30, pp. 175-187

[10] Bartolucci, C (2010) "Gender Wage Gaps Reconsidered: A Structural Approach using Matched Employer-Employee Data"Carlo Alberto Notebook no.116

[11] Becker, G. (1971) "The economics of discrimination", 2nd edition (The University of Chicago Press, Chicago)

[12] Black, Dan A. (1995) "Discrimination in an Equilibrium Search Model."Journal of Labor Economics 13, pp. 309-334

[13] Bowlus, A. and Z. Eckstein (2002), "Discrimination and Skill Differences in an Equilibrium Search Model," International Economic Review, 43(4), pp. 1309-1345

[14] Bratsberg, B. and J. Ragan (2002), "The Impact of Host-Country Schooling on Earnings" Journal of Human Resources, 37(1), pp. 63-105

[15] Borjas, G. (1999) "The Economic Analysis of Immigration"O. Aschenfelter & D. Card (ed.), Handbook of Labor Economics, Elsevier edition 1, Volumen 3, Number 3

[16] Carnevale, A., R. Fry and B. Lowell (2001), "Understanding, Speaking, Reading, Writing, and Earnings in the Immigrant Labor Market" American Economic Review, 91(2), pp. 159-64

[17] Campos-Vazquez, R. "Relative Wages and Relative Productivity of Immigrants in Germany "unpublished manuscript

[18] Chiswick, B. and W. Miller (1995), "The Endogeneity Between Language and Earnings: International Analyses" Journal of Labor Economics, 13(2), pp. 246-87

[19] Coate, S. and G. Loury (1993), "Antidiscrimination enlbrcement and the problem of patronization". American Economic Review 83(2), pp. 92 98

[20] Crepon B. ,N. Deniau and S. Pérez-Duarte (2002), "Wages, Productivity, and Worker Characteristics: A French Perspective "CREST WP 2003/04

[21] Dong X, and L Zhang (2009) "Economic transition and gender differentials in wages and productivity: Evidence from Chinese manufacturing enterprises"Journal of Development Economics 88(1), pp. 144-156

[22] Dustmann, C. and A. van Soest (2002), "Language and the Earnings of Immigrants" Industrial and Labor Relations Review, 55(3), pp. 473-92

[23] Ferber, M. and c. Green (1982) "Traditional or Reverse sex discrimination? A Case Study of a large public university"Industrial and Labor Relations Review, 35(4), pp. 550-564

[24] Friedberg, R. (2000), "You Can't Take It With You? Immigrant Assimilation and the Portability of Human Capital,"Journal of Labor Economics, 18(2), pp. 221-51

[25] Griliches, Zvi and Jacques Mairesse. (1998). Production Functions: The Search for Identification. In Z. Griliches, ed., Practicing Econometrics: Essays in Method and Application (Chentenham, England: Edgar Elgar), pp. 383-411.

[26] Hellerstein, J., Neumark, D. (1998) "Wage discrimination, segregation, and sex differences in wage and productivity within and between plants"Industrial Relations 37, 232260.

[27] Hellerstein J. and Neumark D. (1999) "Sex, Wages, and Productivity: An Empirical Analysis of Israeli Firm-Level Data,"International Economic Review, 40(1), pp. 95-123

[28] Hellerstein, J., Neumark, D., Troske, K. (2000) "Market forces and sex discrimination"Journal of Human Resources 37, 353380.

[29] Hellerstein J., Neumark D. and Troske K. (1999) "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Function and Wage Equations"Journal of Labor Economics, 17(3), pp. 409-446.

[30] Lopez-Acevedo, G., M. Tinajero and M. Rubio (2005), "Mexico: Human Capital Effects on Wages and Productivity "World Bank Policy Research Working Paper No. 3791

[31] Lundberg, S. (1991), "The enforcement of equal opportunity laws under imperfect information: affirmative action and alternatives", Quarterly Journal of Economics 106(1), pp. 309-326

[32] Lundberg, S. J, and R. Startz (1983), "Private discrimination and social intervention in competive labor markets", American Economic Review 73, pp. 340-347

[33] Milgrom E., T. Pettersen and V. Snartland (2006) "Are Female Workers Less Productive than Male Workers", Research in Social Stratification and Mobility 25(1) Pp 13-37

[34] Rickne, J. (2010)"Gender, Wages, and Social Security in Chinas Industrial Sector", IFN Working Paper No. 827.

[35] Rudolph, H. (1994) "Dynamics of Immigration in a Non-immigrant Country: Germany."In Fassman, He. and Münz, R. (eds.) European Migration in the Late Twentieth Century. Laxenburg, Edward Elgar, pp. 113-127

[36] Van Biesebroeck J. (2009) "Wage and Productivity Premiums in Sub-Saharan Africa,"in S. Bender, J. Lane, K. Shaw, F. Andersson, and T. von Wachter (eds.) The Analysis of Firms and Employees: Quantitative and Qualitative Approaches"(forthcoming) University of Chicago Press

[37] Verner, D. (1999) "Wage and Productivity Gaps: Evidence from Ghana,"World Bank Policy Research Working Paper No. 2168