Immigration and Distribution of Wages in Austria

by

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Immigration and the Distribution of Wages in Austria *

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Abstract

Using detailed micro data on earnings and employment, I analyze the effects of immigration on the wage distribution of native male workers in Austria. I find that immigration has heterogeneous effects on wages, differing by type of work as well as the wage level. While there are small, but insignificant, negative effects for blue collar workers at the lower end of the wage distribution there are positive effects on wages at higher percentiles. For white collar workers positive effects occur at most percentiles. The estimated effects of immigration are relatively small in size and not significant for most workers. Overall it seems that most of potentially adverse effects of immigration on natives’ wages are offset by complementarities stemming from immigration of workers with different skill levels.

Keywords: Immigration, Labor market, Wage distribution

JEL classification: J31, J61

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1 Motivation

Austria, as well as many other European countries, faced a sharp increase in immigration within the last decades. Between 1972 and 2009 the share of immigrants in Austria rose from around 2.5 to over 10%\(^1\). Alongside this transition many concerns arose about the social and economic consequences that are (thought to be) associated with this change in the population structure. Only recently the EU-enlargement and the associated freedom to migrate within the EU raised additional concerns on the fortunes of native workers. Dustmann et al. (2003) state “the possible negative effects of immigration on wages and employment outcomes of resident workers is one of the core concerns in the public debate on immigration”\(\text{(p.8)}\). Naturally these transitions had a great impact on economic research, leading to a huge number of studies analyzing theoretically and empirically causes and consequences of increasing immigration.

The impact of immigration on natives’ labor market outcomes are broadly discussed in economic studies. While most studies on the effects of immigration on wages find only weak - if any - effects of increasing immigration on natives’ wages (see Friedberg and Hunt (1995)) others do find strong adverse effects for native workers (Borjas (2003)). When workers are heterogeneous with respect to skills, ability and education one would expect to observe different impacts of immigration on native workers’ wages (see e.g. Dustmann, Glitz and Frattini (2008)). Depending on immigrants’ skill composition an increase in the number of immigrants increases the supply of certain types of

\(^1\)Statistics Austria, “Statistik des Bevölkerungsstandes”.
labor which in turn leads to increasing or decreasing demand for native workers with given characteristics - depending on patterns of substitutability or complementarity in the production process (Winter-Ebmer and Zweimüller (1996)). It is therefore most likely that the effect of immigration varies between different skill groups (see e.g. Dustmann, Fabbri and Preston (2005)) which should be reflected by heterogeneous impacts of the share of immigrants along the wage distribution. Assessing relative winners and losers from increased immigration is important. Understanding the heterogeneous consequences of immigration may imply policies that help to cushion potentially negative impacts on concerned workers.

Notice however that it is not sufficient to regress the change in immigrant shares separately for e.g. high and low income earners in order to assess the impact of immigration on high and low income workers. As Koenker and Hallock (2001) point out, this strategy of “segmented OLS regression” may lead to severely biased results, due to sample selection bias that arises from non-random sorting of workers along the wage distribution (Heckman (1979)).

While the effects of immigration on (un)employment rates and average wages of native workers have been studied extensively so far, only few studies deal with the causal effects of immigration on the wage distribution of native workers. Following the approach of Dustmann, Frattini and Preston (2008) I assess how the change in the region specific share of immigrants over time affects the wage distribution of male native workers in Austria. Using detailed data on the yearly total gross income of all non self employed workers in
Austria allows me to analyze these effects consistently for different groups of workers over a time period of 12 years.

I find that immigration has heterogeneous effects on wages, differing by type of work as well as the wage level. While there are small, but insignificant, negative effects for blue collar workers at the lower end of the wage distribution there are positive effects on wages at higher percentiles. For white collar workers positive effects occur at most percentiles. The estimated effects of immigration are relatively small in size and not significant for most workers. Overall it seems that most of potentially adverse effects of immigration on natives’ wages are offset by complementarities stemming from immigration of workers with different skill levels.

2 Previous Literature

Previous work on the effects of immigration on labor market outcomes in Austria mostly focus on average wage and employment effects. For example Winter-Ebmer and Zweimüller (1996) find that Austrians earn higher wages in regions and industries with higher immigrant shares. Results on wage growth however appear to be mixed, yielding positive effects at the industry level but negative effects at the firm level. While immobile workers (i.e. job-stayers) experience small adverse effects from immigration, mobile workers’ (job-changers) wage growth rates are not or even positively affected by immigration. In a subsequent study Winter-Ebmer and Zweimüller (1999)

\footnote{Their estimates suggest an increase of natives’ wages between 2.1-3.7\% at the regional and 0.2-1.0\% at the industry level in response to an increase in the share of foreign workers by 1\%.}
consider employment prospects of young native workers and find only weak
displacement effects from increased immigration. Both papers focus on the
years 1988 to 1991 which corresponds to the steepest increase of immigration
into Austria due to the fall of the iron curtain and the Baltic wars.

Hofer and Huber (2003) use a representative sample of Austrian workers
for the years 1991 to 1994 and find that immigration has a small negative
(positive) effect on the wage growth of native blue (white) collar workers.

In a more recent paper Wagner (2010) finds negative effects of immigration
on already resident migrants but no effect on natives’ wages in Austria.

Overall empirical evidence shows that the Austrian labor market reacts com-
plexly to migration, yielding different impacts for different time periods and
types of workers (see Hofer and Huber (2003)).

In recent years the literature has shifted toward assessing the heterogeneous
effects of immigration across different types of workers or on wage inequality.
Most papers in this context distinguish between skilled and unskilled workers
(see e.g. Altonji and Card (1991), Card (2001) or Jaeger (2007)). Card (2009)
e.g. finds for the US that immigrants and natives within education groups
are imperfect substitutes and that immigration has only minor effects on
wage inequality. Only few studies directly assess the effect of immigration on
the distribution of wages. Dustmann, Frattini and Preston (2008) study the
effect of immigration on local labor markets’ wage distributions in the UK by
regressing changes of the percentiles of region specific wage distributions over
time on changes in the share of immigrants. They find that wages below the
20th percentile are depressed while the upper part of the distribution exhibits
modest wage increases. Borjas (2003) exploits differences in the supply of foreign labor by education-experience groups and finds large negative wage effects for native workers. While these effects are small - and sometimes even positive - for some workers, there are large adverse effects for e.g. high school drop outs.

3 Empirical Strategy

Manacorda et al. (2006) show that immigrants tend to downgrade considerably when arriving in the host country. This can severely bias estimation results if immigrants are assigned to skill groups according to their observable characteristics. To assess the impact of immigration on the wage distribution in Austria I therefore follow the approach developed by Dustmann, Frattini and Preston 2008.\(^3\) In a first step I derive for each year (1994 to 2005) the percentiles of the regional (35 NUTS3 regions) wage distributions of native male blue and white collar workers aged 16 to 59. These percentiles are then regressed on region and time specific shares of immigrant workers and additional controls. Formally,

\[
\ln(W_{prt}) = \alpha_{pr} + \beta_p S_{rt} + \gamma_p X_{rt} + \epsilon_{prt},
\]

where \(W_{prt}\) is the \(p\)th percentile of the wage distribution in region \(r\) at time \(t\), \(\alpha_{pr}\) is a region specific intercept, \(S_{rt}\) is region specific share of immigrant

\(^3\)Alternatively one could also apply quantile regressions to assess the impact of immigration on the distribution of wages. Notice however that quantile regressions with instrumental variables in a panel data environment - as is needed in this study - turn out to be numerically instable and therefore not used here.
workers and $X_{rt}$ are region and time specific characteristics such as average age, tenure, experience and years of schooling. $\beta$ gives the effect of immigration on each percentile of the wage distribution and is estimated using 420 observations (35 regions over 12 years).

In equation (1) individual observations are aggregated to the regional level. This aggregation eliminates the bias that occurs if e.g. immigrants’ allocation to firms is correlated with native workers’ abilities or skills. To see why consider an identification strategy where wage effects of immigration are estimated by comparing wages across firms with different shares of immigrant workers. If immigrants tend to work in firms with higher shares of low ability natives, estimates would be biased downward. Aggregation to regional levels averages out these effects. For a similar argument see Card and Rothstein (2007).

OLS estimation of equation (1) is likely to yield biased estimates of the effect of immigration on workers’ wages for several reasons. Firstly, immigrants’ allocation to certain regions may occur endogenously (see e.g Dustmann et al. (2003)). Since the inflow of immigrants into certain regions may be correlated with unobserved region specific shocks in the demand for labor - causing changes in wages and changes in immigrant inflows simultaneously - OLS estimates will be upward or downward biased. If, for example, immigrants are attracted by regions with currently high economic activity OLS estimates will be upward biased. If on the other hand declining industries supply their demand for labor by employing low wage immigrants OLS estimates will be downward biased. Instrumental variable estimation can solve this problem.
of endogenous allocation of immigrants to regions.

Following Altonji and Card (1991) and Wagner (2010) I instrument the current region specific shares of immigrants by

\[ Z_{rt} = \sum_j \frac{N^j_{r,1972-81}}{N^j_{1972-81}} \times S^j_t, \tag{2} \]

where \( N^j_{r,1972-81} \) denotes the net inflow of workers from country \( j \) within the time period 1972 to 1981 into region \( r \). In equation (2) the current share of immigrants from each country \( j \) is predicted using the historic settlement patterns from 1972 to 1981. Summing these shares over all countries of origin gives a predicted share of immigrants within a certain region at time \( t \).\(^4\) Thus, current shares of migrant workers are instrumented by immigrants’ historic settlement patterns. Numerous studies on the labor market effects of immigration apply this strategy (see e.g. Card (2001), Dustmann, Frattini and Preston (2008), or Friedberg and Hunt (1995)). The resulting first and second stage equations are given by,

\[ S_{rt} = a_0 + a_1 X_{rt} + a_2 Z_{rt} + u_{rt} \tag{3} \]

\[ \ln(W_{prt}) = \alpha_p + \beta_p S_{rt} + \gamma_p X_{rt} + \epsilon_{prt} \tag{4} \]

Secondly, region specific fixed effects that are both, correlated with the share of immigrants within the region as well as with economic outcomes of natives could imply a positive or negative spatial correlation between a region’s share of immigrants and natives’ labor market outcomes even if there is no

\(^4\)See next subsection for a motivation for this instrument.
causal effect of immigration at all. For example, areas with high population densities may offer better economic infrastructure with higher wages and lower unemployment rates for natives and attract more immigrants than rural areas. Region fixed effects control for such effects.

Finally, OLS estimates of equation (1) could also be biased due to native residents’ reaction to increased immigration. If (higher wage earning) natives respond to increasing (low wage) immigration by moving to areas with lower immigrant shares, OLS will result in upward biased estimates. To address this issue I present consistency tests that were proposed by Card (2001) and show that native outmigration is not likely to bias the results (see section 6.1).

3.1 Interpretation and Validity of the instrument

Validity of the instrumental variable strategy requires that the instrument chosen is uncorrelated with any determinant of the outcome variable other than the instrumented variable itself, i.e. the share of immigrants within each region. To fulfill this exclusion restriction the instrument may therefore not be correlated with e.g. current economic conditions.

As has been noted by Bartel (1989) immigrants tend to settle in regions where other immigrants have already settled. The main reason for this behavior is that immigrants prefer to settle in regions where they can rely on existing social networks according to their own language and culture. The instrument used here builds on this observation.

Equation (2) derives the predicted number of immigrants in period t within
each region under the assumption that the distribution of the total number of immigrants arriving at time $t$ is the same as the distribution within the baseline period. This predicted inflow is independent of current region-specific demand shocks but strongly correlated with observed immigrant inflows. Choosing a long baseline period (10 years in this case) ensures that historic shocks do not affect the prediction. The predicted share of immigrants is therefore independent of current economic conditions within regions because the prediction is entirely based on historic settlement patterns.

Since the instrument is motivated by a social network argument it is convenient to distinguish immigrants by their country of origin. If, for example, thirty percent of German immigrants arriving in the baseline period settled in Vienna, the instrument allocates thirty percent of new immigrants arriving from Germany in a given year to Vienna (Cortes (2008)).

Besides fulfilling the exclusion restriction the instrument must also be strongly correlated with observed immigration patterns. If the instrument is weak in the sense that the correlation with endogenous variable is low, instrumental variable estimates may be biased in small samples (Angrist and Pischke (2009)). It is therefore important to verify the strength of the instrument used. Figure 1 shows observed versus predicted shares of immigrants by region according to the equation (2). As shown in the graph the instrument is highly correlated with observed changes in immigrant shares. All regressions presented below show first stage F-statistics to verify the strength of the instrument.5

5Stock et al. (2002) suggest to use instruments only if the first stage F-statistic exceeds 10.
4 Data and construction of main variables

To analyze the impact of immigration on natives’ labor market outcomes I use four different administrative data sources covering all non self-employed workers in Austria. Detailed wage information is obtained from pay-slips ("Lohnzettel") covering the years 1994 to 2005. Here the total gross earnings for all non-self employed workers in Austria are collected. The main virtue of this data source is that the wage information is not top coded which allows me to derive the precise wage distribution for each region. The wage data are combined with Austrian social security data (ASSD) that allow me to observe workers’ entire labor market history back to 1972. (For a detailed description see Zweimüller et al. (2009).) From these I derive worker specific labor market characteristics such as labor market experience and the current employment tenure. Additionally, data from the Austrian Public Employment Service (AMS) provide information on migration background, unemployment benefits and education for the time period 1987 to 1998. Finally data from the Labor Market Database (Arbeitsmarktdatenbank - AMDB) provide information on workers’ migration background from 1997 onward.

Figure 2 depicts the change in immigrants’ share of the workforce separately for each decile of the wage distribution for two different years, 1994 and 2005. Two facts are noteworthy here. The graph confirms that immigrants tend to be low wage workers. We see that this is less true as we move from 1994 to 2005 suggesting that low wage immigration decreases relatively to mean and high wage immigration.

6Excluded are civil servants, self-employed and farmers
5 Results

Table 1 shows estimation results for blue and white collar workers in columns 1 and 2. Results for white collar workers reveal some positive effects at the 7th decile but no significant effects at the other parts of the distribution. These estimates imply a pattern similar to that observed for blue collar workers. It appears that immigration has a small negative effect at the second decile while it increasingly raises wages as we move to higher deciles. This implies that the overall mean effect of immigration is close to zero. These findings are consistent with results obtained by Dustmann, Frattini and Preston (2008) for the UK.\(^7\)

It may be argued that the overall degree of immigration is not the relevant measure to consider since workers’ wages are affected mostly by the number of immigrants with whom they directly compete with in the labor market.\(^8\) Instead of measuring the degree of immigration at the regional level only, I therefore derive two alternative measures of immigration intensity and repeat the above analysis. The first measure derives the region and decile specific share of immigrants and the second includes also those immigrants from lower deciles.\(^9\) Results are presented in columns 3 (4) and 5 (6) in table 1 for blue (white) collar workers. As expected the estimates imply stronger negative effects for some workers but the overall picture remains the same. Under this

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\(^7\)They actually find even positive effects of immigration on mean wages.

\(^8\)Notice however that this argument ignores any potential positive effects of immigration on workers’ wages stemming from complementarities from immigration at all other deciles.

\(^9\)Including immigrants from lower deciles may be important if immigrants are paid less than natives for the same jobs, especially if downgrading occurs upon arrival (see e.g. Manacorda et al. (2006) or Dustmann, Frattini and Preston (2008)).
more restrictive definition of immigrant shares, the effect of a one percentage point increase in immigrant shares results in approximately 0.8, 0.6 and 0.3 percent wage loss for blue collar workers at the first, second and third decile. Contrasting the previous results I now also find significantly positive effects for blue collar workers at the upper end of the wage distribution.

For white collar workers, all measures of immigration intensity yield similar results.

It appears that under the more restrictive definition of immigrant shares blue and white collar workers at the low end of the wage distribution experience some wage losses from immigration while high income blue and above median white collar workers gain from immigration.

A convenient interpretation of these findings is shown in figure 3 (4). The graph shows the results derived in column 5 (6) of table 1 ("competition effect") together with the difference between the overall effect in column 1 (2) and the competition effect. The latter is labeled the "complementarity effect". As the graph shows, those workers who experience strong negative competition effects also gain most from the complementarity effect. Thus, most of the adverse effects implied by direct competition between natives and foreigners is offset by complementarities.

6 Robustness and consistency

Consistency of the estimates presented above requires that native workers do not react to immigration by moving to other areas. I therefore perform
a consistency test suggested by Card (2001). Consistency of the results also requires that the overall composition of the workforce does not change in response to immigration. Negative as well as positive effects of immigration on natives’ wages could be driven by natives dropping out of employment. If e.g. immigration drives low educated (or low ability) natives out of employment, observed positive wage effects at higher deciles may simply result from a change in the composition of workers observed in employment. Negative wage effects of immigration could be understated for the same reason. If low ability workers within each decile drop out of employment as a consequence of increased immigration, the wage effects underestimate the true negative effects of immigration. The second subsection deals with this issue by analyzing labor market transition rates for native workers within each decile of the wage distribution.

6.1 Natives’ response to immigrant inflows

The identification strategy applied here relies on the assumption that native workers do not react to increasing immigration by moving out of certain regions. To assess whether this assumption holds I follow Card (2001) and regress native workers’ outflow rates on immigrant workers inflow rates and a set of control variables. Native workers’ response to immigrant inflows

\[10\] If a worker is observed as working in a different region from one year to the next, I code this as an outflow. Transitions of workers to other labor market states (unemployment, out of labor force or retirement) are not considered as outflows.
are derived by

\[ O^N_{rt} = X_{rt} \beta + \gamma S_{rt} + \rho_r + \tau_t + \epsilon, \]  

where \( O^N \) denotes native workers outflow rate, \( X \) captures region characteristics (mean age, tenure, experience and wage), \( S_{rt} \) denotes immigrant workers inflow rate into region \( r \) at time \( t \) and \( \rho \) and \( \tau \) denote region and time dummy variables.

Table 2 shows OLS and IV estimation results for native blue and white workers in different deciles of the wage distribution. Immigration does not lead to increasing outmigration at any decile. For workers at the lower end of the wage distribution - for blue collar workers at the second to fourth decile and white collar workers at the second and third decile - immigration is associated with a modest decrease in outmigration rates.\(^{11}\)

### 6.2 Labor force participation effects

As argued above, consistency of the estimation strategy requires that the overall composition of the workforce does not change in response to immigration. To assess the effect of immigration on the overall workforce composition within regions, I therefore derive for each region native workers’ transition rates into and out of employment. These transition rates are then related to the share of immigrants entering the region in a given year.

Table 3 shows estimation results for natives’ employment to unemployment

\(^{11}\)For e.g. blue collar workers at the second decile a one percentage point increase in the share of foreign workers is associated with a 0.06% decrease in outmigration.
(ETU) and unemployment to employment (UTE) transitions separately for blue (columns 1 and 2) and white collar workers (columns 3 and 4). With exception of UTE transitions of white collar workers at the second, seventh and eighth decile and ETU transition for blue collar workers at the eighth percentile I do not find adverse labor force participation effects in response to increased immigration. These effects appear to be small in size or only weakly significant. Results obtained in tables 1 are therefore not likely to be driven by labor force composition effects.

7 Conclusion

I assess the impact of region specific immigrant shares along the distribution of wages in Austria over a time period of 12 years. My findings indicate that there are small but insignificantly negative wage effects of immigration for blue and white collar workers at the lower end of the income distribution. I find positive income effects for high income blue and some white collar workers. All effects found here are small in size and, with one exception, not significant.

Using more restrictive measures of immigration intensity as an indication of the exposure to immigration results in stronger adverse effects for low income earners, especially for blue collar workers. The estimated gains for higher income earners remain more or less unchanged. It has to be stated, that these measures, while possibly being more accurate measures of the degree

\[12\text{Wage percentiles for unemployment to employment transitions are defined by considering the last wage earned by the unemployed worker. Workers who are unemployed for more than 2 years are not considered.} \]
of direct labor market competition between natives and immigrants, neglect potential gains from immigration via complementarities between different skill groups. These latter estimates do not represent the overall effect of immigration on wages at a given decile but the wage impact that results from the direct competition with immigrant workers only.

My results imply that potentially negative effects induced by increased immigration are offset by complementarities in the production process stemming from immigration of workers with different skills. As a result the overall wage effects are close to zero or even positive. These results are in line with results obtained by Dustmann, Frattini and Preston (2008) for the UK labor market.

Immigration therefore appears to have only small effects on natives’ wages even though natives are affected differently, depending on their position in the wage distribution and on the type of work. Immigration of low skilled labor may adversely affect low income earners while high skilled immigration raises wages at higher income levels. On the other hand, low income earners profit from immigration of higher skilled workers due to complementarities in the production process.
References


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Borjas, G.J. (2003), ‘The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market*’, Quarterly journal of Economics 118(4), 1335–1374.


## 8 Tables and Graphs

Table 1: Effect of immigration on different deciles of workers wage distribution by different measures of migrant shares.

<table>
<thead>
<tr>
<th></th>
<th>Overall Blue</th>
<th>Overall White</th>
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<th>Own Percentile White</th>
<th>Own plus lower Blue</th>
<th>Own plus lower White</th>
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<td>-0.3878</td>
<td>-0.7463**</td>
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|       | YD yes       | yes           | yes                  | yes                  | yes                  | yes                  |
|       | RD yes       | yes           | yes                  | yes                  | yes                  | yes                  |
|       | Other yes    | yes           | yes                  | yes                  | yes                  | yes                  |
|       | FStat 13.65  | 13.65         | 44.43                | 32.11                | 60.84                | 49.50                |

Notes: Estimated effects of the region specific immigrant shares on different deciles of native blue collar workers. Standard errors in parentheses. ***, ** and * indicate significance at the 1, 5 and 10% level respectively. Specifications with “other” control for region specific means in age (squared), tenure (squared), experience (squared) and years of schooling.
Table 2: Effect of immigration on native workers’ outflow rates by wage category.

<table>
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<th>blue IV</th>
<th>white OLS</th>
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Notes: Estimated coefficient of the impact of immigration on native blue workers outflow rates within each wage category. Wage categories are defined by deciles of native workers’ wage distribution. Additional controls: age (squared), tenure (squared), experience (squared), years of schooling, region and time dummies. Robust standard errors in parenthesis. ***, ** and * indicate significance at the 1, 5 and 10% level respectively.
Table 3: Effect of immigration on native blue collar workers’ labor market transition rates.

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Notes: Estimated coefficient of the impact of immigration on native blue collar workers’ labor market transition rates within each wage category. Wage categories are defined by deciles of native workers’ wage distribution. Additional controls: age (squared), tenure(squared), experience(squared), years of schooling, region and time dummies. Robust standard errors in parenthesis. ***, ** and * indicate significance at the 1, 5 and 10% level respectively.
Figure 1: Observed and predicted year to year change in the region specific share of migrant workers.

Figure 2: Share of immigrants by wage decile
Figure 3: Estimated competition and complementarity effects (blue collar).

Figure 4: Estimated competition and complementarity effects (white collar).