UNIVERSITY OF CALIFORNIA, BERKELEY
ECONOMICS DEPARTMENT

RELATIVE PRODUCTIVITY AND RELATIVE WAGES OF IMMIGRANTS IN GERMANY.

Raymundo M. Campos-Vazquez
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Comments welcome
rcampos@econ.berkeley.edu

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ABSTRACT

The goal of the paper is the estimation of the marginal productivity of immigrants relative to natives. One reason why firms may hire immigrants is because immigrants are more productive than natives. I test this hypothesis using a confidential matched employer-employee dataset from Germany for the years 1996-2004. Using a production function approach, I find that immigrants are similar to natives in terms of marginal productivity and wages in the manufacturing sector. For the services sector, my results imply a slightly lower wage for immigrants but with the same marginal productivity. Dividing immigrants into workers from EU and Non-EU countries, I find similar results for manufacturing but not for services. In this sector, relative productivity of immigrants from Non-EU countries is less than natives, while the relative productivity of immigrants from EU-countries is higher than natives. As marginal productivity and wages do not seem to differ largely between natives and immigrants, the benefits of immigration for the firms that employ immigrants need to come from non-wage sources or immigrant labor flexibility.

1 Introduction

Immigrant minorities, generally low skilled, are present in most of the developed world. As the net benefits of immigration for the whole economy and especially for low skilled workers are uncertain, immigration is a highly debated topic. Scholars have tried to disentangle the effects of immigration on natives' labor market outcomes and, as in the political arena, economists have disagreed about these effects. Although there is abundant research on how immigrants affect natives at the aggregate or local level, research on how individual firms use immigrants is scant. In order to understand the net benefits of immigration, we first need to understand why there is demand for immigrant labor. The fastest answer to this question is that immigrants are paid a lower wage which causes a decline in the wages of workers, especially low skilled. A different story could be that immigrant labor provides an added value in terms of higher productivity to the plant that hires immigrant labor. In this paper, I analyze whether this hypothesis is correct for a sample of firms from Germany.

Newer datasets, like matched employer-employee, can be used to estimate how immigrants and natives are used at the plant level. Analysis at the plant level can provide a clearer picture of how immigrants affect natives' labor market outcomes. For example, it can tell us what type of firms hire immigrants, how do they use them in the plant, the level of segregation of immigrants across plants and whether plants hire immigrants with a lower wage than natives. Moreover, it is possible to analyze the degree of substitutability between immigrants and natives across and within plants. Hence, as opposed to previous research, matched employer-employee data provides an opportunity to explain the link between immigration and natives' labor market outcomes.

The debate on the benefits of immigration is centered on the extent of how low-skilled immigrants put a downward pressure on native wages and employment outcomes. Previous research has relied on testing the degree of this pressure *assuming* immigrants and natives are perfect substitutes within some specified labor group aggregation.[1] This argument also assumes natives and immigrants are equally productive within that labor group aggregation. Hence, as natives and immigrants are equally productive, the employer's decision to hire immigrants relies only on the wage margin. In other words, immigrants and natives are *assumed* to be similar and as such they produce the same amount of output in equal circumstances. However, one of the issues that has not been considered in the literature of immigration is precisely testing the assumption that productivity of immigrants is the same to natives' productivity.

In order to test this hypothesis, I use a strategy first proposed by Hellerstein et al. (1999).

[1]See Card (2001), Borjas (1999), Borjas (2003) and Ottaviano and Peri (2006).

Although they are interested in how women are underpaid relative to similar men, we are more interested in the relative marginal productivity of immigrants. Hence, the goal of the paper is the estimation of the marginal productivity of immigrants relative to natives. Once the marginal productivity of immigrants is estimated, it is contrasted to their relative wage. If immigrants are equally productive to natives but they earn less on average than natives, it is possible to conclude that firms are taking advantage of cheap labor. On the other hand, if we find evidence that immigrants are more productive than natives and at the same time immigrants are underpaid, we cannot conclude that immigrants are only hired because of a lower wage, but possibly also due to their higher productivity or another type of skills or attitudes that are valued by firms.

Why could we expect a different productivity among natives and immigrants? The literature on the self-selection of immigrants concludes that selection on unobservables is an important determinant for the decision to immigrate in the first place (Butcher, 1994). If workers are selected on unobservables, like their motivation to succeed, it is possible that immigrants put more effort in their work. Another possible channel relies in a power purchasing story. Immigrants think of their wage as goods they can purchase in their home country, given that goods are relatively cheaper there they put more effort than natives. If either hypothesis is correct, immigration could have more benefits than previously thought.

In order to estimate the relative productivity of immigrants, I use a unique longitudinal confidential data from Germany. This dataset is ideal to test differences in marginal productivities and wages. For a national representative sample of plants each year, I observe characteristics of the full workforce as well as the wage of each worker. This allows me to compare directly marginal productivity of immigrants relative to natives as well as their wages at the plant level for all workers in the plant. My results indicate that immigrants are as productive as natives and that they earn similar to slightly lower wages than natives. Dividing immigrants into workers from EU and Non-EU countries, I find similar results for manufacturing but not for services. In this sector, relative productivity of immigrants from Non-EU countries is less than natives, while the relative productivity of immigrants from EU-countries is higher than natives. I also use the methodology proposed by Olley and Pakes (1996) in order to control for the endogeneity of capital and the results do not change. These results are not very informative about why firms hire immigrants. It is possible that there are other reasons of why firms hire immigrants without relying on differences in productivity. For example, one hypothesis that I am unable to test is whether immigrant labor causes a decrease in non-fringe benefits paid by the firm.

Germany is an interesting case to study the effects of immigration.[2] Germany started

[2]Herbert (1990) describes the history of foreign labor in Germany during the twentieth century. Göktürk

to recruit foreign workers as Guest Workers after the Second World War and stopped the recruiting process after the oil shock in 1973. From that moment it changed the immigration policy towards family reunification. Given the history of the country, Germany also had an open border policy towards refugees until the beginning of the 1990s. Both processes caused a change in the cultural landscape, and transformed the country into a de facto diverse society when the Basic Law Act was modified in order to give German nationality to those born in German soil. In particular, the share of immigrants in the population is similar to the U.S. around 10 percent (for example the proportion of foreign born in the U.S. is 11.1 percent while in Germany is 12.6 percent).[3] Moreover, minorities among the immigrants can be easily identified, as in the United States. Turks, a group that is considered mostly low skilled, represent around 27 percent of immigrants in Germany, a similar figure (37%) arises for Mexicans in the U.S. For instance, Sinn (2007) even defines this similarity as "Turkey is 'Europe's Mexico'". The rest of the immigrants come from former Yugoslavia (low skilled) and countries from the European Union.

The similitude between Germany and the U.S. does not restrict only to the characteristics of the immigrants and to the politics of immigration. Researchers have also found mixed effects of immigration on natives' labor market outcomes, but most of the empirical estimates suggest a close to zero effect of immigration. For the period 1985-1989, Pischke and Velling (1997) , using local labor market information, find that immigration does not incur in displacement effects. For a more long run perspective, Bonin (2005) uses the 1975-1997 period and replicates the analysis of Borjas (2003) at the aggregate level dividing immigrants and natives in experience and education cells. He finds that immigration does not have negative consequences on employment outcomes and at most a 10 percent increase in immigration will decrease wages by 1 percent. On the other hand, Glitz (2006) uses a quasi-experiment in the location of ethnic Germans. By law ethnic Germans (foreigners but with German ethnicity) are considered Germans. After the Iron Curtain fell, Germany saw a surge in immigration of ethnic Germans. Immigration authorities decided to allocate randomly these ethnic Germans into different counties for the period 1996-2001. Glitz (2006) finds that ethnic German immigration has no effect on wages and a negative effect on employment, although this effect disappears once controlling for selection into labor markets is included. In sum, similarly to research in the U.S., immigration in Germany does not seem to have a drastic negative effect on natives' labor market outcomes. Rather, the effect on wages and employment is null.

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et al., eds (2006) and Chin (2007) describe a cultural history of the Guest Workers in Germany after the Second World War.

[3] Shares obtained from Sinn (2007).

The results of research done in the U.S. and Germany are encouraging in order to understand why immigration seems to have a close to zero effect on natives' labor market outcomes. The mechanism of the impact of immigration is missing. Micro level data is needed to understand what immigrants do, and more fundamentally, the accounting of the benefits at the firm level and the type of tasks immigrants do in their jobs. Given the similitude between Germany and the U.S., the use of German data can shed light on the mechanism of the impact of immigration.

The main conclusion of this paper is that immigrants are surprisingly similar to natives in terms of productivity and wages, although some differences across different types of immigrants do exist. The paper is organized as follows: first I discuss the model I will use, then I explain the contents of the dataset, Section III presents the results and finally I comment the results and conclude with the implications of the findings.

2 Model

Previous research on immigration has focused on how immigrants affect natives' wages and employment. This literature can be summarized with the following equation:

$$\Pi = AF(N, I) - w(L) - C(N, I) \tag{1}$$

This equation decomposes the benefits of the firm in production, labor costs and labor adjustment costs driven by hiring or firing costs. In the margin, firms hire immigrants because the profits they enjoy from hiring immigrants are higher than otherwise. This can occur for three reasons: (i) Given same productivity and hiring costs, wages of immigrants are lower than wages of natives, (ii) Given same wages and hiring costs, productivity of immigrants is higher than productivity of natives, and finally (iii) because hiring costs of natives are too high compared to immigrants. Of course a combination of (i)-(iii) can occur as well. The point of equation (1) is to show that there are at least two reasons why immigrants are employed in firms rather than for lower wages. The goal of the paper is to show the relevance of the first part of equation (1).

Hellerstein et al. (1999) show how it is possible to estimate relative productivities of different labor inputs. Consider the following production function of general form:

$$Y_{pt} = A_{pt} G \left[K_{pt}, QL_{pt} \right] \tag{2}$$

where Y and K represent sales and capital respectively and p refers to plant or establishment and t to year. QL represents the quality of labor variable and the variable A is just a technology shifter. From now on, I will assume all labor inputs are perfect substitutes for each other. For example, Females, Immigrants and High Skilled workers are substitutes. This assumption is in line with the literature of production function estimation (Ackerberg et al. (2005a), Olley and Pakes (1996), Pavcnik (2002)). In order to understand how the model works, first I assume that all labor inputs are equally productive. For simplicity, assume we can differentiate the workforce in terms of gender and nationality, later in the paper I include other labor inputs. The variable QL_{pt} is defined as:

$$QL_{pt} = MN_{pt} + FN_{pt} + MI_{pt} + FI_{pt} \tag{3}$$

where M and F refers to male and female and N and I refer to native and immigrant. In this case the quality of labor is restricted to the total number of workers in the plant $QL_{pt} = L_{pt}$ and the estimation only takes into account total labor and not the quality of labor. Substituting equation (3) into (2) just results in a standard production function with only one labor input. Instead of assuming all labor inputs are equally productive, assume labor inputs have different productivity:

$$QL_{pt} = MN_{pt} + \varphi_F FN_{pt} + \varphi_I MI_{pt} + \varphi_F \varphi_I \varphi_{FI} FI_{pt} \tag{4}$$

where φ_F, φ_I, and $\varphi_F \varphi_I \varphi_{FI}$ are the marginal productivities of females, immigrants and females immigrants relative to male natives. The literature on immigration has assumed all these terms are equal to one, but this need not be the case. In what follows I explain how to test for different marginal productivities. In order to simplify the estimation, as Hellerstein et al. (1999) does, I restrict equation (4) in two ways. First, I assume an equiproportionate restriction among two different inputs. For example, the proportion of female natives among females is equal to the proportion of natives in that plant ($FN/F = N/L$). The second restriction is that the ratio of marginal productivity of two inputs within one demographic group (i.e. females) is equal to the ratio of marginal productivity of the same two inputs within other demographic group. In other words, the marginal productivity of immigrants relative to natives among females is $\varphi_I \varphi_{FI}$ and as the marginal productivity of immigrants relative to natives among males is φ_I, the condition requires $\varphi_{FI} = 1$.

Imposing these two conditions we can define QL_{pt} as

$$QL_{pt} = \left\{ \left(L_{pt} + \left[\varphi_F - 1\right] F_{pt}\right) \left(1 + \left[\varphi_I - 1\right] \frac{I_{pt}}{L_{pt}}\right) \right\} \tag{5}$$

where F refers the number of females in the plant and I to the number of immigrants.[4]

[4] After doing some algebra $QL = (L + (\varphi_F - 1)FN + (\varphi_I - 1)MI + (\varphi_F \varphi_I - 1)FI)$ which can be expressed as $(L + (\varphi_F - 1)F(1 - I/L) + (\varphi_I - 1)I(1 - F/L) + (\varphi_F \varphi_I - 1)F * I/L)$. This can be rewritten as

Equation (5) is the main equation in the paper as it describes how marginal productivities are estimated. The key parameters are φ_F and φ_I. They refer to the relative marginal productivity of females and immigrants. Notice that if females and immigrants are equally productive to males and natives ($\varphi_F = \varphi_I = 1$) the term QL limits to L. Remember that females and immigrants are assumed to be perfect substitutes in the production function (2).

The goal is to estimate φ_F and φ_I using this framework. In the empirical application, I include not only females and immigrants but also low and high skilled workers as well as age groups in the establishment (I use four age groups: less than 30 years old, 31-40, 41-50, more than 50 years old). The share of low and high skilled workers can affect the productivity of the plant in ways related to the share of females or immigrants. Also, the age structure in the establishment can affect how immigration affects productivity. Doing the same analysis as in equation (5), the inclusion of low and high skilled workers and three age ranges will modify the term QL_{pt} as follows:

$$QL_{pt} = \left\{ \begin{array}{c} \left(L_{pt} + [\varphi_F - 1] F_{pt}\right) \left(1 + [\varphi_I - 1] \frac{I_{pt}}{L_{pt}}\right) \\ \left(1 + [\varphi_{LOW} - 1] \frac{B_{pt}}{L_{pt}} + [\varphi_{HIGH} - 1] \frac{W_{pt}}{L_{pt}}\right) \\ \left(1 + [\varphi_{A1} - 1] \frac{A1_{pt}}{L_{pt}} + [\varphi_{A3} - 1] \frac{A3_{pt}}{L_{pt}} + [\varphi_{A4} - 1] \frac{A4_{pt}}{L_{pt}}\right) \end{array} \right\} \tag{6}$$

where B stands for lower educated and W for college educated workers. Age group 1 $A1$ refers to workers less than 30 years old, $A3$ to workers between 41-50 years old and $A4$ to workers more than 50 years old. The omitted group for education is vocational education and in age is individuals 31-40 years old.[5]

Using a Cobb-Douglas production function and taking logs to equation (2), we obtain

$$\ln Y_{pt} = \ln(\widetilde{A}_{pt}) + \beta_K \ln(K_{pt}) + \beta_{QL} \ln QL_{pt} + \varepsilon_{pt} \tag{7}$$

Parameters β_K and β_L give the usual capital and labor shares. The "new" part in the estimation of production function (7) is the inclusion of the Quality of Labor term. In this way the parameters φ_F and φ_I will give the marginal productivity of females and immigrants with respect to the omitted group (males and natives respectively). If marginal productivities are the same, we expect $\varphi = 1$. If immigrants are relatively more productive than natives,

$(L + (\varphi_F - 1)F - (\varphi_F)F * I/L + (\varphi_I - 1)I - (\varphi_I)F * I/L + (\varphi_F\varphi_I + 1)F * I/L)$. Finally, this term is equal to $(L + (\varphi_F - 1)F + (\varphi_I - 1)I - F * I/L(\varphi_F - 1 + \varphi_I - \varphi_F\varphi_I)$. This expression leads to equation (5) in the text because $\varphi_F - 1 + \varphi_I - \varphi_F\varphi_I = -(1 - \varphi_F)(1 - \varphi_I)$.

[5] Check the Appendix for variable definitions. I define lower educated workers as those workers with no qualifications or training, and college educated workers to workers with a university degree. The rest are in middle education.

then $\varphi_I > 1$. Notice that equation (7) is non-linear in the relative productivities parameters such that a non-linear estimation procedure is needed.

The main problem in estimating production functions is the endogeneity of inputs. It is reasonable to think that the firm takes an input decision when observing a productivity shock (Marschak and Andrews, 1944). A positive productivity shock causes an increase in the demand for labor, leading to believe that labor is too important in the production process. If this is the case, the estimates will be upward biased. On the other hand, suppose there are some firms that consistently hire more females or immigrants (say small and low wage firms). If this is the case, the estimates will be downward biased because unobserved components of sales will be negatively correlated to the share of females or immigrants. Hence, we will conclude spuriously that the marginal productivity of females or immigrants is too low just because they are segregated in low productivity firms.

The literature on the estimation of production function has tried to solve the endogeneity of inputs in different ways.[6] The first strategy is to use Instrumental variables that are correlated to inputs but not to unobserved components in the production function. A straightforward instrument is the use of input prices. However, there needs to be sufficient variation across plants in input prices in order for the prices to be a valid instrument. Wage rigidity is recognized to occur in Germany so wages are not a very good source of variation. The second strategy relies in the use of plant fixed effects (Mundlak, 1961). The main assumption behind this procedure relies on unobserved productivity being not time variant. In the example described above, suppose there are firms that hire females and immigrants just because they are low productivity. Including plant fixed effects solves this problem because the estimator will include only the labor input variation within each plant and will not consider plants are similar to each other. The drawbacks in including plant fixed effects are that inputs need to be strictly exogenous to obtain consistent estimates and also because fixed effects absorb important variation. Moreover, as the main parameters enter the regression equation in a non-linear way the estimation procedure becomes fairly difficult. The last procedure relies in a semiparametric approach first proposed by Olley and Pakes (1996). This procedure assumes labor is a variable static input and capital is a dynamic quasi-fixed factor. This means that labor is not endogenous only capital stock is. They assume that labor is not correlated to previous decisions by the plant or unobserved shock components. Nevertheless, capital stock is correlated with unobserved components, but once investment in the previous period is taken into account, it is possible to estimate consistent estimates of labor and capital using a two stage procedure. The procedure consists in including a flexible polynomial in capital and investment in regression (7). Hence, assuming that unobserved

[6] For a literature review on this topic see Ackerberg et al. (2005b).

productivity can be modelled as a semiparametric function of investment and capital, the coefficient on labor can be identified.[7]

It is important to mention that any method relies on different assumptions about the unobservable factors. Below, I will implement the Olley and Pakes (1996) procedure. Estimating the production function with establishment fixed effects proved to be unfeasible.[8] The estimation of regression (7) is by Non-Linear Least Squares. In order to control for unobserved heterogeneity I use industry, region, year fixed effects and a different trend for each of the 22 industries. It is important to mention that as I am unable to control for any other unobserved productivity shocks, the relative productivity parameters cannot be interpreted as causal estimators. In other words, the parameters do not imply that hiring one more immigrant will *cause* an increase in productivity by φ_I. The parameter φ_I, instead, refers to the marginal productivity of immigrants relative to natives such that if we find a value less than one we cannot know whether this is because of true low productivity or just because immigrants self-select into low productivity plants. The same applies to females and other labor inputs.

The goal is to compare the marginal productivity estimates φ_F and φ_I to the relative wage of those groups. φ_F and φ_I provide only an estimate of the productivity of females and immigrants and if markets are competitive we expect this productivity to be equal to the wage paid to them. If we believe that natives and immigrants are perfect substitutes, the argument for hiring immigrants implies that immigrants put downward pressure on wages (or that they are consistently paid less than natives). Hence the appropriate test will be to estimate the following regression at the plant level:

$$\ln w_{pt} = \alpha + \ln QL_{pt} + \upsilon_{pt} \tag{8}$$

where $\ln w_{pt}$ is the log of total wages in plant p at time t and the quality of labor term is defined as

$$QL_{pt} = \left\{ \left(L_{pt} + [\lambda_F - 1]\, F_{pt}\right) \left(1 + [\lambda_I - 1]\, \frac{I_{pt}}{L_{pt}}\right) \right\} \tag{9}$$

where the coefficient λ represents the relative wage of that group with respect to the omitted group. The term λ represents how females and immigrants are underpaid or overpaid with respect to males and natives respectively. $\lambda > 1$ implies the sociodemographic group is paid

[7] Olley and Pakes (1996) are interested in estimating the coefficients on labor and capital. As opposed to their paper, I am interested only in identifying the coefficient on labor. As such, I only estimate the first stage in their procedure such that I can recover the labor coefficient.

[8] I estimated regressions using plant fixed effects, but the fixed effects absorbed all variation in the labor inputs because standard errors are large as well as some of the coefficients.

more than the omitted group and similarly for $\lambda < 1$. If factor markets are competitive, then $\lambda = \varphi$. Hellerstein et al. (1999) argue that $\lambda < \varphi$ is evidence in favor of discrimination in the labor market given that inputs are not paid their relative contribution to production in the plant. Instead of arguing in favor of discrimination, I just recognize a gap between productivity and wages. This could be driven by hiring costs for example in equation (1).

Hellerstein et al. (1999) run regression (8) at the plant level. They do this mainly for two reasons: 1. The wage reported in the Census is not directly comparable to total wages for the plant, and 2. Their matched sample represents only 12% of the workforce. In contrast to their dataset, we have access to the full workforce and the wage reported is the one paid by the firm. I present results not only using wage aggregation at the plant level, but also I use individual data to obtain estimates of λ in order to test the robustness of the results. As λ is just the relative wage ($\lambda_F = \frac{w_F}{w_M}$ or $\lambda_I = \frac{w_I}{w_N}$), I estimate a regression using log wages at the individual level:

$$\ln w_{ipt} = \alpha + \beta_F F_{ipt} + \beta_I I_{ipt} + \varepsilon_{ipt} \tag{10}$$

where F and I are indicator variables and the constant represents the average wage of the excluded group in the plant (native males). In order to recover λ, a transformation $\lambda = \exp(\beta)$ is used. Regression (10) is simpler than regression (8) at the individual level:

$$\ln w_{ipt} = \alpha + \ln QL_{ipt} + v_{ipt} \tag{11}$$

because the equation is nonlinear in the parameters of interest.[9] As the dataset used in this study is large at the individual level, I will use regression (10) to estimate the parameters of interest. However, regression (10) refers to variation across individuals and regression (8) refers to variation across plants. I argue that the former regression is more informative than the latter. As the dataset includes wage information, it is better to use this information to calculate the relative wage across individuals than across plants. Suppose the following scenario: the share of immigrants is positive but wage inequality within the firm is large, hence a regression at the plant level will give too much weight to immigrant wages when in fact immigrants are paid less. This will lead to overestimate the wage of immigrants and may lead to conclude that firms are not using immigrant labor because of its cheaper price. Hence, using individual information to calculate relative wage can be informative about the difference between wages and productivity and will tend to show a larger wage gap than establishment level information.

Regressions (8) and (10) have the same possible biases as the estimation of the production

[9] $QL_{ipt} = \{(1 + [\lambda_F - 1] F_{ipt}) (1 + [\lambda_I - 1] I_{ipt})\}$

function (7), so the solutions to this problem are similar to that case. However, the goal of the paper is to estimate the productivity of immigrants and contrast it with the wage they are paid. If both regressions are biased, we expect the bias to be in the same direction.

3 Data

I use the LIAB data from Germany. This is a matched employer-employee dataset that links information for the firms in the Establishment Panel Dataset (IAB) with workers in the Employment Statistics Register (Social Security Records) from 1993-2004.[10] The Establishment Panel Data (IAB) is an annual survey of German establishments, administered since 1993 by Infratest Burke Sozialforschung. The establishment panel is based on a stratified random sample with respect to 10 categories of the establishment size and 16 categories of the industry from the population of all establishments and only includes establishments with at least one employee covered by social security. In 1993 the sample included 4,265 plants accounting for 0.27% of all plants in West Germany and 11% of total employment. Since 1996 East Germany is included, and the sample size increased to 8,879 plants. The sample size has increased since then and in 2004 it covered 19,234 plants. Plants are kept in subsequent years only if they are still considered representative and if the plant has not closed. Some of the variables included in the panel data set are: number of employees, investment, sales, overall wage bill, technological status, assessment of overall company economic situation, establishment size and industry.

The IAB data is matched to information on individuals from the German Employment Register which contains information on all employees and trainees subject to social security taxes. By law employers have to provide information to the social security agencies for those employees registered by the social security system. Excluded from the sample are self employed, civil servants, family workers and students enrolled in higher education. Among the variables that employers are obliged to declare about their workers are occupation, gender, year of birth, nationality, marital status, number of children, and schooling. Other labor market variables include: start and end of each employe notification and average daily wage for an employment spell.

I analyze groups divided by gender, nationality, education and age with full time worker status. I define an immigrant as a worker with foreign nationality. The data does not distinguish between foreign born or German born with foreign nationality. In this sense, I am unable to distinguish second generation of immigrants and first generation. I define three broad education groups: unqualified, vocational education or training and college. There is

[10]See Alda et al. (2005) and Andrews et al. (2004) for more details about the LIAB dataset.

some evidence that the education variable is measured with error. I follow the methodology by Fitzenberger et al. (2005) to correct the education variable. More details can be found in the Appendix. I define four age groups: less than 30 years old, 30-39, 40-49, and older than 50 years old.

One main limitation in the IAB data is that it does not have a capital stock measure. The dataset only includes investment expenditures. Previous research has used the sum of current and previous investment as a proxy for capital stock.[11] Instead of following this approach, I construct a proxy for capital stock based on four investment periods and sales growth. This procedure is valid only for plants that are present at least four years in the sample. For the rest of the plants, I multiple impute capital stock for the initial period.[12] The Appendix contains full details in the procedure.

I calculate real sales using industry price indexes for manufacturing establishments. For services establishments I use the Consumer Price Index. Although the ideal production function uses value-added instead of production measured by sales, the LIAB dataset does not include a variable that can be used for those purposes. The dataset includes a variable that measures the percentage of intermediate costs, but around 50 percent of plants do not report this variable. Moreover, some firms that do report a value for this variable include a value of zero and greater than one. Instead of including more noise to the data, I decide not to transform sales into a value added specification. Although previous literature has emphasized the benefits of such transformation, Basu and Fernald (1997) argue that the value added specification is valid only if we assume there is perfect competition, absent this aspect we could make things worse by including a value added specification. In order to control for this possible bias, I control for industry trends in all the regressions.

Before the cleaning procedure, we have information on 138,431 year observations and around 24 million worker observations. The Appendix includes exact details about the cleaning procedure. I restrict the sample to those firms that declare at least 15 employees in the Social Security records in all years and I drop all firms in which the number of workers from the Social Security records differs by more than 30% from the IAB dataset. I drop those plants that do not declare sales as their turnover measure (mainly financial institutions) and industries like Recycling, Utilities, Public Administration, Finance, and Household Services. As the IAB changed their sampling procedures in 1996 (East Germany is included and more smaller establishments), I use data since 1996 to avoid problems of comparison between sampling procedures. I focus only in establishments in the manufacturing and services sector.

[11] Addison et al. (2005) uses the sum of current and lagged investment as a proxy for capital stock and Addison et al. (2003) uses replacement investment.

[12] I follow the procedure described in Rubin (1987) and Rubin and Little (2002).

My final sample consists in 22,153 plant-year observations and 5,236 different plants with an average duration of a plant in the dataset close to 4 years.

Table 1 shows some basic descriptive statistics using the sample weights. For simplicity, I just present statistics for three years: 1996, 1999, 2002. In general, all variables are fairly constant throughout the period of analysis. The number of workers is around 80 workers for the three years and their average age is close to forty years old. The proportion of workers is fairly constant among immigrants and females. Native females represent one-third of natives and female immigrants represent close to one-third of immigrants. However, immigrants are not equally represented in the occupational structure. Immigrants are predominantly low skilled.[13] While 90 percent of immigrants are in low skilled occupations, natives only account for 35 percent of the same group. Nevertheless their disadvantage in the occupational structure, the wage gap between immigrants and natives is not large (around 3 percent). Among plant characteristics, the sample is fairly representative of four regions in Germany. Using the sample weights, small firms represent 65 percent of the total number of plants. Immigrants are not hired only by a few firms, around 65 percent of the plants hire immigrants and, among those with positive immigrant employment, the share of immigrants in the workforce is around 10 percent. Immigrants are not equally located through all Germany. Immigrants in West Germany represent between 8 and 10 percent of the workforce, while in East Germany they represent less than one percent of the workforce. As this is the case, I present results for establishments located across Germany and establishments located only in West Germany.

4 Results

Table 2 and 3 present the main results divided by Manufacturing and Services establishments. The regressions include year, industry and region fixed effects, I also include a different trend for each industry to control for possible shocks across industries. Using regression (7) and quality of labor term (6), the first three columns (1)-(3) show the relative marginal productivity of immigrants, females, low and high education and age groups. Column (1) includes all four regions while Column (2) only includes West Germany. In the manufacturing sector, immigrants are slightly more productive than natives for all Germany and 5 percent less productive than natives in the West, although these results are not significantly different from one. As immigrants are not present in East Germany and as West German establishments are more productive than Eastern ones, the result is not surprising.

[13]Only for this part I include trainees, part time and blue collar workers together as a single group. In the analysis below, I refer as low skilled workers only to blue collar workers.

On the other hand, females are consistently less productive than males. Females are around 43-52 percent less productive than males. Column (3) presents the results using the Olley and Pakes (1996) procedure for West Germany (only correcting for the endogeneity of capital stock) restricting the sample only for those plants with positive investment. The coefficients do not vary too much and the same conclusion arises for females and immigrants. The finding of females being less productive than males confirms the results in Hellerstein et al. (1999), they find that females are only 16 percent less productive than males for the U.S. The magnitude of the estimate is surprising. It is likely that low productivity firms employ more females. In fact, in my sample females are overrepresented in low wage firms. Around 60 percent of the workforce among the lowest wage firms employ women.[14]

Other coefficients like the productivity of low and high education workers are interesting. Low education workers are around 30 percent less productive than workers with vocational education, and college workers are more than 100 percent productive than workers with vocational education. Hellerstein et al. (1999) find only a gap of 60 percent.

Opposite to the manufacturing sector, the services sector imply basically identical productivities of immigrants and females with respect to natives and males. This is robust to restricting the sample to Western establishments and for correcting the endogeneity of capital. The productivity of low educated workers with respect to middle education workers is reduced to a gap of 60 percent.

The relative marginal productivities need to be contrasted to the relative wages. Columns (4)-(5) in Table 2 show the estimation using total wages in the plant instead of sales, in particular, it shows regression (8) using industry, region, year fixed effects and industry trends. Column (4) includes all Germany and Column (5) includes only West Germany, Columns (6) and (7) uses regression (10) for individual data instead of plant level data. The coefficients are more precisely estimated than in the case of the production function. For all Germany, relative wages of immigrants are 20 percent higher than natives in all Germany. However, once we compare wages of immigrants across the population they earn 2 percent less than natives. This difference could be driven by the fact that some firms face fixed costs in hiring immigrants. For example, there are training costs or learning costs such that is not profitable to hire an immigrant even at a lower wage, hence they hire natives. This effect says that immigrants will tend to be employed on firms, productive enough, to face the training or learning cost. The services sector shows more homogenous results. Immigrants are similarly paid than natives using variation across plants, and slightly less paid than

[14] I do not present a table for this result. I obtained the median wage paid by each firm, then I sort the firms according to this median wage and assign them into quintiles. The workforce of the first quintile is around 60 percent female. In contrast, the workforce of the fifth quintile is around 19 percent female. The same is not true for immigrants. The share of immigrants is fairly constant accross the quintiles.

natives using individual data.

In the case of females employed in manufacturing, we cannot reject the null hypothesis that relative productivity and relative wages are the same for Western Germany. Even more interesting is the fact that using individual data, females appear to be paid more than their average productivity. On the other hand, the services sector appear to pay females less than their relative productivity for All and West Germany. Hellerstein et al. (1999) results imply that females are paid less than their relative productivity in the manufacturing sector for the U.S. The results shown imply a similar story for the case of Germany but only in the services sector.

4.1 Immigrants from Non-EU Countries

Low skilled immigration in Germany is mainly from Non-EU countries particularly Turkey and countries from the former Yugoslavia. In order to understand the role of different immigrants groups, I estimate similar regressions as above but differentiating immigrants by EU and Non-EU countries. For more interesting results, I include workers from developed countries like Australia, Canada and the U.S. in the EU group.[15] Tables 4 and 5 show the results.

Immigrants from Non-EU countries show a lower relative productivity than natives. In manufacturing, immigrants from Non-EU countries are around 20 percent less productive than natives and in services this number is equal to 40 percent. However, standard errors are large and we cannot reject the null of equal productivity to natives in the manufacturing sector. Surprisingly, differences in relative wages do not arise at least in the manufacturing sector. The services sector show some wage gap between natives and immigrants but not enough to make it similar to the relative productivity. Overall, the results show evidence that the relative productivity of immigrants from Non-EU countries is less than natives in services but not in manufacturing.

Immigrants from EU countries are more productive than native workers although the difference is not statistically significant in manufacturing. It is surprising the productivity in the services sector. The results imply that immigrants from EU countries are 140 percent more productive than natives. Even though wages are higher than natives, they are still less than the estimated productivity.

In sum, given large standard errors in the manufacturing sector we cannot reject the null hypothesis that immigrants are equally productive than natives. Plant level data results

[15] EU countries represent Western Europe plus other developed countries. Even though Germany signed Guest Worker Programs with Spain, Italy and Greece, I decided to include these countries in the EU block. Non-EU countries are represented by Eastern Euopean countries and mainly developing countries.

imply that wages are higher for immigrants, but using individual level data suggest that wages are similar to slightly lower. In the services sector, we can reject the null of equal productivity to natives. In particular, immigrants from Non-EU countries are relatively less productive than natives while immigrants from EU countries are more productive than natives. Wages are five lower for immigrants from Non-EU countries than natives while immigrants from EU countries have similar wages to natives.

5 Robustness Tests

- Control for Establishment Size
- Relaxing Education and Immigration
- Relaxing Female and Immigrant
- Restricting the sample for those with positive share in immigration.

6 Conclusions

My results imply that immigrants, in both the manufacturing and services sectors, are as productive as natives and they are not systematically underpaid relative to natives and if they are underpaid is by a small amount. I find that marginal productivity of females is 40 percent less than marginal productivity of males in the manufacturing sector but the relative wage is similar to the relative productivity. As oppose to the U.S. case, females are paid more than their marginal productivity using individual data. However, females in the services sector do appear to be underpaid compared to their relative productivity.

I find that marginal productivity of immigration from EU and Non-EU countries is substantially different, especially for services. Marginal productivity of immigrants from Non-EU countries is lower than natives in services but the relative wage is not low enough to match the lower marginal productivity. In manufacturing, a similar case arises but we cannot reject the null hypothesis that marginal productivity of immigrants from Non-Eu countries is equal to marginal productivity of natives or immigrants from EU countries.

If natives are similar to immigrants in terms of wages and productivity, the economic benefits of immigration, as defined by Borjas (1995), are close to zero. However, before stating that conclusion other channels need to be explored. If firms hire immigrants, a reason should exist on why they do so. Among the possible reasons are non-wage benefits (holidays), adjustment costs or labor flexibility, and management practices (monitoring costs). The literature on the effects of immigration needs to move on testing whether those reasons have an effect or not.

My results suggest than non-wage and non-productivity reasons must be important in the decision of firms to employ immigrants. State dependence in hiring immigrants could be important as well as labor flexibility. If future demand is uncertain and the costs of firing natives is high, immigrants could provide a smooth adjustment in labor for firms. If the negative demand shock occurs, the first fired will be the immigrants. Indeed, there is some evidence that this is occurring in Germany (Kogan, 2006). Future research agenda needs to look at the possible benefits for the firm when employing immigrants.

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Table 1. Sample Description

Variables	1996	1999	2002	Variables	1996	1999	2002
log Sales	15.5	15.5	15.5	Num. Workers	76.72	78.21	82.34
sd	[1.26]	[1.26]	[1.29]	% Female	0.31	0.32	0.33
log K	13.8	14	14.1	% Immigrant	0.07	0.07	0.07
sd	[1.63]	[1.62]	[1.64]	Age	39.5	40	40.7
Firm Size				%Male-Native	0.64	0.63	0.62
15-50	0.65	0.66	0.64	%Female-Native	0.29	0.3	0.31
51-100	0.19	0.19	0.2	% Female-Immig	0.017	0.016	0.019
101-200	0.09	0.09	0.1	%Male-Immig	0.057	0.052	0.053
+200	0.07	0.06	0.06	%Native-Blue	0.60	0.62	0.61
Region				%Native-White	0.32	0.31	0.32
North	0.15	0.14	0.15	%Immig-Blue	0.065	0.06	0.06
Center	0.36	0.32	0.33	%Immig-White	0.008	0.008	0.012
South	0.25	0.31	0.29	Hire Immigrant	0.65	0.61	0.63
East	0.24	0.26	0.23	Wage Native	92.7	91.7	93.5
N	1,968	2,312	3,463	Wage Immig	90.3	91.4	91.3

Note: Calculations by the author.

Table 2. Regression Coefficients

Manufacturing

	Production				Wages			
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
	All	WEST	OP		All	WEST	All	WEST
$\boldsymbol{\varphi}_I$	1.0327	0.957	0.941	$\boldsymbol{\lambda}_I$	1.219	1.10	0.989	0.98
	[0.076]	[0.079]	[0.087]		[0.021]	[0.016]	[0.0005]	[0.0004]
$\boldsymbol{\varphi}_F$	0.475	0.57	0.566	$\boldsymbol{\lambda}_F$	0.603	0.639	0.848	0.85
	[0.0223]	[0.037]	[0.041]		[0.007]	[0.008]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{LOW}$	0.769	0.651	0.686	$\boldsymbol{\lambda}_{LOW}$	0.882	0.826	0.854	0.844
	[0.039]	[0.044]	[0.051]		[0.011]	[0.009]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{HIGH}$	2.498	3.339	3.144	$\boldsymbol{\lambda}_{HIGH}$	2.163	2.306	1.387	1.352
	[0.106]	[0.195]	[0.203]		[0.023]	[0.027]	[0.0006]	[0.0007]
$\boldsymbol{\varphi}_{A1}$	0.449	0.636	0.578	$\boldsymbol{\lambda}_{A1}$	0.528	0.622	0.874	0.871
	[0.051]	[0.099]	[0.109]		[0.017]	[0.021]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{A3}$	0.524	0.645	0.672	$\boldsymbol{\lambda}_{A3}$	0.838	0.942	1.043	1.051
	[0.041]	[0.084]	[0.097]		[0.017]	[0.021]	[0.0005]	[0.0005]
$\boldsymbol{\varphi}_{A4}$	0.468	0.856	0.901	$\boldsymbol{\lambda}_{A4}$	0.822	1.067	1.073	1.084
	[0.031]	[0.072]	[0.084]		[0.013]	[0.018]	[0.0005]	[0.0005]
β_K	0.147	0.165						
	[0.005]	[0.006]						
β_L	0.915	0.884	0.837					
	[0.0072]	[0.009]	[0.011]					
N	12053	7106	6428	**N**	12053	7106	4092803	3379636
Inv>0			Y					
West		Y	Y			Y		Y
Individuals							Y	Y

Notes: Calculations by the author. Standard errors in parenthesis. Inv>0 includes only observations with positive investment. Columns (6) and (7) are regressions at the individual level.

Table 3. Regression Coefficients

Services

	Production				Wages			
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
	All	WEST	OP		All	WEST	All	WEST
$\boldsymbol{\varphi}_I$	1.151	1.008	0.995	$\boldsymbol{\lambda}_I$	1.027	0.969	0.967	0.958
	[0.146]	[0.145]	[0.168]		[0.027]	[0.025]	[0.0009]	[0.0009]
$\boldsymbol{\varphi}_F$	1.041	1.034	1.042	$\boldsymbol{\lambda}_F$	0.836	0.832	0.879	0.857
	[0.049]	[0.067]	[0.078]		[0.008]	[0.009]	[0.0008]	[0.0008]
$\boldsymbol{\varphi}_{LOW}$	0.535	0.388	0.359	$\boldsymbol{\lambda}_{LOW}$	0.772	0.711	0.844	0.851
	[0.055]	[0.052]	[0.056]		[0.013]	[0.012]	[0.0008]	[0.0008]
$\boldsymbol{\varphi}_{HIGH}$	2.764	2.035	2.079	$\boldsymbol{\lambda}_{HIGH}$	2.031	1.881	1.446	1.41
	[0.153]	[0.163]	[0.187]		[0.024]	[0.026]	[0.001]	[0.001]
$\boldsymbol{\varphi}_{A1}$	0.492	0.483	0.537	$\boldsymbol{\lambda}_{A1}$	0.423	0.465	0.822	0.82
	[0.083]	[0.116]	[0.152]		[0.016]	[0.021]	[0.0008]	[0.0008]
$\boldsymbol{\varphi}_{A3}$	0.746	0.621	0.603	$\boldsymbol{\lambda}_{A3}$	0.886	0.992	1.047	1.0618
	[0.095]	[0.130]	[0.161]		[0.021]	[0.028]	[0.001]	[0.001]
$\boldsymbol{\varphi}_{A4}$	0.828	1.307	1.482	$\boldsymbol{\lambda}_{A4}$	0.885	0.996	1.046	1.068
	[0.077]	[0.142]	[0.187]		[0.016]	[0.022]	[0.001]	[0.001]
β_K	0.252	0.224						
	[0.005]	[0.008]						
β_L	0.684	0.737	0.697					
	[0.008]	[0.012]	[0.014]					
N	10100	5476	4507	**N**	10100	5476	1489218	939785
Inv>0			Y					
West		Y	Y			Y		Y
Individuals							Y	Y

Notes: Calculations by the author. Standard errors in parenthesis. Inv>0 includes only observations with positive investment. Columns (6) and (7) are regressions at the individual level.

Table 4. Effects by Immigrant Group
Manufacturing

	Production				Wages			
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
	All	WEST	OP		All	WEST	All	WEST
$\boldsymbol{\varphi}_I^{Non-EU}$	0.911	0.791	0.833	$\boldsymbol{\lambda}_I^{Non-EU}$	1.267	1.089	0.984	0.971
	[0.096]	[0.099]	[0.114]		[0.028]	[0.021]	[0.001]	[0.001]
$\boldsymbol{\varphi}_I^{EU}$	1.237	1.208	1.088	$\boldsymbol{\lambda}_I^{EU}$	1.143	1.134	0.996	0.994
	[0.134]	[0.132]	[0.141]		[0.035]	[0.026]	[0.001]	[0.001]
$\boldsymbol{\varphi}_F$	0.474	0.568	0.565	$\boldsymbol{\lambda}_F$	0.604	0.639	0.849	0.85
	[0.022]	[0.037]	[0.041]		[0.007]	[0.008]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{LOW}$	0.779	0.667	0.698	$\boldsymbol{\lambda}_{LOW}$	0.878	0.828	0.854	0.845
	[0.04]	[0.045]	[0.051]		[0.011]	[0.010]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{HIGH}$	2.493	3.321	3.133	$\boldsymbol{\lambda}_{HIGH}$	2.164	2.305	1.387	1.352
	[0.106]	[0.194]	[0.203]		[0.023]	[0.028]	[0.0007]	[0.0007]
$\boldsymbol{\varphi}_{A1}$	0.451	0.638	0.579	$\boldsymbol{\lambda}_{A1}$	0.528	0.622	0.875	0.872
	[0.051]	[0.098]	[0.108]		[0.017]	[0.022]	[0.0004]	[0.0004]
$\boldsymbol{\varphi}_{A3}$	0.519	0.632	0.662	$\boldsymbol{\lambda}_{A3}$	0.841	0.940	1.043	1.05
	[0.041]	[0.083]	[0.095]		[0.017]	[0.022]	[0.0005]	[0.0005]
$\boldsymbol{\varphi}_{A4}$	0.467	0.851	0.896	$\boldsymbol{\lambda}_{A4}$	0.823	1.066	1.074	1.084
	[0.031]	[0.071]	[0.083]		[0.013]	[0.018]	[0.0005]	[0.0005]
β_K	0.147	0.165						
	[0.005]	[0.006]						
β_L	0.915	0.885	0.838					
	[0.007]	[0.009]	[0.01]					
N	12053	7106	6428	**N**	12053	7106	4092803	3379636
Inv>0			Y					
West		Y	Y			Y		Y
Individuals							Y	Y

Notes: Calculations by the author. Standard errors in parenthesis. Inv>0 includes only observations with positive investment. Columns (6) and (7) are regressions at the individual level.

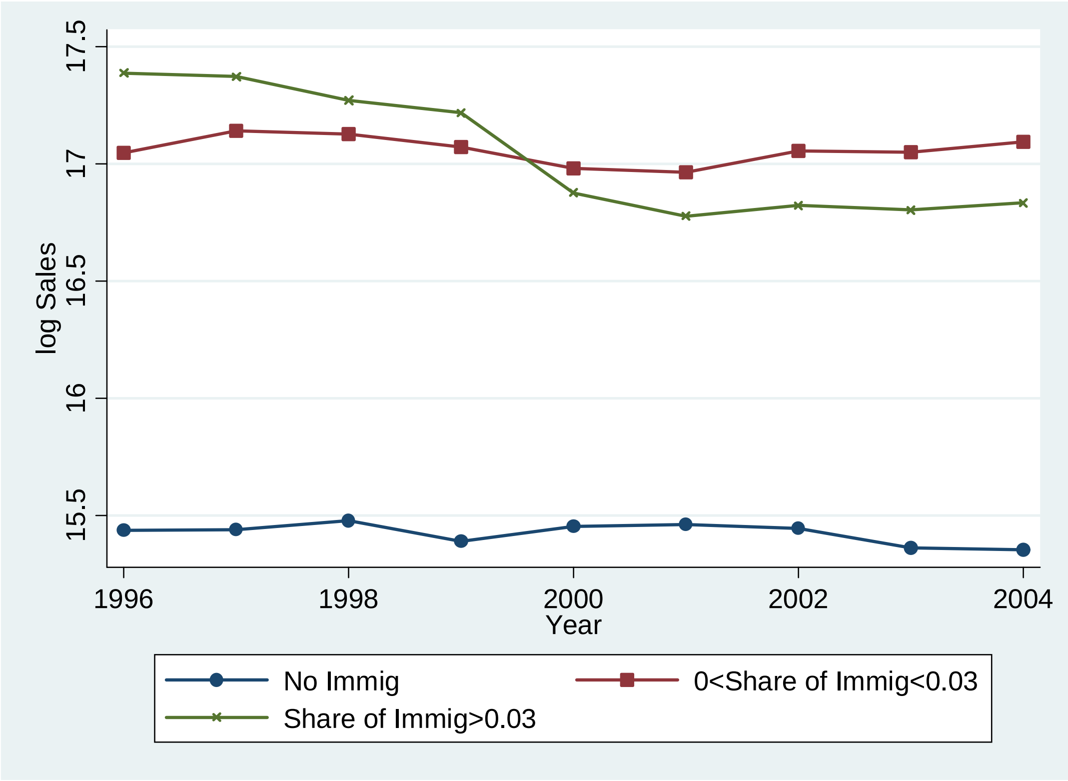
Table 5. Effects by Immigrant Group

Services

	Production				Wages			
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
	All	WEST	OP		All	WEST	All	WEST
$\boldsymbol{\varphi}_I^{Non-EU}$	0.704	0.610	0.601	$\boldsymbol{\lambda}_I^{Non-EU}$	0.859	0.826	0.957	0.944
	[0.163]	[0.163]	[0.187]		[0.033]	[0.029]	[0.0010]	[0.0009]
$\boldsymbol{\varphi}_I^{EU}$	2.618	2.238	2.419	$\boldsymbol{\lambda}_I^{EU}$	1.427	1.293	0.991	0.988
	[0.376]	[0.353]	[0.429]		[0.061]	[0.051]	[0.0020]	[0.0020]
$\boldsymbol{\varphi}_F$	1.040	1.027	1.037	$\boldsymbol{\lambda}_F$	0.835	0.828	0.879	0.857
	[0.049]	[0.066]	[0.077]		[0.008]	[0.009]	[0.0009]	[0.0009]
$\boldsymbol{\varphi}_{LOW}$	0.555	0.401	0.372	$\boldsymbol{\lambda}_{LOW}$	0.786	0.721	0.844	0.852
	[0.056]	[0.053]	[0.058]		[0.013]	[0.0128]	[0.0008]	[0.0009]
$\boldsymbol{\varphi}_{HIGH}$	2.702	1.965	2.020	$\boldsymbol{\lambda}_{HIGH}$	2.018	1.8660	1.444	1.406
	[0.150]	[0.159]	[0.182]		[0.023]	[0.026]	[0.001]	[0.0014]
$\boldsymbol{\varphi}_{A1}$	0.493	0.493	0.559	$\boldsymbol{\lambda}_{A1}$	0.424	0.469	0.822	0.821
	[0.083]	[0.116]	[0.154]		[0.016]	[0.0203]	[0.000]	[0.0008]
$\boldsymbol{\varphi}_{A3}$	0.743	0.611	0.607	$\boldsymbol{\lambda}_{A3}$	0.882	0.985	1.046	1.061
	[0.095]	[0.129]	[0.161]		[0.021]	[0.027]	[0.001]	[0.001]
$\boldsymbol{\varphi}_{A4}$	0.826	1.304	1.491	$\boldsymbol{\lambda}_{A4}$	0.884	0.995	1.046	1.068
	[0.076]	[0.141]	[0.188]		[0.016]	[0.0215]	[0.001]	[0.001]
β_K	0.252	0.223						
	[0.005]	[0.008]						
β_L	0.684	0.739	0.6996					
	[0.008]	[0.012]	0.0142					
N	10100	5476	4507	**N**	10100	5476	1489218	939785
Inv>0								
West	Y		Y			Y		Y
Individuals		Y	Y				Y	Y

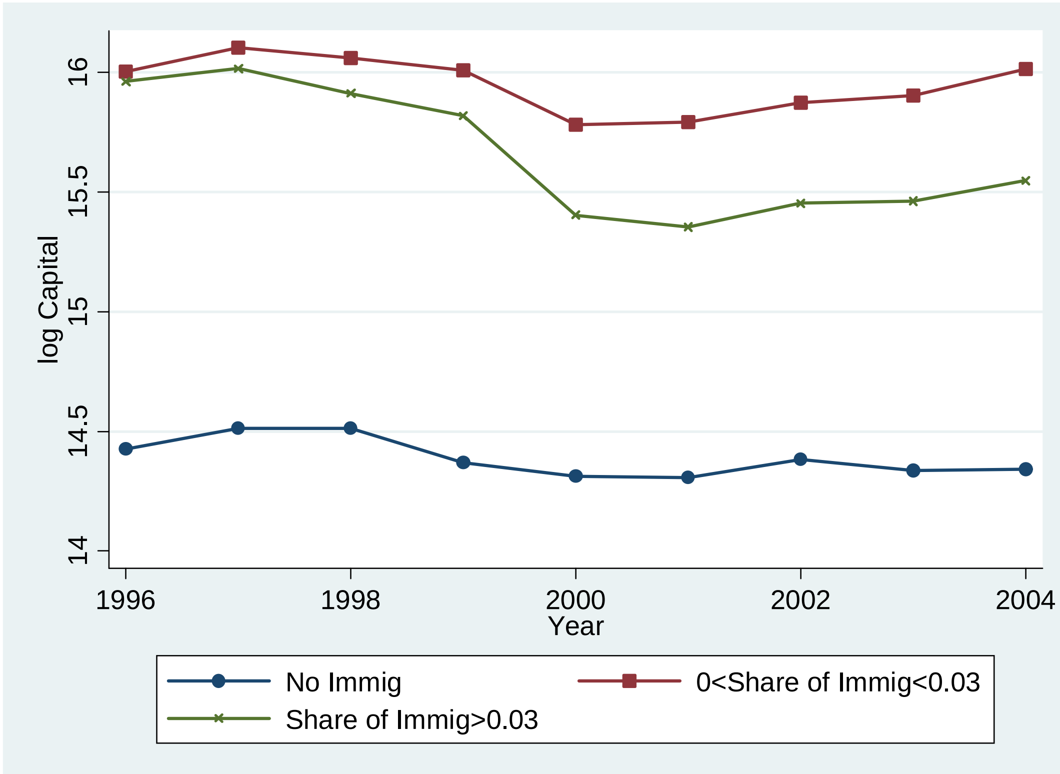
Notes: Calculations by the author. Standard errors in parenthesis. Inv>0 includes only observations with positive investment. Columns (6) and (7) are regressions at the individual level.

Figure 1: Sales by Immigrant Share in Establishment



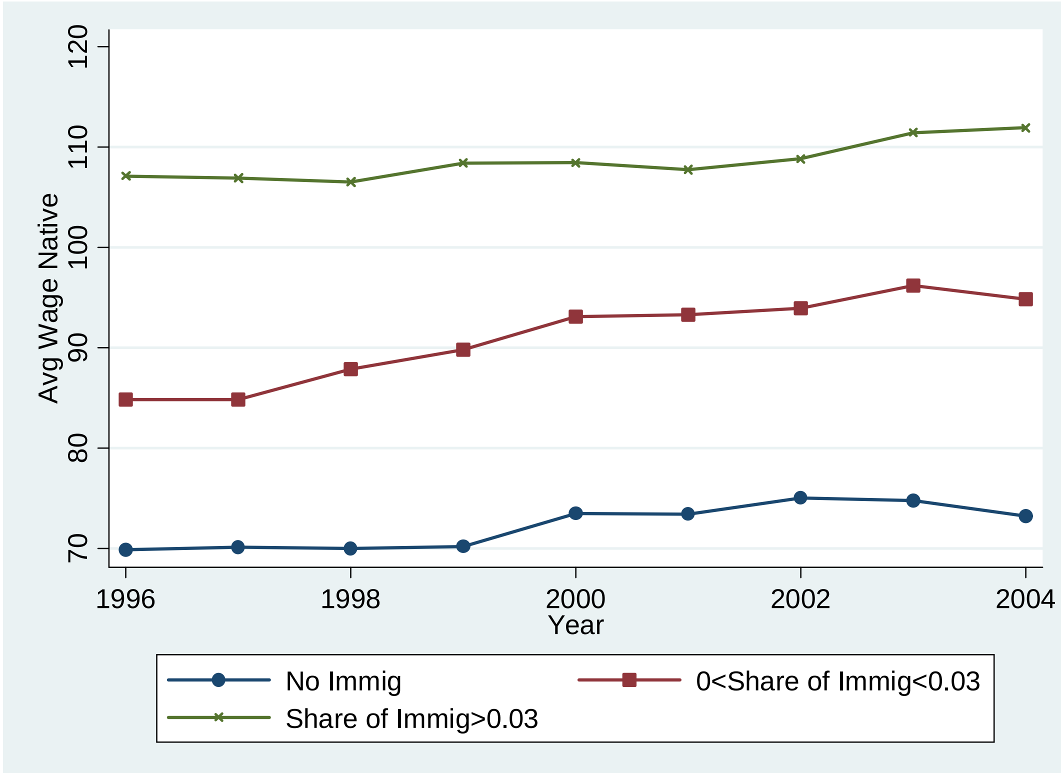
Note: Calculations by the author for valid establishments in the dataset.

Figure 2: Capital Stock by Immigrant Share in Establishment



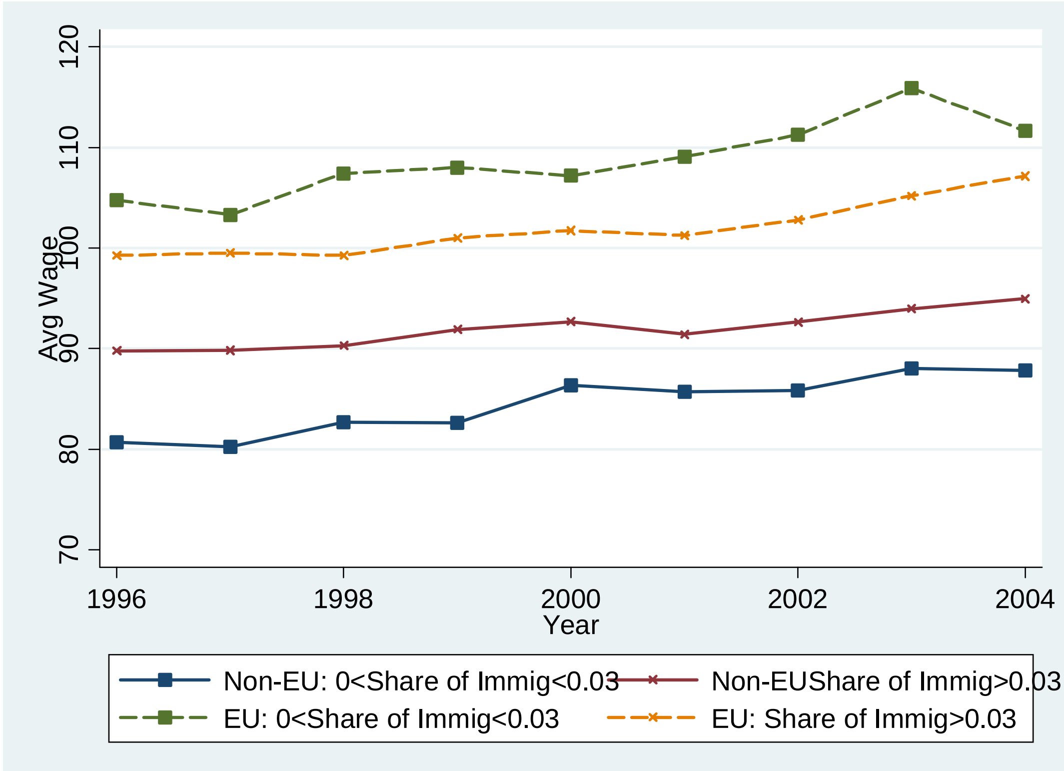
Note: Calculations by the author for valid establishments in the dataset.

Figure 3: Average Wage of Natives by Immigrant Share in Establishment



Note: Calculations by the author for valid establishments in the dataset.

Figure 4: Average Wage of Immigrants by Immigrant Share in Establishment



A Capital

I follow the method proposed by Letterie and Pfann (2007) and Verick et al. (2004) to obtain a measure of capital stock. From the IAB data, I keep those firms that are present at least four years and have valid information in sales and investment. I proceed as follows:

1. (a) Using the Perpetual inventory method $K_t = (1-\delta)K_{t-1}+I_{t-1}$, estimate recursively Capital stock as $K_T = \sum_{t=1}^{T}(1-\delta)^{t-1}I_{T-t} + (1-\delta)^T K_0$ where $T = 4$ in our case.

   (b) As Letterie and Pfann (2007), assume capital stock grows at the same rate as sales: $K_T = \prod_{t=1}^{T}(1+g_t)K_0$. Here I smooth sales by the average in the four years and calculate $K_T = (1+\overline{g})^T K_0$

   (c) Solving the two equations and two unknowns we get $K_T = \frac{\sum_{t=1}^{T}(1-\delta)^{t-1}I_{T-t}}{1-\frac{(1-\delta)^T}{(1+\overline{g})^T}}$ and $K_0 = \frac{\sum_{t=1}^{T}(1-\delta)^{t-1}I_{T-t}}{(1+\overline{g})^T-(1-\delta)^T}$. In order to guarantee positive capital stocks, I restrict $\overline{g}$ to be non-negative.

   (d) In order to keep as many observations as possible, I keep K_0 and take it as a good estimate of capital stock in the initial period. I use the perpetual inventory method to calculate $K_1, ..., K_t$.

(e) Firms with less than four years have missing values in capital. In order to maximize the sample size, I multiple impute capital stock for those plants using labor, sales, industry and state as explanatory variables under the Missing at random assumption. Rubin (1987) and Rubin and Little (2002) propose that the multiple imputation model has to be richer than the analyst model, and argue that not including the dependent variable (sales) can seriously biased the estimated of capital on sales. I multiple impute capital only for the first period and then I use the perpetual inventory method to calculate following capital stocks.

B Variables

All variables are in 2004 Euros.

- Investment: Investment is deflated by the Investment Price Index given by the Statistical Office (Statistiches Bundesamt) in its series Fachserie 17, R2, 1/2007. I use Euros instead of Deutsche Mark.

- Sales: Sales are deflated using a two digit NACE industry classification (28 industries). This classification starts since 1995. The Index is found in the Series: "Preise. Index der Erzeugerpreise gewerblicher Produkte (Inlandsabsatz) nach dem Güterverzeichnis für Produktionsstatistiken" published by the Statistical Office. For services, I use the Consumer Price Index.

- Labor: This variable is obtained from the Social Security Records.

  - Immigrant: All individuals with different nationality than German are considered Immigrants. In some cases, the plant declares that the worker is immigrant and the following year the same worker is native. I consider measurement error as those workers classified as Germans and in different periods the same worker is classified as foreigner, and hence I construct a foreigner variable that is constant across time. This measurement error is very small, accounting for around 1% of all immigrants.
  - Occupation: I have two different measures of occupation. A three index category of occupation, and a general classification that divides the workforce in six categories: Trainees, Part time workers, White Collar workers, Not Qualified, Skilled workers and Craftsmen. I consider blue collar workers as the last three occupations.
  - Education: It is well known that the education variable has serious problems of measurement error, see for example Fitzenberger et al. (2005). The problem relies in that plants, in general, do not ask employees their education or it is difficult to infer for foreigners, as such in some cases we observe that education can decrease for some workers. The problem is exacerbated for Immigrants. There is a problem of missing values for immigrants especially. For example, there are around 8 percent of missing values for immigrants while only 3 percent for natives. I imputed the missing values using an ordered logit from the sample with valid education categories as a function of observable characteristics: occupation, wage, industry, age and year.

- Wages: Wages are converted into euros and deflated using the Consumer Price Index. Wages refer to the average daily wage in the employment spell of each individual.

- Industry: The IAB includes an industry classification. It is worth mentioning that this industry classification is not consistent over time. In some cases, it is possible to assign new plants in some industries to the old classification. The Social Security records include industry as well. I use the industry classification (WZ73) given in the Social Security records mainly for two reasons: 1. It is more detailed, and 2. Even though the classification is not consistent over time (the classification changed in 1999 to WZ93), I was able to match the industries from one classification to other using the German Classification of Economic Activities, Edition 1993 (WZ93) published by the Statistical Office.

- State: I use the state classification provided in the Social Security records. There are sixteen states.