Immigration, Working Conditions, and Health

Osea Giuntella
University of Oxford, IZA

Fabrizio Mazzonna*
University of Lugano, MEA

Draft

*Please do not quote without authorization

November 14, 2013

Abstract

This paper studies the effects of immigration on health. We combine information on individual characteristics from the German Socio-Economic Panel with detailed local labor market characteristics for the period 1984 to 2010. We exploit the longitudinal component of the data to analyze how immigration affects the health of both immigrant and natives over time. Immigrants are shown to be healthier than natives upon their arrival ("healthy immigrant effect"), but their health deteriorates over time spent in Germany. We show that the convergence in health is heterogeneous across immigrants and faster among those working in more physically demanding jobs. Immigrants are significantly more likely to work in these types of jobs and to be exposed to job-related health risks for longer periods. In the light of these facts, we investigate whether changes in the spatial concentration of immigrants affect natives’ and previous immigrants’ health by changing the allocation of working condition in the resident population. Our results suggest that immigration reduces residents’ likelihood to work in physically demanding jobs increasing the likelihood of reporting good health and decreasing the risk of work-related injury in the resident population. These effects are concentrated in blue-collar occupations and larger among previous cohorts of immigrants.

*Giuntella: Blavatnik School of Government, University of Oxford, 10 Merton Street, OX14JJ, Oxford, Oxfordshire, UK. Email: osea.giuntella@bsg.ox.ac.uk. Mazzonna: University of Lugano. Department of Economics, via Buffi 13, CH-6904, Lugano. Email: fabrizio.mazzonna@usi.ch. We thank Rafael Gruber for precious research assistance.
1 Introduction

Several studies analyzed the effects of immigration on wages, employment and prices (Card, 1990; Hunt, 1992; Friedberg and Hunt, 1995; Borjas, 1995; Carrington and Lima, 1996; Borjas et al., 2011, 2008; Ottaviano and Peri, 2012), but little is known about the possible effects on other working conditions that are known to affect health. A separate strand of literature provides evidence of the existence of a “healthy immigrant effect”. Immigrants are healthier than their population of origin and then natives upon their arrival, but their health deteriorates with time spent in the host country. These striking facts are observed across several countries and different metrics of health (Antecol and Bedard, 2006; Chiswick et al., 2008). However, the mechanisms underlying these health trajectories are not fully understood. This paper contributes to both set of studies by investigating how the sorting of immigrants across jobs affects their health trajectories and in turn the health of natives and previous immigrant cohorts.

Previous work focused on selection, behaviors and return migration as possible factors underlying the convergence observed in immigrants’ health (Giuntella, 2013; Antecol and Bedard, 2006; Chiswick et al., 2008; Jasso et al., 2004). There is evidence that immigrants are more likely to work in riskier occupations, have worse schedules and more generally worse working conditions (Orrenius and Zavodny, 2012, 2009; Giuntella, 2012). A growing literature analyzing the relationship between occupation and health suggests that physical requirements and environmental conditions affect the aging profile with negative effects on health (Case and Deaton, 2005; Fletcher and Sindelar, 2009; Fletcher et al., 2011; Ravesteijn et al., 2013). In the light of these findings, we hypothesize that the sorting of immigrants in occupation with higher physical requirements and worse environmental conditions contributes to explain the observed deterioration in the health of immigrants.

Similarly to Akay et al. (2012) who analyze the effect of immigration on individual well being we focus on Germany, a country characterized by a large and diverse immigrant population. We exploit the richness of the German Socio-Economic Panel (GSOEP) which allows to analyze the health trajectories of a representative sample of both natives and immigrants in Germany. The GSOEP contains information on self-reported and doctor-assessed health conditions as well as a large set of socio-demographic characteristics. In addition, it includes occupational titles that can be used to classify occupations based on the total burden or physical intensity associated with relative working conditions.

We document that regardless of their arrival cohort, immigrants are healthier than German-born upon arrival, but their health rapidly converges to the health of natives. While the rate of convergence depends on the health outcome considered and on the immigration
cohort, the overall trend is uniform across cohorts, and independently of the health metric considered. However, the convergence is heterogeneous across immigrants and faster among immigrants working in more physically demanding jobs. We show that immigrants are more likely to be in blue-collar jobs and to be exposed to work-related health risks for longer periods.

These facts can be explained by a standard Grossman (1972) health capital model with low-skilled individuals more willing to accept risky occupations trading off health for higher lifetime earnings (Case and Deaton, 2005; Grossman, 1972). In our case, as suggested by Orrenius and Zavodny (2009) immigrants may be more willing than natives to trade off higher wages for worse conditions. Furthermore, as immigrants appear to be positively selected on health with respect to their population of origin, their incentives to trade-off money for health capital are even larger.

Having shown important differences in the likelihood of immigrants to work in riskier occupations, we turn to investigate how immigration affects the allocation of working conditions and the health trajectories of both natives and immigrants in Germany. Merging the GSOEP with local labor market characteristics allows us to analyze how changes in the spatial concentration of immigrants over time affects the distribution of jobs and health risk in the resident population. Controlling for local labor market fixed effects and a set of time varying labor market characteristics, we are able to account for the omitted variable bias associated with permanent local area characteristics or correlated with important time-varying factors (GDP, unemployment etc.).

We find that a higher immigration rate both decreases the likelihood of working in physically demanding jobs and increases the likelihood of reporting better health outcomes. The effects are robust to the inclusion of individual fixed effects which allow to analyze how changes in the individual exposure to immigrants affected his working conditions and health over time. Our results show larger effects on previous cohorts of immigrants. Consistently with our hypothesis the positive effects are concentrated in blue-collars. At the same time and consistently with previous studies we find no evidence of significant effects on wages and employment. Our results are robust to alternative model specifications and estimation methods.

We argue that differences in the initial endowments and composition of capital (health, human, and financial endowments) between immigrant and natives can explain the reallocation of tasks in the population and the positive effects of immigration on health outcomes. Both the lack of detrimental effects on employment and wages, and the reallocation of working conditions can be explained by the complementarity of tasks in the production function (Peri and Sparber, 2009; D’Amuri and Peri, 2010).
Our contribution is twofold. First, we shed light on the mechanisms affecting immigrants’ health convergence by analyzing the role of occupations. Secondly, to the best of our knowledge this is the first paper studying the effects of immigration on working conditions and health outcomes.

The paper is organized as follows. Section 2 presents the data. In Section 3, we document immigrant-native differences in health capital and illustrate the role of occupation in affecting the convergence over time. Section 4 discusses the effects of immigration on the health of resident population and the role of occupational sorting. Concluding remarks are reported in Section 5.

2 Data

Our main data are drawn from the German Socio-Economic Panel dataset (GSOEP). The GSOEP is a longitudinal panel dataset that contains information on a rich set of individual socio-economic characteristics. This annual household based study started in 1984 and includes annual information on about 12,000 households, and more than 20,000 individuals. Annually, each household member above the age of 16 is asked questions on a broad range of socio-economic indicators. In addition, the head of the household answers a household questionnaire collecting information on household income, housing, and children below the age of 16. The panel is unbalanced as some respondents enter the sample after 1984 and other left the sample before 2010. The GSOEP oversamples immigrants and contains several questions on both health outcomes and job characteristics, making it an ideal source to investigate the relationship between immigration, working conditions and health of both natives and immigrants.

In particular, the GSOEP provides information on self-reported general health status and more objective health metrics, though these health measures have not been included in every wave. We focus on four different health outcomes. Self-rated health status is used to construct an indicator for good health. As standard in surveys, respondents are asked to rate their general health according to five possible categories (excellent, very good, good, fair, poor). To facilitate the interpretation of the results the variable is recoded as a dummy variable equal to 1 for those that report at least good health. We also consider satisfaction with health. In this case, respondents are asked to rate their satisfaction on a 0-10 scale. Finally, we consider two alternative metrics that are less likely to suffer from self-reporting bias: a dummy variable equal to 1 for those reporting a handicap (impediment in carrying out day-to-day activities) due to poor health\(^1\), and an indicator equal to 1 for those reporting

\(^1\)since handicap is asked only up to 2001, it will be excluded in the second part of the paper where we
a doctor-assessed *disability* greater than 30%.

The GSOEP includes occupational titles that are coded into the International Standard Classification of Occupations (OECD, ISCO-88) at the 4-digit level. Using the ISCO classification and the General Index for Job Demands in Occupations (Kroll, 2011), we constructed a 1-10 metric of the physical intensity (*physical burden*) associated with a given occupational title. Furthermore, we can classify workers in major occupations (1-digit) and identify blue and white collars using the standard OECD classifications.

Using the information on the geographical residence of the individual we merged individual-level information with data on local labor market characteristics drawn from the INKAR dataset at the level of German regional policy regions (ROR). Regional policy regions are defined based on their economic inter-linkages by the Federal Office for Building and Regional Planning. There are 97 regional policy areas. The information on detailed geographical residence allows us to control persistent differences across labor markets. Our main variable of interest is the percentage of immigrants in the total resident population in a ROR. From the INKAR dataset we also draw information on employment rate, GDP per capita, and gross value added per worker. As this dataset is available only for the period 1996-2010, we restrict the analysis of the effects of immigration (Section 4) to this time period.

We report summary statistics for the main variables used in Table 1. Columns 1-4 report means and standard deviation by immigrant status for the sample used in this section. When considering the unconditional mean differences immigrants are less likely to report doctor-assessed disability. However, if anything, Germans report better health status, higher health satisfaction, lower likelihood of reporting a handicap due to poor health. These differences partially reflect the socio-economic differences between the two populations. Immigrants are less educated and have lower wages. They are also more than twice as likely than Germans to work in blue-collar occupations and on average work 2.6 years more in these occupations in our sample. 60% of the immigrants arrived before the 80s, with the remaining 40% almost equally divided between the 80s and post80s cohorts. We divide immigrants in these three main cohorts of arrival as these roughly correspond to three main waves of immigration identified by previous scholars\(^2\).

---

\(^2\)Preliminary analysis conducted to identify the most important waves of immigration in Germany had also shown that this waves are also strongly connected with the most important nationality groups present in the data (see Table 10, in the Appendix). In particular, the first wave of migration considered, immigrant arrived before the '80s, is composed mainly by immigrants from Turkey, ex-Jugoslavia and other Mediterranean countries (Italy, Greece and Spain). The first wave was mostly composed by low-skilled individuals employed in blue-collar occupations. The second and third waves are instead more heterogeneous As a matter of the fact, the largest share of immigrants came from Eastern Europe and Russia. On average more
Column 5-8 show the same statistics for the sample analyzed in Section 4, where we investigate the effects of immigration on health. We restrict the analysis to individuals aged between 25 and 59 to avoid changes in perceived or actual health after retirement (Mazzonna and Peracchi, 2012). Furthermore, this restriction allows us to ignore changes in the legal retirement age over the years considered in the sample. While the summary statistics differ in the two samples because of the imposed age restrictions, we observe similar differences between immigrants and Germans.

3 Stylized Facts: Immigrant Health and Working Conditions

3.1 Healthy Immigrant Effect

Table 2 illustrates health differences between immigrants and natives. We account for cohort differences in health at arrival and analyze their health trajectories by including a quadratic in years since migration (YSM). We condition for standard socio-demographic controls, namely dummies for age, marital status, educational dummies (3 groups), regional fixed effects (NUTS2\(^3\)), and survey year fixed effects. Column 1, 3 and 5 estimate random effects models to allow us the inclusion of time-invariant characteristics (e.g., immigrant cohort), while columns 2, 3 and 6 use individual fixed effects models. Remarkably, the results are very similar across the two estimation models considered. Standard errors are clustered at the individual level. We estimated the models separately by gender.

Panel A focuses on men. Regardless of their arrival cohort, immigrants are found to be healthier than German-born upon arrival, once we control for socio-demographic characteristics. However, their health converges to the health status of natives over time. Column 1 reports these trends when examining health satisfaction. Immigrants are more likely to report higher health satisfaction (about 10% difference with respect to the mean of the dependent variable), however with time spent in Germany the gap shrinks by around 10% each year with full convergence occurring in about 15 years for the 1980 cohort, and about 10 for previous and more recent immigrants. Column 2 shows that the differences in the coefficient of YSM between random and fixed effects models are not significant.

recent immigrants show higher educational attainment.

\(^3\)The Nomenclature of Territorial Units for Statistics (NUTS) is a geocode standard developed and regulated by the European Union. NUTS2 is the lowest level of geographical detail available for the entire period in the GSOEP data (1984-2010). While we do have information on regional policy regions (ROR), these were redefined in 1996 and, therefore, can only be used for pre/post 1996 analysis ignoring the readjustment of ROR (Knies and Spiess, 2007).
Columns 3 and 4 report the differences in the likelihood of reporting very good and good health. Upon arrival immigrants have an advantage ranging between 8% (90s and later) and 14% (80s) with respect to the mean of the dependent variable and depending on the arrival cohort. This advantage reduces by around 1% each year (10% of the initial advantage). Columns 5 and 6 show analogously that immigrants are less likely to report a handicap due to poor health, but the coefficient shrinks with time spent in Germany. Similarly, immigrants are 40% less likely to be assessed with a reduced capacity to work greater than 30% (columns 7 and 8), but their advantage deteriorates by 2% every year.

In Panel B, we report the same estimates for women. We find that the health advantage upon arrival is similar among women when analyzing more subjective health measures (health satisfaction and good health). However, when focusing on handicap and disability status both the initial advantage and the following convergence are less marked. This suggests that women might be less selected on health at the time of migration.4

The estimates presented in Table 2 pooled immigrants and Germans to estimate the health advantage of different immigrant cohorts and the health trajectories following migration. One could argue that the coefficient on YSM might also reflect a different rate of depreciation of the immigrants’ health with respect to natives. However, when we implement the same estimates only on the immigrant sub-sample the results are substantially unchanged.

3.2 The role of occupation

One potential explanation for the deterioration of immigrant health over time spent in Germany is that immigrants who arrive with better health capital, but lower financial capital self-select into jobs demanding higher physical intensity to increase their salaries through compensating wage-differentials.

Table 3 illustrates immigrant native differences in the likelihood of working in physically demanding jobs. Column 1 considers our index of physical burden (1-10), while in column 2 we use as a dependent variable a dummy equal to 1 if the worker is in a blue-collar occupation and in column 3 we consider the number of years worked in a blue-collar jobs. Overall, immigrants are more likely to work in jobs characterized by higher physical intensity independently of the metric considered. In particular, being an immigrant is associated with an increase in the index of physical intensity of the job ranging between 20% and 30%.

4To assess this hypothesis we examined separately single versus married women and found significant differences between the two groups. In particular, there was no evidence of an advantage when considering married women who are more likely to have migrated for family rather than economic reasons and, therefore, less selected.
depending on the cohort considered. The fact that more recent cohort of immigrants report a smaller probability to work in physical demanding occupations than immigrants from previous waves can be partially explained by the higher presence of skilled immigrants from East Europe and Russia (see Section 2).

As already observed in Table 1 immigrants are more than twice as likely to work in high physically demanding jobs, and depending on their cohort of entry they work between one and two years more in blue-collar jobs than natives in the same age range. This is true also for women. However, looking at the number of observations, it is evident that this is a selected sample, given the low women’s labor force participation.

Ravesteijn et al. (2013) using the Finnish Job Exposure Matrix (FINJEM) to map occupational titles in the GSOEP into occupational stressors confirm previous findings of a negative relationship between physically intensive tasks and health status (Case and Deaton, 2005; Fletcher et al., 2011). We find similar results using our metric of physical burden and studying the effect of occupation on health status, health satisfaction, and doctor-assessed disability. As expected, the coefficient on working in physical demanding jobs is associated with a better health status, reflecting the fact that individuals in better health self-select in physically demanding jobs, because of compensating wage differentials. On the other hand, more years spent into physical demanding jobs are associated with a lower health status.\(^5\) Having assessed the larger presence of immigrants in these jobs, a natural question to ask is whether the observed deterioration of immigrants’ health is partially explained by occupational sorting. Table 4 shows that when controlling on previous year type of job, the coefficient of health deterioration is always larger among those who were employed in high physically demanding jobs. In particular, the yearly rate of health depreciation associated with time spent in Germany is significantly higher among individuals in blue collar occupations.

4 Effects of Immigration on Health

In the light of the facts documented in the previous section, it is natural to ask whether immigration affected the distribution of jobs among natives and their working conditions. In particular. in this section we investigate whether changes in the spatial concentration of immigrants affect the likelihood of German-born population on working in physically demanding jobs and consequently their health. Figure 2 shows a negative association between

\(^5\)In particular, we find that one additional year spent in physical demanding occupation is associated with an increase of almost 1% of the probability of being in bad health or reporting handicap (with respect to the mean) and 3% of being disable. Results are available upon request.
immigration and the average physical burden of the respondents’ job at the ROR level. At the same time, in Figure 1, we observe a positive relationship between immigration and the share of individuals reporting good health in a ROR. These associations are in line with our conjecture that immigration, by increasing the supply of workers willing to trade-off health for higher life-time earnings, might induce a reallocation of tasks in the resident population and in turn affect their health. However, these unconditional correlations might simply reflect composition effects and, more generally, confounding factors that might be correlated with both immigrant location choices, working conditions and health outcomes (e.g., local economic environment). We now turn to address these important identification issues.

4.1 Empirical Specification

The empirical strategy implemented in this paper mainly exploits the time and geographical variation of immigration rate at local level (ROR) to identify the effect of immigration on the health of the resident population. In our preferred specification we model health according to the following static fixed effect linear model:

\[
H^*_{irt} = \alpha_i + \beta IR_{t-1} + X'_i \gamma + Z'_r \lambda + \delta_r + \theta_t + \epsilon_{irt},
\]

where \(H^*_{irt}\) is the latent health status of individual \(i\) at time \(t\) in ROR \(r\); \(\alpha_i\) is a time-invariant individual fixed effect, \(IR_{t-1}\) is the immigration rate in ROR \(r\) in the previous year, \(X\) is a vector of time varying individual characteristics (such as age, education, marital status and number of children), \(Z'_r\) is a vector of time-varying labour market and economic conditions, \(\delta_r\) and \(\theta_t\) are ROR and years fixed effects, and \(\epsilon_{irt}\) captures the residual variation in health status. The preferred estimation method for this model is the within estimator which allows the unobserved time-invariant individual heterogeneity \(\alpha_i\) and our regressors to be correlated.

A number of identification issues may arise in the estimation of the parameters in equation (1) and in particular of the parameter of interest, \(\beta\), the effect of immigration rate on health. Firstly, since \(H^*_{irt}\) is not directly observed, we use three different health indicators: self reported good health, health satisfaction and disability status. The first two measures are self-assessed, while the third is assessed by a doctor. None of these indicators accurately measures the true health status. However, assuming that the noise in these measurements is not systematically related with our regressors, it should not bias our estimates, but at most affect the standard errors. A relevant issue concerns the discrete nature these health indicators. In particular, good health and disability are binary, while health satisfaction is measured on a scale from 0 to 10. Since we are interested only in estimating the causal effect of immigration averaged across the population, the linear model might represent a good
approximation of the effect of interest even if some predicted values might be outside the unit interval. However, as robustness for the two binary variables (health good and disability), we also estimate equation (1) using a correlated random effect probit estimator in which we allow a restricted dependence between $\alpha_i$ and the regressors in $X'_{irt}$ (see Wooldridge (2002)). This corresponds to a random-effects model augmented with means of time-variant individual characteristics.

Other important identification issues regard the model specification. First of all, the model proposed in equation (1) is static. If the true model is instead dynamic, allowing health to depend on its lagged values, the within estimator might produce a bias estimates of $\beta$ because $IR_{rt-1}$ is correlated with the composite residual terms $\epsilon_{irt}$. As stressed by Ravesteijn et al. (2013), the problem cannot be solved by simply adding a lagged value of the dependent variable among the regressors of equation (1) because the residual from the fixed effect estimator is necessarily correlated with lagged dependent variable. However, following Angrist and Pischke (2008) we can estimate the bounds of $\beta$ using both the fixed effect estimator on the static model and OLS of the lagged dependent model. Given the bracketing properties of these two estimators we can check the robustness of our results to alternative identification assumptions. It is worth noting that estimating equation (1) by including both fixed-region and fixed-individual effects would essentially correspond to estimating the impact of immigration only on individuals who actually change their region of residence. To give power to our estimation strategy, as in Akay et al. (2012), we also show the results using a linear correlated random effect model (quasi fixed effect) in which, as for the probit version discussed before, we augment the model with means of time-variant individual characteristics.

Another issue deriving from the model specification in (1) is the timing of the effect of immigration on health. There is no reason to think that immigration should have immediate effects on residents’ health. On the contrary, we hypothesize that immigration affects health through its impact on labor market and in particular on working conditions. For this reason, similarly to Fletcher et al. (2011) and Ravesteijn et al. (2013) —who used the lagged values of occupation on health to predict the effect of working conditions— we used lagged values of immigration rate to predict its effects on health. To give power to our estimation strategy, we show results using only immigration rate at time $t-1$, but, as robustness check, we also consider past values of immigration rate up to $t-3$.

Finally, one could argue that the large number of controls for labor market and economic condition at ROR level might not be sufficient to account for all the time-varying unobservables (at ROR level) that might drive the relationship between immigration rate and health. Although we think that this is unlikely, in some specifications, we additionally control for
ROR specific time trends and as robustness checks (see Section 4.3) we implement placebo tests on forward value of the immigration rate (up to $t + 2$)

### 4.2 Results

Table 5 and 6 illustrate the effect of immigration on health for men and women aged between 25 and 59 years old residing in Germany. Respectively, panel A, B, and C examine the effect of immigration on the likelihood of reporting good health, on health satisfaction (1-10), and on the likelihood that a doctor assessed a level of disability above 30%. As explained in Section 4.1, we present the results using three different methodologies: OLS with lagged dependent variable, individual quasi-fixed effects and individual fixed effects. For each of these estimation strategies we report two main models. Model A controls for a set of individual socio-demographic controls (a quadratic in age, gender, a dummy for East Germany, education, marital status, the logarithm of household size), ROR fixed effects, survey year fixed effects, and a set of time-varying characteristics at the ROR level (gross value added, GDP per capita, employment rate, the logarithm of total population). Model B adds ROR-specific time trends.

In Panel A, we show that immigration is positively associated with the likelihood of reporting good health (columns 1-6). The point-estimates of the different models are non-significantly different. We therefore focus on our preferred specification using individual fixed effects (column 3-4). The effects are moderate but significant with one standard deviation increase in the immigration rate (about 4.5 percentage points) increasing the share of individuals reporting good health by about 5% with respect to the mean of the dependent variable (0.51, column 3). The coefficient is slightly lower but not significantly different when including ROR-specific time trends (column 4). The estimates are substantially unchanged when restricting the sample to natives. Consistently with the idea that immigrants (and in particular previous cohorts) are those who were more likely to be in risky jobs and therefore more likely to be affected by immigration, the point-estimate is larger when restricting the sample to immigates. However, the coefficient is not precisely estimated, due to the limited number of observations.

The effect is also positive when considering health satisfaction (Panel B). Using fixed effects the effect is again larger and statistically significant for immigrants with one standard deviation increase in the immigration rate raising health satisfaction by 4% with respect to the average health satisfaction (6.68). Though not significantly different from zero when using fixed effects, the coefficients on the overall sample and the natives are more precisely estimated when using a quasi-fixed effects model.
Interestingly, when using a more objective metric of health looking at disability status (Panel C), as assessed by a physician the effect of immigration is slightly larger with one standard deviation increase in immigration reducing by 10% the risk of disability among natives and by 30% among immigrants. However, the latter estimate is extremely sensitive to the addition of ROR-specific time trends.

On the contrary, we find no significant effects on women (see Table 6). This can be in great part explained by their lower likelihood of being employed in blue-collar and physical demanding jobs and more generally by their lower labor force participation. Remarkably, in the next section, we find evidence of a marginally significant reduction in the risk of disability when focusing on blue-collar women (Panel C, Table 7).

4.2.1 Effects of Immigration by Occupational Type

In Section 2 we showed that immigrants are more likely to work in riskier jobs (see Table 3). At the same time, we confirmed previous research finding, namely that worse working conditions and more physically demanding jobs negatively affect health (see Table 4). A natural conjecture is that immigration might affect both the allocation of tasks and indirectly the health of resident population. Furthermore, one could expect the effects to be larger when focusing on individuals that are more likely to work in riskier jobs.

In Table 7, we examine the heterogeneity of the effect of immigration on health across individuals working in different occupations. In particular we compare blue and white collars. Consistently with our prior discussion and regardless of the health metric considered, the point estimate is larger when focusing on blue-collars (column 3), while not significantly different from zero when analyzing white-collar workers (column 2). In particular, we find that one standard deviation increase in the immigration rate increases the likelihood of reporting good health by 8% (column 3, Panel A) and doctor-assessed disability by 19% (column 3, Panel C) among blue collars. The effect on health satisfaction (Panel B) is not precisely estimated for both white and blue collars, but we still find a larger point estimate for the latter group. As mentioned above, while we do not find evidence of significant differences when analyzing women’s health status and health satisfaction, there is a large and significant effect on the likelihood of doctor-assessed disability among blue-collar women. The blue-white collars differences in the effect of immigration on health outcomes are magnified when focusing on immigrants, though less precisely estimated due to the lower number of observations.

6 Alternatively, we classified individuals according to the physical burden measure. Although the results are qualitatively similar, they are rather sensitive to the threshold we choose to classify the jobs as physical demanding. We think that this is due to the fact that the affected individuals should be those at the margin, namely those that have the higher probability to move across the physical burden distribution.
To shed further light on the potential mechanism underlying our reduced-form results on the effects of immigration on health, we analyze whether immigration affected the likelihood of individuals of being employed in occupations involving different level of physical burden. Column 1 in Table 8 shows no effect of immigration on the likelihood of working in a blue-collar occupation. However, when considering a more precise measure of the physical intensity associated with a given occupation we do find evidence of immigration reducing the total burden of resident workers (Column 2). In Column 3, we show that this effect is concentrated in blue-collar occupations with one standard deviation increase in immigration decreasing by 4% the average physical burden in a given occupation. There is no evidence of significant effects on women, while again we find that effects are larger for immigrants.\(^7\)

Overall, these findings suggest that the moderate effect of immigration on the health of resident population, with larger effects on previous immigrant cohorts and blue-collar workers, can be partially explained by the re-allocation of more physically demanding occupations. We do not observe dramatic shifts across white, blue collar jobs, but rather changes in the degree of physical intensity of jobs undertaken by the resident population, with larger effects on those individuals at the margin, those more likely to be employed in occupations involving a high physical burden (e.g., previous cohort of immigrants).

### 4.3 Robustness checks

We tested the sensitivity of our estimates to the use of different measures of exposure to immigrants in a region, and different model specifications.

In Table 9, we estimated the effect of immigration on resident population health using gender-specific immigration rates. Column 1, 3, and 5 reproduces the effects estimated in Table 5 and 6. Column 2, 4, and 6 use gender specific immigration rates. The idea is that these measures might better capture the actual exposure to immigrants in the labor market. Notably, the effects are consistently when using gender-specific immigration rates. The point-estimate is about double across the different health outcomes considered and independently of the gender.\(^8\)

As mentioned in Section 4.1, we verify the robustness of our assumption about the timing of the effect of immigration on health. In particular we replicate the estimates of our preferred specification (fixed effect model as in column A of Table 5), but using the immigration rate at different points in time (both past and forward values). This also allows us to implement a sort of placebo test, by looking at the effect of immigration rate at time \(t + 1\)

\(^7\)Results by immigrant status for both Table 7 and Table 8 are available upon request.

\(^8\)Table 9 reports estimates for the entire sample (Germans and immigrants). Results go in the same direction when considering Germans and immigrants separately.
and $t+2$, that should not affect the respondents’ health. It is worth noting that a different evidence would cast doubt on our estimation strategy. Table 11 shows the results of this analysis. Two are the main results that arise from this table. As expected, forward values of immigration rate does not affect respondents’ health. On the other hand, past values, up to time $t-2$ are strongly associated with respondents’ health. When considering good health and health satisfaction the contemporaneous immigration rate (at time $t$) seems to matter. In particular, both point estimates and standard errors increase. Separated estimates by immigration status show that this is effect is driven by immigrants. However, the effect of immigration at time $t$ on health among immigrants might be confounded by the "healthy immigrant effect" discussed in Section 3, namely by the fact that they are healthier than the resident population when they arrive in Germany. Finally, as already mentioned, the binary nature of the health satisfaction and good health suggests to evaluate the robustness of our results to non-linear panel data model. For this reason, we also estimate Model B as in Table 5 using a correlated random effect probit that includes the individual mean over time of some socio-demographic characteristics, among the regressors in the model. Despite the difficulty of the interpretation of the coefficients using a non-linear model, the result confirms the positive effect of immigration rate on health outcome.

5 Conclusion

This paper contributes to the literature on the effects of immigration by analyzing its impact on working conditions and health. We first shed light on the mechanisms behind the observed health trajectories following migration. Secondly, we study how the shock to labor supply induced by immigration affects health outcomes by changing the allocation of tasks and working conditions in the resident population.

Using the German Socio-Economic Panel, we show that the convergence in health is heterogeneous across immigrants and in particular that it is faster among those working in more physically demanding jobs. Immigrants are significantly more likely to work in these type of jobs and to be exposed to job-related health risks for longer periods.

In the light of these facts, we investigate whether changes in the spatial concentration of immigrants affect the likelihood of German-born population on working in physically demanding jobs and consequently their health. We find that immigration increases the likelihood of reporting good health and decreases the risk of work-related injury among natives. The effects are mostly concentrated on individuals previously working in physically demanding occupations and larger on previous cohorts of immigrants. We also find that

\footnote{Results are available upon request.}
immigration reduces the physical burden of jobs for blue-collars.

Overall, these results are consistent with the Grossman (1972) health capital model. Indeed, our findings suggest that, as they arrive in the hosting country with higher health endowments but human and financial capital, immigrants might be more willing to trade-off health for larger lifetime earnings than natives and earlier immigrants cohorts.

Our results suggest that immigration reduces work-related deterioration of health by affecting the likelihood of natives and previous immigrant cohorts of working in riskier occupations. Further investigation is needed to assess of the welfare effects of increased immigration. However, consistently with previous studies (D’Amuri and Peri, 2010) we find no evidence of detrimental effects on wages and employment. Differences in the initial endowments and composition of capital (health, human, and financial endowments) between immigrant and natives can explain the reallocation of tasks in the population. The complementarity of tasks in the production function can account for both the lack of detrimental effects on employment and wages, and the reallocation of natives and previous immigrants in jobs involving less physical burden (Peri and Sparber, 2009; D’Amuri and Peri, 2010). These labor market effects explain the positive effects of immigration on health outcomes.
References


Case, Anne, and Angus Deaton (2005) ‘Analyses in the economics of aging.’ *NBER Chapters* (7588), 185–212


Knies, Gundi, and C. Katharina Spiess (2007) ‘Regional data in the German Socio-economic Panel Study (soep).’ DIW Data Documentation


Figure 1: Immigration and Physical Burden Across German RORs

Notes - Data on immigration are drawn from the INKAR dataset (1996-2010). The average physical burden are obtained collapsing the information drawn from the GSOEP (1996-2010) at the ROR level.
Figure 2: Immigration and Health Status Across German RORs

Notes - Data on immigration are drawn from the INKAR dataset (1996-2010). Data on average health status are obtained collapsing information drawn from the GSOEP (1996-2010) at the ROR level.
Table 1: Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample 1</th>
<th></th>
<th>Sample 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>German Immigrants</td>
<td>German Immigrants</td>
<td>German Immigrants</td>
<td>Immigrants</td>
</tr>
<tr>
<td>Variable</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>Health good</td>
<td>0.598 (0.490)</td>
<td>0.569 (0.495)</td>
<td>0.563 (0.490)</td>
<td>0.536 (0.499)</td>
</tr>
<tr>
<td>Health sat.</td>
<td>7.004 (2.130)</td>
<td>6.918 (2.276)</td>
<td>6.828 (2.130)</td>
<td>6.767 (2.168)</td>
</tr>
<tr>
<td>Handicap</td>
<td>1.317 (0.564)</td>
<td>1.372 (0.607)</td>
<td>1.339 (0.564)</td>
<td>1.367 (0.595)</td>
</tr>
<tr>
<td>Disable</td>
<td>0.060 (0.238)</td>
<td>0.053 (0.233)</td>
<td>0.071 (0.238)</td>
<td>0.061 (0.241)</td>
</tr>
<tr>
<td>Age</td>
<td>37.93 (12.01)</td>
<td>39.14 (11.47)</td>
<td>42.16 (12.01)</td>
<td>42.01 (9.717)</td>
</tr>
<tr>
<td>Female</td>
<td>0.511 (0.500)</td>
<td>0.501 (0.500)</td>
<td>0.517 (0.500)</td>
<td>0.525 (0.499)</td>
</tr>
<tr>
<td>Married</td>
<td>0.570 (0.495)</td>
<td>0.757 (0.429)</td>
<td>0.654 (0.495)</td>
<td>0.811 (0.393)</td>
</tr>
<tr>
<td>HS</td>
<td>0.762 (0.426)</td>
<td>0.687 (0.464)</td>
<td>0.746 (0.426)</td>
<td>0.708 (0.454)</td>
</tr>
<tr>
<td>Employed</td>
<td>0.173 (0.378)</td>
<td>0.087 (0.282)</td>
<td>0.228 (0.378)</td>
<td>0.143 (0.348)</td>
</tr>
<tr>
<td>Blue collar</td>
<td>0.309 (0.462)</td>
<td>0.666 (0.472)</td>
<td>0.271 (0.462)</td>
<td>0.592 (0.493)</td>
</tr>
<tr>
<td>Years blue</td>
<td>1.905 (3.844)</td>
<td>4.514 (4.887)</td>
<td>2.204 (3.844)</td>
<td>5.803 (6.390)</td>
</tr>
<tr>
<td>Physical burden</td>
<td>5.264 (2.842)</td>
<td>7.321 (2.438)</td>
<td>5.027 (2.842)</td>
<td>6.976 (2.438)</td>
</tr>
<tr>
<td>Work. hours</td>
<td>39.27 (12.59)</td>
<td>37.84 (11.18)</td>
<td>39.17 (12.59)</td>
<td>36.93 (12.13)</td>
</tr>
<tr>
<td>Years since migration (YSM)</td>
<td>18.49 (9.263)</td>
<td>20.60 (10.48)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imm. pre 80s</td>
<td>0.600 (0.490)</td>
<td>0.441 (0.494)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imm. 80s</td>
<td>0.205 (0.404)</td>
<td>0.254 (0.428)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imm post 80s</td>
<td>0.195 (0.396)</td>
<td>0.305 (0.473)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N = 297,776 53,821 156,036 25,738

Notes: The number of observations reported corresponds to the sample without missing observation for health satisfaction. The other health variables (health good, handicap and disable) are not asked in all waves and then they present a smaller number of observations. However, the descriptive statistics for these smaller subsamples are in line with those reported above.
Table 2: Healthy immigrant effects by sex

### Panel A: Men

<table>
<thead>
<tr>
<th>Health sat.</th>
<th>Good Health</th>
<th>Handicap</th>
<th>Disable</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE FE</td>
<td>RE FE</td>
<td>RE FE</td>
<td>RE FE</td>
</tr>
<tr>
<td>Imm pre 80s</td>
<td>0.3189***</td>
<td>0.0537</td>
<td>-0.0670*</td>
</tr>
<tr>
<td>(0.119)</td>
<td>(0.035)</td>
<td>(0.039)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Imm 80s</td>
<td>0.4793***</td>
<td>0.0841***</td>
<td>-0.0910***</td>
</tr>
<tr>
<td>(0.101)</td>
<td>(0.027)</td>
<td>(0.031)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Imm post 80s</td>
<td>0.3278***</td>
<td>0.0424**</td>
<td>-0.0563**</td>
</tr>
<tr>
<td>(0.086)</td>
<td>(0.019)</td>
<td>(0.024)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>YSM</td>
<td>-0.0241**</td>
<td>-0.0311***</td>
<td>-0.0054***</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>YSM2</td>
<td>0.0002</td>
<td>0.0004</td>
<td>0.0001*</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

| N obs. | 157,118 | 157,118 | 119,760 | 119,760 | 62,528 | 62,528 | 139,563 | 139,563 |
| N individuals | 19,881 | 19,881 | 17,553 | 17,553 | 14,648 | 14,648 | 19,504 | 19,504 |

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, NUTS2 dummies, and time dummies. Standard errors are robust and clustered at individual level.

### Panel B: Women

<table>
<thead>
<tr>
<th>Health sat.</th>
<th>Good Health</th>
<th>Handicap</th>
<th>Disable</th>
</tr>
</thead>
<tbody>
<tr>
<td>QFE FE</td>
<td>QFE FE</td>
<td>QFE FE</td>
<td>QFE FE</td>
</tr>
<tr>
<td>Imm. pre 80s</td>
<td>0.1928*</td>
<td>0.0682**</td>
<td>-0.0094</td>
</tr>
<tr>
<td>(0.113)</td>
<td>(0.034)</td>
<td>(0.040)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Imm 80s</td>
<td>0.4985***</td>
<td>0.0936***</td>
<td>-0.0793***</td>
</tr>
<tr>
<td>(0.090)</td>
<td>(0.026)</td>
<td>(0.031)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Imm post 80s</td>
<td>0.3219***</td>
<td>0.0467**</td>
<td>-0.0362</td>
</tr>
<tr>
<td>(0.075)</td>
<td>(0.018)</td>
<td>(0.024)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>YSM</td>
<td>-0.0401***</td>
<td>-0.0455***</td>
<td>-0.0071***</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>YSM2</td>
<td>0.0006***</td>
<td>0.0006***</td>
<td>0.0001</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

| N obs. | 162,974 | 162,974 | 126,682 | 126,682 | 63,318 | 63,318 | 145,605 | 145,605 |
| N individuals | 20,000 | 20,000 | 17,828 | 17,828 | 14,648 | 14,648 | 19,663 | 19,663 |

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, NUTS2 dummies, and time dummies. Standard errors are robust and clustered at individual level.
Table 3: Immigrant occupational sorting

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th></th>
<th>Women</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Physical burden</td>
<td>Blue collar</td>
<td>Years blue</td>
<td>Physical burden</td>
</tr>
<tr>
<td>Imm. pre80s</td>
<td>1.8943***</td>
<td>0.2913***</td>
<td>1.7515***</td>
<td>1.7582***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.012)</td>
<td>(0.105)</td>
<td>(0.078)</td>
</tr>
<tr>
<td>Imm. 80s</td>
<td>1.2875***</td>
<td>0.2095***</td>
<td>1.2101***</td>
<td>1.1369***</td>
</tr>
<tr>
<td></td>
<td>(0.102)</td>
<td>(0.018)</td>
<td>(0.128)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Imm. post 80s</td>
<td>1.0810***</td>
<td>0.1543***</td>
<td>0.8315***</td>
<td>1.1529***</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.013)</td>
<td>(0.077)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>N</td>
<td>123,517</td>
<td>123,517</td>
<td>123,517</td>
<td>100,809</td>
</tr>
</tbody>
</table>

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, NUTS2 dummies, and time dummies. The model is estimated using the within estimator (fixed effects). Standard errors are robust and clustered at individual level.
Table 4: Health deterioration after arrival by (previous years) occupational group

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Women</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Health sat.</td>
<td>Health good</td>
<td>Handicap</td>
<td>Disability</td>
<td>Health sat.</td>
<td>health good</td>
<td>handicap</td>
<td>Disability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YSM</td>
<td>-0.0576</td>
<td>-0.0194***</td>
<td>0.0035</td>
<td>0.0027</td>
<td>-0.0808***</td>
<td>-0.0164***</td>
<td>0.0014</td>
<td>0.0051***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.004)</td>
<td>(0.012)</td>
<td>(0.004)</td>
<td>(0.010)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blue collar</td>
<td>0.3191**</td>
<td>-0.0110</td>
<td>-0.1498**</td>
<td>-0.0432***</td>
<td>0.2010</td>
<td>0.0872**</td>
<td>-0.0903</td>
<td>0.0165</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>(0.043)</td>
<td>(0.070)</td>
<td>(0.014)</td>
<td>(0.143)</td>
<td>(0.043)</td>
<td>(0.078)</td>
<td>(0.013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>YSM*blue collar</td>
<td>-0.0132**</td>
<td>0.0000</td>
<td>0.0078***</td>
<td>0.0021***</td>
<td>-0.0085</td>
<td>-0.0021</td>
<td>0.0059*</td>
<td>-0.0009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>17,087</td>
<td>11,207</td>
<td>7,504</td>
<td>14,428</td>
<td>11,071</td>
<td>8,120</td>
<td>4,427</td>
<td>9,684</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, NUTS2 dummies, and time dummies. The model is estimated using the within estimator (fixed effects). Standard errors are robust and clustered at individual level.
Table 5: Effect of lagged immigration rate on health, Men

<table>
<thead>
<tr>
<th></th>
<th>Panel A Good Health</th>
<th>Panel B Health satisfaction</th>
<th>Panel C Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lagged OLS FE QFE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All (N=69890)</td>
<td>A 0.005*** B 0.004*</td>
<td>A 0.006*** B 0.005***</td>
<td>A -0.001 B -0.002</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Natives (N=59932)</td>
<td>0.005** B 0.004*</td>
<td>0.006**</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Immigrants (N=9858)</td>
<td>0.002 -0.006</td>
<td>0.009 0.002</td>
<td>-0.005*</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All (N=69873)</td>
<td>0.013* 0.010</td>
<td>0.013 0.011</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Natives (N=59923)</td>
<td>0.010 0.010</td>
<td>0.006 0.008</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.008)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Immigrants (N=9850)</td>
<td>0.037 0.007</td>
<td>0.058* 0.023</td>
<td>0.006***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.031)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Panel C</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All (N=69654)</td>
<td>-0.001 -0.000</td>
<td>-0.002** -0.002***</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Natives (N=59729)</td>
<td>-0.000 -0.000</td>
<td>-0.002* -0.002**</td>
<td>-0.001*</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Immigrants (N=9825)</td>
<td>-0.005 -0.002</td>
<td>-0.006*** -0.001</td>
<td>0.006*** -0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, ROR and survey year fixed effects, and a set of variables for local economic conditions (gross value added, GDP per capita, employment rate and log of the total population). Model B adds to model A a full set of ROR specific linear trends. The first column also includes the lag value of the dependent variable and is estimated using OLS (Lagged OLS); the second column shows the result using the within estimator (FE); the third column presents results from the correlated random effect estimator (QFE) which includes the individual mean over time of demographic variables (age, education, marital status and number of children) among the regressors. Standard errors are robust and clustered at ROR level.
Table 6: Effect of lagged immigration rate on health, Women

<table>
<thead>
<tr>
<th>PANEL A</th>
<th>Good Health</th>
<th>Lagged OLS</th>
<th>FE</th>
<th>QFE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>All ((N=75119))</td>
<td>-0.002 (0.003) &amp; -0.002 (0.003) &amp; 0.002 (0.003) &amp; 0.001 (0.002) &amp; 0.001 (0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natives ((N=64150))</td>
<td>-0.002 (0.003) &amp; -0.002 (0.003) &amp; 0.001 (0.003) &amp; 0.001 (0.003) &amp; 0.002 (0.003)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immigrants ((N=10854))</td>
<td>0.006 (0.007) &amp; 0.003 (0.009) &amp; -0.003 (0.009) &amp; -0.006 (0.007) &amp; 0.003 (0.009) &amp; -0.001 (0.008)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL B</th>
<th>Health satisfaction</th>
<th>Lagged OLS</th>
<th>FE</th>
<th>QFE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>All ((N=75086))</td>
<td>0.001 (0.010) &amp; -0.001 (0.010) &amp; 0.001 (0.009) &amp; -0.004 (0.009) &amp; 0.005 (0.009) &amp; 0.002 (0.008)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natives ((N=64119))</td>
<td>0.002 (0.010) &amp; 0.002 (0.010) &amp; 0.001 (0.010) &amp; -0.002 (0.010) &amp; 0.008 (0.009) &amp; 0.005 (0.009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immigrants ((N=10852))</td>
<td>0.003 (0.026) &amp; -0.000 (0.030) &amp; -0.035 (0.027) &amp; -0.030 (0.028) &amp; -0.008 (0.026) &amp; -0.012 (0.027)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL C</th>
<th>Disability</th>
<th>Lagged OLS</th>
<th>FE</th>
<th>QFE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>All ((N=74846))</td>
<td>-0.000 (0.000) &amp; -0.000 (0.000) &amp; 0.001 (0.001) &amp; 0.000 (0.001) &amp; 0.001 (0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natives ((N=63915))</td>
<td>-0.000 (0.000) &amp; -0.000 (0.000) &amp; 0.001 (0.001) &amp; 0.000 (0.001) &amp; 0.001 (0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immigrants ((N=10818))</td>
<td>0.000 (0.001) &amp; -0.000 (0.001) &amp; 0.000 (0.002) &amp; -0.000 (0.001) &amp; 0.000 (0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, ROR and survey year fixed effects, and a set of variables for local economic conditions (gross value added, GDP per capita, employment rate and log of the total population). Model B adds to model A a full set of ROR specific linear trends. The first column also includes the lag value of the dependent variable and is estimated using OLS (Lagged OLS); the second column shows the result using the within estimator (FE); the third column present results from the correlated random effect estimator (QFE) which includes the individual mean over time of demographic variables (age, education, marital status and number of children) among the regressors. Standard errors are robust and clustered at ROR level.
Table 7: Effect of lagged immigration rate on health conditional on previous job

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Good Health</th>
<th>Women</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>White collar</td>
<td>Blue collar</td>
<td>All</td>
</tr>
<tr>
<td>Imm. rate</td>
<td>0.006 **</td>
<td>0.006</td>
<td>0.009 **</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>N</td>
<td>49947</td>
<td>27129</td>
<td>22818</td>
<td>42971</td>
</tr>
</tbody>
</table>

PANEL B

<table>
<thead>
<tr>
<th></th>
<th>Health satisfaction</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Imm. rate</td>
<td>0.010</td>
<td>0.006</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>N</td>
<td>49932</td>
<td>27126</td>
<td>22806</td>
</tr>
</tbody>
</table>

PANEL C

<table>
<thead>
<tr>
<th></th>
<th>Disability</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Imm. rate</td>
<td>-0.003 ***</td>
<td>-0.002</td>
<td>-0.004 ***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>N</td>
<td>49831</td>
<td>27098</td>
<td>22733</td>
</tr>
</tbody>
</table>

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, ROR and survey year fixed effects, and a set of variables for local economic conditions (gross value added, GDP per capita, employment rate and log of the total population). For each sex we report estimates for the entire sample and separated for those employed in white collar occupation or not employed (second column) and for those in blue collar occupations (third column) at t − 2 (before the change in immigration rate). The model is estimated using the within estimator (FE). Standard errors are robust and clustered at ROR level.
Table 8: Effect of lagged immigration rate on working conditions

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blue collar</td>
<td>Physical burden</td>
</tr>
<tr>
<td>Imm rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>-0.037</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Blue collar</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imm. rate*blue</td>
<td></td>
<td>-0.045***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>66053</td>
<td>65170</td>
</tr>
<tr>
<td>Imm. rate</td>
<td>-0.002</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Blue collar</td>
<td></td>
<td>2.288***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Imm. rate*blue</td>
<td></td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>56749</td>
<td>56331</td>
</tr>
</tbody>
</table>

Notes - Each model also includes a full set of age dummies, dummies for educational attainment (HS drop outs, HS and college), marital status dummies, number of children, ROR and survey year fixed effects, and a set of variables for local economic conditions (gross value added, gdp per capita, employment rate and log of the total population). The dependent variable in the first column is a blue collar dummy; in the second and the third column the dependent variable is the physical burden index. In the third column the effect of immigration rate is interacted with the blue collar dummy. The model is estimated using the within estimator (FE). Standard errors are robust and clustered at ROR level.
Table 9: Robustness checks 1: Effects of lagged immigration on health, gender-specific immigration rate

<table>
<thead>
<tr>
<th>Sample</th>
<th>All</th>
<th>Men Good Health</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immigration Rate</td>
<td>0.004** (0.002)</td>
<td>0.006*** (0.002)</td>
<td>0.002 (0.003)</td>
</tr>
<tr>
<td>Immigration Rate by Gender</td>
<td>0.009** (0.004)</td>
<td>0.011*** (0.004)</td>
<td>0.004 (0.006)</td>
</tr>
<tr>
<td>% of Male Immigrants</td>
<td>0.011*** (0.004)</td>
<td>0.004 (0.006)</td>
<td></td>
</tr>
<tr>
<td>% of Female Immigrants</td>
<td>0.004 (0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>144,022</td>
<td>144,022</td>
<td>69,890</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Health Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Immigration Rate</td>
</tr>
<tr>
<td>Immigration Rate by Gender</td>
</tr>
<tr>
<td>% of Male Immigrants</td>
</tr>
<tr>
<td>% of Female Immigrants</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Disability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Immigration Rate</td>
</tr>
<tr>
<td>Immigration Rate by Gender</td>
</tr>
<tr>
<td>% of Male Immigrants</td>
</tr>
<tr>
<td>% of Female Immigrants</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>
### Appendix A

Table 10: Immigrant composition by cohort of migration, country of origin and average years of education

<table>
<thead>
<tr>
<th>Origin</th>
<th>Imm. pre 80’s</th>
<th></th>
<th>Imm. 80’s</th>
<th></th>
<th>Imm. post 80s</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Education</td>
<td>%</td>
<td>Education</td>
<td>%</td>
<td>Education</td>
<td>%</td>
</tr>
<tr>
<td>Mediterranean</td>
<td>9.243</td>
<td>34.805</td>
<td>9.588</td>
<td>10.139</td>
<td>10.052</td>
<td>8.264</td>
</tr>
<tr>
<td>Germans*</td>
<td>10.989</td>
<td></td>
<td>11.310</td>
<td></td>
<td>12.124</td>
<td></td>
</tr>
</tbody>
</table>

*We report the average years of education in the sample of the corresponding German reference group: for immigrants pre 80’s we consider as reference group Germans over 40 in the waves 1985-1989; for immigrants 80’s we consider all Germans in the waves 1985-1989; for immigrants 90’s we consider all Germans in the waves 1990-2010.
Table 11: Placebo test: effect of immigration rate at different point in time

<table>
<thead>
<tr>
<th>time:</th>
<th>mean(t-1,t-2)</th>
<th>t-2</th>
<th>t-1</th>
<th>t</th>
<th>t+1</th>
<th>t+2</th>
<th>mean(t+1,t+2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imm. rate</td>
<td>0.006 **</td>
<td>0.004 **</td>
<td>0.006 ***</td>
<td>0.018 **</td>
<td>0.004</td>
<td>-0.001</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>N</td>
<td>59545</td>
<td>60567</td>
<td>69890</td>
<td>78051</td>
<td>71033</td>
<td>62093</td>
<td>61014</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>time:</th>
<th>mean(t-1,t-2)</th>
<th>t-2</th>
<th>t-1</th>
<th>t</th>
<th>t+1</th>
<th>t+2</th>
<th>mean(t+1,t+2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imm. rate</td>
<td>0.009</td>
<td>0.008</td>
<td>0.013</td>
<td>0.023</td>
<td>0.000</td>
<td>-0.007</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.037)</td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>N</td>
<td>59532</td>
<td>60547</td>
<td>69873</td>
<td>78031</td>
<td>71013</td>
<td>62066</td>
<td>60988</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>time:</th>
<th>mean(t-1,t-2)</th>
<th>t-2</th>
<th>t-1</th>
<th>t</th>
<th>t+1</th>
<th>t+2</th>
<th>mean(t+1,t+2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imm. rate</td>
<td>-0.003 ***</td>
<td>-0.002 ***</td>
<td>-0.002 **</td>
<td>-0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>N</td>
<td>59354</td>
<td>60369</td>
<td>69654</td>
<td>77776</td>
<td>70789</td>
<td>61877</td>
<td>60799</td>
</tr>
</tbody>
</table>

**Notes** - We replicate fixed effects estimates presented in Table 5 column A, by using each time a different immigration rate: past rates, average of past rates, A(t-2, t-1), contemporaneous rate, forward rates and average of forward rates, A(t+1, t+2).