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Abstract

This paper investigates the impact of a large shock to labor supply from immigration on occupational wages, labor costs and industry growth. We develop a simple factor-proportions theory where individuals sort into occupations, and industries use occupations with different factor intensities. The model delivers an empirical framework and testable hypotheses that we confront with a rich data set on industry performance, occupational characteristics and immigration. We apply the methodology to one of the largest labor immigration shocks of the 21th century: The immigration wave to Norway after the Eastern enlargement of the European Union. We introduce a novel instrument that exploits the fact that the language requirements are significant barriers for foreign workers and these requirements vary across occupations. The results point to labor migration leading to large adjustments in relative industry employment, labor costs and wages, and these effects are particularly strong in industries that are initially intensive in the use of immigrant occupations. Finally, a quantification of the general equilibrium of our model shows that the welfare effect of immigration was close to zero for natives, but negative for the existing population of immigrants.

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sponsored by the Norwegian Ministry of Labour and Social Affairs.

Opening the Floodgates: Industry and Occupation Adjustments to Labor Immigration*

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April 2019

Abstract

This paper investigates the impact of a large shock to labor supply from immigration on occupational wages, labor costs and industry growth. We develop a simple factor-proportions theory where individuals sort into occupations, and industries use occupations with different factor intensities. The model delivers an empirical framework and testable hypotheses that we confront with a rich data set on industry performance, occupational characteristics and immigration. We apply the methodology to one of the largest labor immigration shocks of the $21th$ century: The immigration wave to Norway after the Eastern enlargement of the European Union. We introduce a novel instrument that exploits the fact that the language requirements are significant barriers for foreign workers and these requirements vary across occupations. The results point to labor migration leading to large adjustments in relative industry employment, labor costs and wages, and these effects are particularly strong in industries that are initially intensive in the use of immigrant occupations. Finally, a quantification of the general equilibrium of our model suggests that the welfare effects of immigration were close to zero for natives, but negative for the existing population of immigrants.

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1 Introduction

What is the impact of a large immigration induced labor supply shock on occupational wages, labor costs and the industry mix of the economy? In many countries, immigration is an important factor in driving changes in labor supply. While most studies of the immigration impact on receiving countries focus on the wage structure (Dustmann et al., 2016a), recent contributions also characterize employment adjustments.[1] However, there is still relatively scant evidence on the general equilibrium adjustment of occupational wages, labor costs and employment by industry in response to immigration shocks. This paper attempts to fill this gap in the literature.

Our starting point is a large wave of migrants to Norway following the 2004 and 2007 enlargements of the EU, which extended the common European labor market to include roughly 100 million individuals from the EU accession countries. With real wages among the highest, and unemployment among the lowest, in Europe, Norway became a popular destination for labor migrants.[2] Over the ensuing decade Norway stands out among the developed countries as the country that received the largest inflow of migrants relative to country size. The immigrant employment share increased from 7 to 17 percent, making this one of the largest immigration waves of the $21th$ century.[3] In addition to the sheer magnitude of the immigration shock, the Norwegian case is particularly useful to study since the policy change was exogenous. As a part of the single market, but not a member of the EU, Norway is bound to adopt EU legislation without representation in the European Parliament and Commission. The policy change was instant, comprehensive and externally imposed, providing a unique setting to study the impact of immigration.

If immigrants sorted into similar occupations as the native population, we would not expect any change in relative wages or the industry mix. However, this was far from the case. We document that immigrants were highly concentrated in certain types of occupations. In line with standard trade and labor market theory, our hypothesis is that an immigrant supply shock lowers relative wages in those occupations which immigrants sort into.

We formalize this idea with the simplest possible economic framework. We model a labor market that consists of many occupations. Individuals sort into occupations governed by

[1] See e.g. Dustmann et al. (2016b), Dustmann and Glitz (2015), Hanson and Slaughter (2002), and Lewis (2011).

[2] The EU accession countries are: Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia (2004) and Bulgaria and Romania (2007). Norway is a member of the European Economic Area (EEA) and therefore part of the EU single market. Norway had few transitional restrictions on immigration from the accession countries compared to most EU countries (Dølvik and Eldring, 2008).

[3] According to OECD data, migration to Norway was higher than migration to all other OECD countries except Luxembourg between 2003 and 2013 (measured as the change in the foreign-born population relative to total population (OECD, 2017).

a Roy-type model, in the spirit of Lagakos and Waugh (2013) and Burstein et al. (2017), where their occupational choice is determined by the individuals' idiosyncratic occupation-specific preferences and the prevailing wage. Immigrants have occupational preferences that can differ from those of natives. An aggregate immigration shock accordingly leads to a labor supply shock that differs across occupations and that affects industries more or less according to their occupational intensities.

This structure gives rise to two simple general equilibrium relationships that will guide the subsequent empirical analysis. First, an aggregate immigration shock will have a heterogeneous effect on labor supply across occupations. In particular, growth in occupation labor supply is determined by the initial immigrant share of that occupation. The reason is that, according to the model, the initial immigrant share is a sufficient statistic for the occupation-specific comparative advantage of immigrants relative to natives. Second, the employment growth of an industry is the weighted average of changes in labor supply across occupations, where the weights are the initial factor intensities of that industry. The mechanism is straightforward: relative wages of occupations with greater labor supply will decline. Industries that are intensive in the use of those occupations will get lower marginal costs and therefore increase their output and employment. In sum, an immigration shock will (i) increase employment in immigrant intensive occupations and push down relative wages in these occupations, which will in turn (ii) increase employment in industries that are intensive in the use of these occupations.

We take the model to the data using high-quality and detailed administrative Norwegian employer-employee data including industry affiliation, geographical location, employment spells, wage costs, occupation and and immigration status. A major identification challenge is that the the change in occupation-specific labor supply due to immigration is endogenous. For example, labor supply might be determined by demand factors. We therefore propose a new instrument and methodology to overcome the identification problem. Our instrument is inspired by previous empirical evidence showing that immigrants sort into occupations that are less language intensive (Peri and Sparber, 2009).[4] After opening the floodgates in 2004, we therefore expect more immigrants to sort into less language intensive occupations.[5] For example, working as a daycare worker, a language intensive occupation, is relatively less attractive for immigrants as it requires extensive local language skills. On the other

[4]A parallel paper estimating the effect of the migration shock on individual earnings growth of natives use the same idea (Hoen, 2018).

[5]We do not follow Bartik-style studies of using past settlements of migrants to instrument immigration shocks (see e.g. Card, 2001). The reason is that the number of pre-enlargement immigrant workers from the EU accession countries was very low, and they were typically either seasonal workers in specific agricultural areas or highly educated dissidents from the communist area. None of these groups represented any network that would facilitate immigration after the migration barriers were removed.

hand, working as a carpenter, a relatively low language intensive occupation, requires only rudimentary Norwegian skills. In our data, the relationship between the initial level of, and the change in, the immigrant share and language intensity is strong. According to our estimates, the change in the immigrant share is 11 percentage points lower in language intensive versus not intensive occupations (comparing the 90th versus 10th percentile) over the 2004-2013 period.

The 2SLS results are in line with what theory predicts. After the floodgates opened, industries that are intensive in the use of immigrant occupations grow faster than other industries, contributing to an adjustment in the industry mix of the economy. In the model, industry size adjusts because relative unit costs across industries change. Therefore, a second testable hypothesis is that average wage costs decline in industries intensive in immigrant occupations. Using the same methodology as described above, we find economically and statistically significant adjustments on industry labor costs as well. Finally, our theory predicts that industry wage costs change because occupation-specific wages adjust in response to the shock. Our analysis confirms large movements in relative occupation wages: occupations with a large increase in labor supply faced 18 percent lower wage growth compared to occupations with a small increase (comparing the 90th versus 10th percentile) over the same 10 year period.

The exclusion restriction of the instrument is violated if language intensity has an impact on wage and industry growth other than the effect going through labor supply. We perform two sets of robustness checks. First, a concern is that the language intensity of occupations/industries is correlated with other occupation/industry characteristics that also determine industry growth. We control for unobserved industry trends by including detailed 2-digit industry and commuting zone fixed effects. We also add controls for observable pre-sample characteristics, such as the skill intensity of the industry. Second, if language intensity is systematically related to industry growth, even in the absence of immigration, then we should obtain significant estimates when regressing the right-hand side on industry growth in the period before the floodgates opened in 2004. Reassuringly, we find no such relationship.

As is well known, a reduced form approach can only identify relative effects, i.e., the common effect of immigration across all occupations and industries is not identified. To address the real wage and overall welfare effects of the migration shock, we therefore quantify the general equilibrium of our model. The counterfactual analysis shows substantial real wage losses in some occupations, whereas other occupations get real wage gains. Interestingly, the relative wage effects in the calibrated model are similar to the reduced form results discussed above, providing support for the empirical and theoretical framework. Although real wages in some occupations decline, the welfare effect of the immigration shock on natives is close to zero, as some natives switch to higher wage occupations. The welfare effect on the existing population of immigrants, on the other hand, is negative, as they have a comparative advantage in low-wage occupations.

This paper makes several contributions. First, we develop a new methodology for estimating the impact of a large immigration shock on industry growth, labor costs and occupational wages. This includes building a model that delivers testable reduced-form expressions derived from general equilibrium theory. Second, we propose a new identification strategy based on exogenous characteristics of occupations, which turns out to be a powerful predictor of immigration flows across occupations. We believe that general equilibrium model and empirical methodology can be used in many different contexts to analyze the effect of migration following major disruptions – both for other time periods and other countries.

There are only a handful of papers exploring the relationship between immigration, wages and industry adjustment. Early contributions are Hanson and Slaughter (2002) and Gandal et al. (2004), who develop a framework to study how changes in labor supply are absorbed in the economy. This approach has since been extended and improved in various directions (see e.g. Dustmann and Glitz, 2015, González and Ortega, 2011, Lewis, 2003 and Wagner, 2010). This body of research differs from ours in several respects. First, our unit of analysis is occupations, instead of skills and/or geographic regions. Second, we develop a new empirical approach derived from general equilibrium theory. Third, as described above, our instrumental variable approach is new to the literature.

Our work is also related to the recent study by Burstein et al. (2017) who examine the impact of immigration on occupational choice and wages. While our main focus is on industry adjustments, they study how occupation or industry tradability shapes local labor market adjustment to immigration. Card (2001), Sharpe and Bollinger (2016), Ortega and Verdugo (2016) and Peri and Sparber (2009) also study immigration using variation across occupations. The last two papers find that immigration induces natives to shift to occupations more intensive in language or communication skills. While this paper does not study occupational switching directly, our theoretical and empirical framework takes into account that individuals sort into, and switch, occupations.

A related and complementary literature analyzes to what extent investment and production techniques also respond to immigration, see e.g. the survey by Lewis (2013) as well as Lewis (2011). Our paper also relates to the extensive literature on how immigration affects the wage structure, see e.g. Borjas (2003), Dustmann et al. (2005) and Manacorda et al. (2012). Recent contributions also include Monras (2018) and Ottaviano et al. (2013), while Dustmann et al. (2016a) offer a review of different approaches and provides a framework for discussing why parameter estimates differ and how they should be interpreted. Unlike most immigration impact studies that focus on the effects on natives (or previously arrived immigrants), we characterize how the distribution of total employment and wages change due to an immigration shock. Moreover, we look at the effect of an aggregate labor supply shock caused by immigration, rather than the adjustment of wages and jobs to a shock in a single cell of the labor market.

Less closely related to our work is a line of quantitative research where labor reallocation plays an important role in shaping the spatial distribution of activity. An exception is the study by Caliendo et al. (2017) that focus specifically on the EU enlargement and build a spatial dynamic general equilibrium model to examine the welfare effects of the enlargement. While they have a rich quantitative model that takes into account both trade and immigration channels, they do not explore occupation and industry adjustments.

The rest of the paper is organized as follows. Section 2 develops the theoretical framework that guides the empirical analysis. Section 3 presents the empirical strategy and the identification strategy. Section 4 describes the data. Section 5 presents the empirical results, while Section 6 examines the mechanisms. Section 7 discusses robustness and assumptions, while Section 8 presents the general equilibrium quantification assessing the welfare effects of migration. Section 9 concludes.

2 Theoretical Framework

We introduce a simple theoretical framework to guide the empirical framework in Section 3 and the quantitative general equilibrium analysis in Section 8. The main objective of the model is to show how an aggregate labor supply shock affects employment and wages across industries and occupations while accounting for all general equilibrium effects. The labor supply side features a Roy-Frechet type model in the spirit of Lagakos and Waugh (2013) and Burstein et al. (2017), and follows the same approach as recent analyses of spatial distribution of activities, see e.g. Monte et al. (2018) and Redding (2016).[6]

The model combines three key ingredients. Following Roy (1951), individuals self-select into occupations based on their preferences and economic fundamentals. Second, inspired by amongst others Peri and Sparber (2009), natives and immigrants may have systematically different preferences for occupations, due to e.g. heterogeneity in communication and manual skills, and therefore sort into different occupations. Third, within a narrowly defined occupation, natives and immigrants are perfect substitutes.

[6]Other recent contributions using a Roy framework to model the choice of industry or occupation are Galle et al. (2016) and Curuk and Vannoorenberghe (2014).

2.1 The Model

We develop a general equilibrium model where production takes place in I industries that are indexed $i = 1, ..., I$ using labor from $o = 1, ..., O$ occupations. The economy is populated by a measure L of workers who may be natives (L_N) or immigrants (L_F), i.e. $L = L_N + L_F$. Each worker is endowed with one unit of labor that is supplied to one occupation.

Production. Production in each industry requires the use of occupation-specific labor. Industries differ according to the intensity with which they use different occupations. The production function in industry i is given by

$$y_i = \varphi_i \prod_o L_{io}^{\omega_{io}}, \tag{1}$$

where L_{io} is the units of labor in occupation o, φ_i is industry productivity and ω_{io} are non-negative weights that sum to one, i.e. $\sum_o \omega_{io} = 1$.

Labor Demand. Product and labor markets are perfectly competitive and workers are perfectly mobile across industries. Final demand is Cobb-Douglas with expenditure shares β_i which sum to one, i.e. $\sum_i \beta_i = 1$ (also see Section 2.2). The demand for occupation o labor in industry i is then

$$L_{io} = \omega_{io} \frac{\beta_i Y}{w_o}, \tag{2}$$

where w_o is the wage paid to a worker with occupation o and Y is aggregate income.

From equation (2) follows that the share of occupation o workers in industry i relative to total employment in occupation o, is

$$\pi_{io} = \frac{L_{io}}{\sum_j L_{jo}} = \frac{\omega_{io}\beta_i}{\sum_j \omega_{jo}\beta_j}. \tag{3}$$

Therefore, the allocation of workers within a given occupation across industries is determined solely by the demand and technology parameters β_i and ω_{io}. Total employment in industry i can accordingly be written as

$$L_i = \sum_o L_{io} = \sum_o \pi_{io} L_o. \tag{4}$$

2.2 Occupational Choice and Labor Supply

Each worker v belongs to a group g, where g is either immigrant (F) or native (N). Workers are mobile across occupations and have idiosyncratic preferences across occupations. The preferences of a worker v are defined over consumption (C_v) and an idiosyncratic shock to the utility from their occupation (z_{vgo}):

$$U_{vgo} = z_{vog} C_v, \tag{5}$$

where the goods consumption index C_v is defined over a set of industries i, $C_v = \prod_i c_{vi}^{\beta_i}, \quad 0 < \beta_i < 1$. The idiosyncratic occupational preference shock captures the idea that workers can have different preferences across occupations. We model this heterogeneity following Eaton and Kortum (2002). For each worker of group g, the idiosyncratic shock to their occupational preferences (z_{vgo}) is assumed to be drawn independently from a Fréchet distribution

$$F_{go}(z) = e^{-A_{go} z^{-\kappa}},$$

where the scale parameter $A_{go} > 0$ controls average preferences for each group of workers and occupation, while the shape parameter $\kappa > 1$ controls the dispersion of preferences across occupations within each group of worker. A greater A_{go} implies that a high utility draw in occupation o for group g workers is more likely. Variation in A_{go} captures the idea that, on average, natives and immigrants may have different preferences across occupations. The parameter κ reflects the variability of preference draws across occupations. For a small κ, a worker typically has very different draws across occupations, while for a large κ, on the other hand, the preference draws across occupations are relatively close to each other. The idiosyncratic preference shock (z_{vgo}) implies that different workers make different choices about their occupation when faced with the same wages.

Our framework is parallel to models where individuals have idiosyncratic preference draws from residing in different locations, or preference/productivity draws for different sectors, and choose a location or sector to maximize utility, see e.g. Monte et al. (2018), Redding (2016) and Lagakos and Waugh (2013), respectively.

All workers with the same occupation o receive the same wage regardless of nativity and preferences.[7] Each worker choose the occupation that maximizes her ex-ante utility, and she offers her entire labor endowment to this occupation. While the total labor supply of both groups is exogenous, the supply to occupation o, L_o, is endogenous. Given the preferences specified in equation (5), the corresponding ex-post indirect utility function for occupation o is $U_{vgo} = z_{vgo} w_o / P$, where P is the Cobb-Douglas price index for the consumption bundle.

[7] While previous research often assumes imperfect substitutability between natives and migrants within similar skill groups (see e.g. Ottaviano et al., 2013), we assume that they are perfect substitutes within narrowly defined occupations. Our framework nevertheless implies imperfect substitutability across natives and immigrants at higher levels of aggregation, such as broad occupation or skill groups. Section 7.2 presents empirical evidence supporting the assumption that natives and immigrants are perfect substitutes within occupations.

Since indirect utility is a monotonic function of the draws z_{vgo}, indirect utility also has a Fréchet distribution. Following Eaton and Kortum (2002), we exploit the properties of the distribution of indirect utility, and express the probability that a worker of group g choose occupation o as

$$\Pi_{go} \equiv \frac{L_{go}}{L_g} = \frac{A_{go} w_o^{\kappa}}{\Phi_g^{\kappa}}, \tag{6}$$

where $\Phi_g \equiv \left(\sum_o A_{go} w_o^{\kappa}\right)^{1/\kappa}$ and $L_g = \sum_o L_{go}$ is the total mass of group g workers. We observe that since native and immigrant occupational preferences may differ, the allocation of workers across occupations will also differ for the two groups.[8] Hence, some occupations will be relative intensive in natives, while others will be relatively intensive in immigrants. Total labor supply to occupation o can then be written as

$$L_o = \sum_g \Pi_{go} L_g. \tag{7}$$

2.3 General Equilibrium

The general equilibrium of the model can be represented by the measure of workers (L_{Fo} and L_{No}) in each occupation o, the wage in each occupation (w_o) and the total income (Y). In equilibrium, labor demand for each occupation o across industries must equal the sum of labor supply by natives and immigrants, i.e.

$$\sum_i L_{io} = \sum_g L_{go} \tag{8}$$

From equation (2) follows that the equilibrium wage must satisfy

$$w_o = \frac{Y \sum_i \omega_{io} \beta_i}{L_o}, \tag{9}$$

while L_o is given by equation (7). In equilibrium, total expenditure must also equal total labor income,

$$Y = \sum_o w_o L_o. \tag{10}$$

Using (6), (7), (9) and (10) we can determine equilibrium wages, the measure of workers in each occupation, and total income.

[8] An alternative model would be to let immigrants have different productivity in occupations than natives, i.e. that z_{vgo} and w_o represent productivity and wages per efficiency unit. While the two modes differ in some respects, they produce broadly similar testable hypotheses.

Welfare. Since workers are mobile across occupations, the expected utility must be the same for all workers in group g. From the indirect utility function above, the expected utility for a worker of group g is

$$\begin{aligned}\bar{U}_g &= \delta\left[\sum_o A_{go}\left(\frac{w_o}{P}\right)^{\kappa}\right]^{1/\kappa} \\ &= \frac{\delta}{P}\Phi_g, \end{aligned} \tag{11}$$

where $\delta = \Gamma\left(\left(\kappa-1\right)/\kappa\right)$ and $\Gamma\left(\cdot\right)$ denotes the Gamma function.

In this class of models, expected ex-ante utility from choosing occupation o is the same across all occupations. On the one hand, higher wages in an occupation raises expected utility from choosing that occupation. On the other hand, higher wages attract workers with lower idiosyncratic utility draws, which reduces expected utility. These two effects cancel each other out.

2.4 Comparative Statics

We consider a shock to the labor supply of immigrants, L_F, and/or natives, L_N, keeping all else constant. To simplify notation, we let $\hat{x} \equiv x'/x$ express the relative change in a variable, where x and x' denote the values in the initial and counterfactual equilibrium, respectively. Using "exact hat algebra" from Dekle et al. (2007), we can express the key relationships of the model in changes. Detailed derivations are found in Appendix Section A.1. First, from equations (7), the relative change in labor supply is

$$\hat{L}_o = \hat{w}_o^{\kappa}\sum_g \mu_{go}\frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}}, \tag{12}$$

where the immigrant/native share is $\mu_{go} = L_{go}/L_o$ and $\hat{\Phi}_g^{\kappa} = \sum_o \Pi_{go}\hat{w}_o^{\kappa}$. Second, from equation (10), the relative change in total spending is

$$\hat{Y} = \sum \frac{w_o L_o}{Y}\hat{w}_o\hat{L}_o. \tag{13}$$

From equation (9), the equilibrium wage must satisfy

$$\hat{w}_o = \hat{Y}/\hat{L}_o. \tag{14}$$

And finally, from equation (11) follows that the change in welfare for group g is

$$\hat{U}_g = \frac{\hat{\Phi}_g}{\hat{P}}, \tag{15}$$

where $\hat{P}$ is the overall price index, $\hat{P} = \prod_i \hat{p}_i^{\beta_i}$ and the change in industry prices is $\hat{p}_i = \prod_o \hat{w}_o^{\omega_{io}}$. The equilibrium wage is a fixed point of equations (12)-(14). Appendix Section A.1 describes the details of the fixed point algorithm. Given equilibrium wages and occupation labor supply, using (4) the relative change in employment in industry i is

$$\hat{L}_i = \sum_o \lambda_{io} \hat{L}_o, \tag{16}$$

where λ_{io} =L_{io}/L_i is the factor intensity of occupation o in industry i.

Combining equations (12) and (14), we summarize the impact of a labor supply shock in the following Proposition.

Proposition 1. *Consider a shock to the labor supply of immigrants (L_F) and/or natives (L_N), keeping all other parameters constant. The change in occupation employment, $\hat{L}_o$ is then*

$$\hat{L}_o = \hat{Y}^{\kappa/(\kappa+1)} \left(\sum_g \mu_{go} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}} \right)^{1/(\kappa+1)}. \tag{17}$$

where μ_{go} refers to the immigrant ($g = F$) or native ($g = N$) share in the initial equilibrium. This translates into a change in industry employment, $\hat{L}_i$,

$$\hat{L}_i = \sum_o \lambda_{io} \hat{L}_o, \tag{18}$$

where $\lambda_{io} = L_{io}/L_i$ is the factor intensity of occupation o in industry i in the initial equilibrium.

According to equation (17), occupation employment growth is determined by a weighted average of the supply shocks to native and immigrant labor, where the weights are the respective initial native/immigrant shares in that occupation. Moreover, according to equation (18), growth in employment in industry i is determined by a weighted average of occupation employment growth, where the weights are the initial occupation intensities (λ_{io}) in this industry. In other words, an immigration shock will (i) increase employment in immigrant intensive *occupations*, which will (ii) increase employment in *industries* that are intensive in the use of those occupations.

The employment response will be larger when κ is low. A low κ means large heterogeneity in preference shocks, so that individuals are relatively unlikely to switch occupations, i.e. that occupations are not very substitutable. In particular, this means that natives are relatively unlikely to switch out of immigrant occupations in response to the immigrant labor supply shock.

Occupational wages adjust according to equation (14). At the industry level, the average wage per worker is $W_i \equiv \sum_o w_o L_{io}/L_i = \beta_i Y/L_i$. In relative changes, we get $\hat{W}_i = \hat{Y}/\hat{L}_i$. This leads to our second proposition:

Proposition 2. *Consider a shock to the labor supply of immigrants (L_F) and/or natives (L_N), keeping all other parameters constant. In general equilibrium, the change in occupational wages and average industry wage costs is $\hat{w}_o = \hat{Y}/\hat{L}_o$ and $\hat{W}_i = \hat{Y}/\hat{L}_i$, respectively.*

Hence, in the absence of aggregate income growth ($\hat{Y} = 1$), wage cost growth is inversely proportional to employment growth in occupations as well as industries.

3 Empirical Strategy

3.1 Empirical Specification

We set out to analyze the impact of a significant labor migration shock on industry adjustments. Our point of departure is Proposition 1, which states that, in general equilibrium, industry employment growth is a weighted average of occupational labor supply shocks. The ur empirical analysis is based on observed initial levels as well as the change in the immigrant share, $\mu_{Fo} = L_{Fo}/L_o$, the change in the total immigrant and native labor force $\hat{L}_F$ and $\hat{L}_N$ and the initial factor intensities λ_{io}. We estimate the combined equations (17) and (18) in logs, approximated by

$$\ln \hat{L}_i = \ln K + \kappa^* \sum_o \lambda_{io} \ln \tilde{L}_o + \epsilon_i, \tag{19}$$

where $\tilde{L}_o \equiv \mu_{Fo}\hat{L}_F + (1-\mu_{Fo})\,\hat{L}_N$, $\kappa^* \equiv 1/(\kappa+1)$, ϵ_i is measurement error and K is a constant term (see Appendix A.2).[9]

Since the change in earnings potential $\hat{\Phi}_g$ is unobserved, we approximate $\hat{\Phi}_F \approx \hat{\Phi}_N$, so that this term is subsumed by the constant term K.[10] Since the variation in $\tilde{L}_o$ comes from variation in initial μ_{Fo}, the regression in equation (19) relates industry employment growth to the weighted average immigrant intensity of occupations prior to opening the floodgates,

[9] $K \equiv \left(\hat{Y}/\Phi\right)^{\kappa/(\kappa+1)}$

[10] The counterfactual analysis in Section 8 shows that the change in earnings potential is modest ($\hat{\Phi}_F = 0.98$ and $\hat{\Phi}_N = 1$) and orders of magnitude smaller than the change in $\hat{L}_F$. Therefore, the approximation $\hat{\Phi}_F \approx \hat{\Phi}_N$ has little impact on the reduced form results.

with weights equal to the initial factor intensities. Details on the measurement of $\tilde{L}_i$, λ_{io}, μ_{Fo} and $\hat{L}_F$ and $\hat{L}_N$ are provided in Section 4 below.

We also report coefficients from a specification of the labor supply shock often used in the literature on impacts of immigration, namely the change in the immigrant share. This implies that we replace the change in total labour supply, $\ln \tilde{L}_o$, with the change in the immigrant share (relative to the initial native share), $\tilde{\mu}_o \equiv \Delta\mu_{Fo}/\left(1-\mu_{Fo}\right)$ (see Appendix A.3). [11]

Our theory also gives predictions on wage cost effects. Based on Proposition 2 and exploiting the same empirical strategy as for employment growth, we examine the impact of a labor supply shock on industry wage costs using the same two measures of the supply shock.

Unit of analysis and time period. We define an industry i as a 3-digit NACE and commuting zone (CZ) combination. This means that technology in a 3-digit sector is allowed to differ across commuting zones, i.e., the pre-period factor intensities λ_{io} can vary across space. In the baseline specification, we include 2-digit NACE and CZ pair fixed effects. Therefore, both trends in industry size at the 2-digit level and trends in CZ employment are controlled for. Further discussion about the identifying assumptions are provided below.

We study industry adjustments over the period 2004 to 2013. This time period captures the bulk of the immigrant shock, see Figure 1, starting from the first year migration restrictions were lifted for EU enlargement countries. The aggregate labor supply shock over this time period was $\hat{L}_F = 2.33$ and $\hat{L}_N = 1.09$. The initial factor intensity matrix, λ_{io}, and the initial immigrant occupation shares, μ_{Fo}, are calculated using 2004 data.

3.2 Instrumental Variables

Estimating equation (19) is not trivial because high growth industries may also attract immigrants to occupations that are intensively used in that industry. We therefore need an instrument.

Since Altonji and Card (1991) many studies have relied on historical settlements to identify effects of immigration on outcomes of residents in the destination country. However, due to the political divide of Europe after the second world war there was hardly any migration from Eastern Europe to Norway before the EU enlargement. Our analysis therefore requires a different approach. Our instrument exploits the fact that occupations differ in terms of language requirements which then represents a barrier to foreign workers since Norwegian is the typical workplace language. In the context of the model, we interpret high language

[11] As shown in Appendix A.3, $\tilde{\mu}_o$ is a valid measure of the supply shock when the change in labor supply is entirely driven by a shock in immigrantion and there is no native occupational mobility; $\Delta L_o = \Delta L_{Fo}$.

intensity as an occupational attribute that attracts relatively more natives than immigrants, i.e. that $A_{No} > A_{Fo}$. We therefore expect that language intensity is a determinant of the immigrant share μ_{Fo}. As discussed above, an alternative interpretation is that high language intensity occupations make natives relatively more productive than immigrants. Our instrument for $\sum_o \lambda_{io} \ln \tilde{L}_o$, or alternatively $\sum_o \lambda_{io}\tilde{\mu}_o$, is therefore the weighted average language intensity, $\sum_o \lambda_{io}\mathbb{L}_o$.

Since language intensity is time-invariant, our instrument is potentially subject to the criticism of the "past settlement" strategy when the inflow of immigrants is autocorrelated, such that the impact of immigration today also captures the longer-term adjustments to previous inflows (Jaeger et al., 2018). As the immigration shock we study was instant, comprehensive and externally imposed, we expect this bias to be of minor importance.

Identification. The exclusion restriction of our instrument is that the weighted average language intensity of occupations in an industry is only related to industry growth through the impact of immigration. Since our baseline specification includes 2-digit industry and CZ pair fixed effects, the identifying variation comes from within 2-digit (across the third digit) differences in average language intensity. A potential concern is that, even within 2-digit industries, differences in language requirements are systematically related to other industry characteristics such as skill intensity, and it may happen that industry growth is correlated with these characteristics. We deal with this issue by including a vector of initial industry characteristics. Specifically, we include initial skill intensity, measured as the share of workers with a completed high school education or higher, average wages, value added, employment, export intensity, measured as total exports relative to total revenue, import intensity, measured as imported intermediates relative to firms' operating costs, and the wage share, measured as wage costs relative to total costs (all in logs).

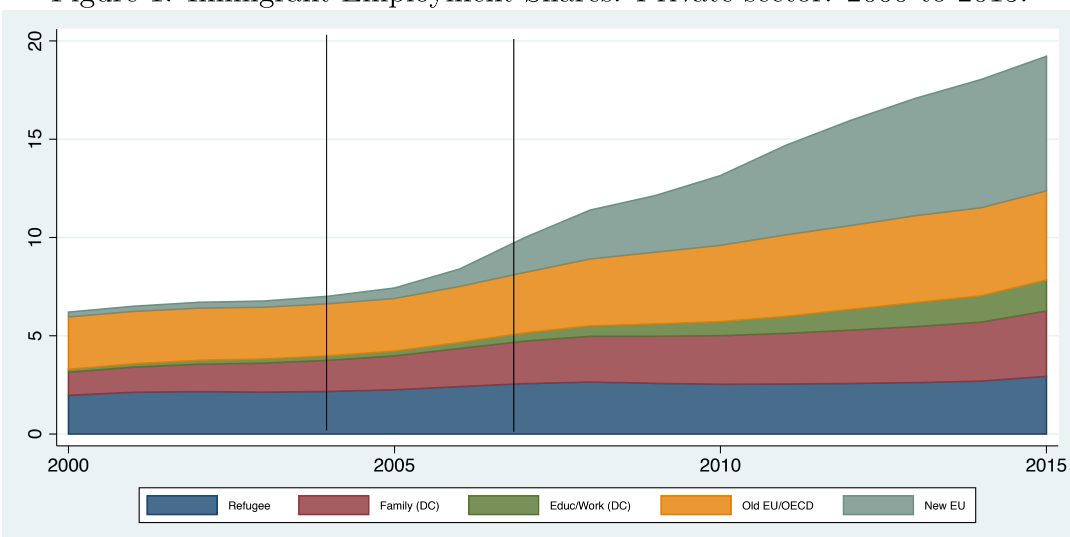
4 Data and Variables

Our empirical analysis of the migration shock is based on three main data sets. The first data set is balance sheet data from Statistics Norway for all private non-financial joint-stock companies for the period 1999 to 2013. The balance sheet data is based on data from annual reports that according to Norwegian law must be filed with the public Register of Company Accounts. The data set contains key account figures related to a firm's income statement and balance sheet including employment, wages, sales and value added. We use the balance sheet data to construct a panel of industry-commuting zone variables. Commuting zones are based on the labor market classification of Statistics Norway, see Bhuller (2009). There are in total 46 CZs and 214 NACE 3-digit industries in our dataset.[12] Industry employment L_i is measured as the total industry-CZ employment while average wage costs W_i is measured as total industry-CZ wage costs relative to total industry-CZ employment.

Our second data set is matched employer-employee data, which includes information on wages and occupations as well as immigrant status (country of birth) by person-firm-year.

The Norwegian nomenclature (STYRK) for occupations is based on the International Standard Classification of Occupations (ISCO–88) prepared by ILO and further developed by the EU and provides us with 4-digit occupational codes. There are in total 325 occupations in our data. We restrict our sample to full-time employees.

Figure 1: Immigrant Employment Shares. Private sector. 2000 to 2015.



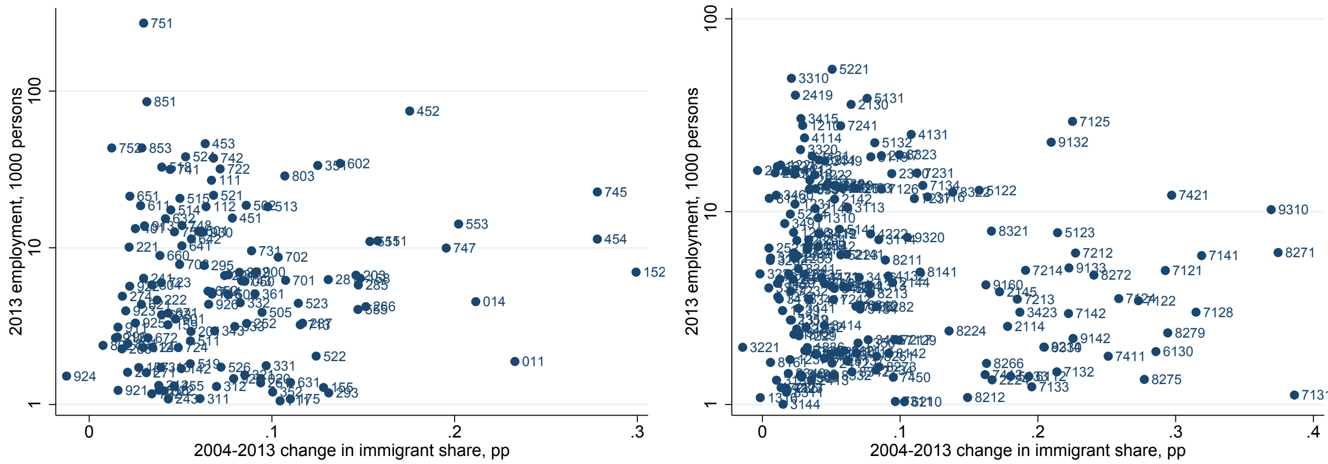
The employer-employee data allow us to construct aggregate native and immigrant employment, L_N and L_F, and the change in these over time. Figure 1 shows how the number of immigrant employees relative to total employment developed over the period 2000 to 2015. Only private sector employment and employees between the age of 20 and 61 are included. Immigrant employees are split into following groups: (i) Refugees, (ii) Family reunion from developing countries (DC), (iii) Education/work from DC, (iv) Old EU/OECD countries, (v) new EU countries. The immigrant share rose from 7 to 17 percent between 2004 and 2013. About 60 percent of migrants came from EU accession countries. Almost 70 percent of population growth was due to net immigration. Figure 1 illustrates that up until the Eastern enlargement of the EU, Norway had hardly received any migration from the accession countries. Before 2004, accession country citizens had very limited access to the Norwegian labor market. Work permits were provided via domestic employers in need of

[12]For details on classification and nace codes, see https://www.ssb.no/en/klass/klassifikasjoner/6/versjon/31.

specialist competence, or on a temporary 3-month seasonal basis, typically for agricultural work.

Based on the employer-employee data we construct the initial factor-intensity matrix λ_{io} for each industry-CZ-occupation using 2004 values. To account for differences in human capital across occupations, we use wage shares instead of employment shares when calculating λ_{io}, i.e. we calculate total wage payments in io and divide by total wage payments in i.[13] Table 9 in the Appendix provides a snapshot of the factor intensity matrix for a few different occupations and industries.

Figure 2: Changes in Immigration Shares and Industry Size: By Industry and Occupation.



Note: The figure shows the percentage point change in the share of immigrant relative to total employees on the x-axis, and total 2013 employment on a log scale on the y-axis (in 1000s persons). The unit of observation is 3-digit NACE sector (left panel) and 4-digit STYRK occupation code (right panel). Industries/occupations with 2013 employment < 1000 persons are omitted from the figures.

The employer-employee dataset is also used to construct the initial immigrant shares, μ_{Fo}, as well as the 2004-2013 change in immigrant shares, $\Delta\mu_{Fo}$, for each occupation o. Figure 2 illustrates the relationship between employment and change in immigrant shares across 3-digit industries (left panel) and occupations (right panel) in our sample. There is no obvious relationship between size of the industries/occupations and the migration shock. A few industries and occupations stand out. The immigrant share in construction (NACE 452 and 454) increased by 20 to 30 percentage points. There was also a significant increase in the immigrant share in processing and preserving of fish (NACE 152). The most

[13] Using employment shares instead does not change the results significantly. Results available upon request.

impacted occupations were helpers and cleaners (STYRK 9132), laborers in construction and maintenance (STYRK 9310) and various carpenter occupations (STYRK 7125 and 7421).

The third data set comes from the O*Net Resource Center that offers detailed information of occupational characteristics.[14] We use the crosswalk provided by Hoen (2016) in order to match the O*Net data with the occupational codes used in the Norwegian data. We use the O*Net data to construct our instrument that is based on occupation specific language requirements. O*Net ranks occupations with respect to a set of requirements. The value 1 means that a given type of skill is not important for the type of work carried out within this occupation, while the value 5 means that it is extremely important. We let occupation specific language intensity, $\mathbb{L}_o$, be computed as a simple average of oral and written comprehension and expression requirements, and we standardize the variable so that the mean of $\mathbb{L}_o$ is zero and the standard deviation is one.

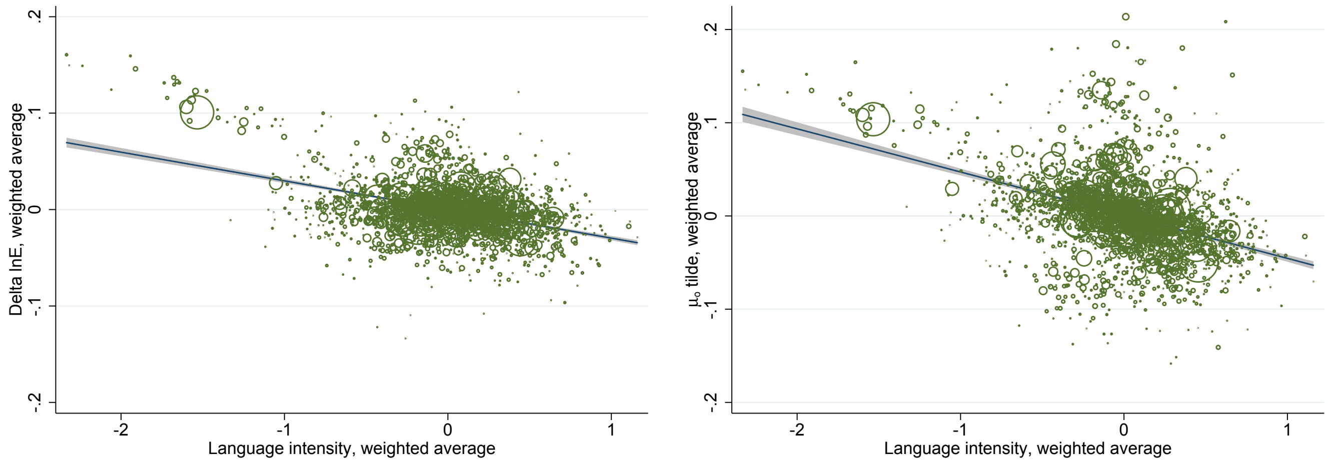
5 Empirical Results

To investigate the effect of the immigration shock, we estimate equation (19), and use the weighted average language intensity, $\sum_o \lambda_{io}\mathbb{L}_o$, to instrument for the weighted average change in labor supply, $\sum_o \lambda_{io} \ln \tilde{L}_o$. [15] The left panel in Figure 3 illustrates the first stage regression, i.e. the relationship between the weighted average change in labor supply (vertical axis) and the instrument (horizontal axis). Both variables are demeaned by 2-digit industry-commuting zone (CZ) averages, which is similar to including 2-digit industry-CZ fixed effects. As pointed out in Section 3.1, an alternative measure of the labor supply shock is the observed change in the immigrant share, $\tilde{\mu}_o$. The right plot in Figure 3 illustrates the first stage regression using this alternative variable. In both cases, the instrument is highly correlated with the endogenous variable, even within 2-digit sectors and the point estimates are reported in Table 1. As illustrated in the scatterplot in Figure 3, the $1st$ stage is precisely estimated across all specifications.

[14] http://www.onetcenter.org/content.html

[15] OLS results are provided in Section B.

Figure 3: Industry-level. 1*st* Stage Regression.



Note: The left panel shows a scatter plot between $\sum_o \lambda_{io}\mathbb{L}_o$ on the x-axis and $\sum_o \lambda_{io} \ln \tilde{L}_o$ on the y-axis, where $\tilde{L}_o = \mu_{Fo}\hat{L}_F + (1-\mu_{Fo})\,\hat{L}_N$. The right panel shows a scatter plot between $\sum_o \lambda_{io}\mathbb{L}_o$ on the x-axis and $\sum_o \lambda_{io}\tilde{\mu}_o$ on the y-axis. The unit of observation is a 3-digit NACE industry-CZ pair. Both variables are demeaned by 2-digit industry-CZ averages. The size of the circles represent size of industry-CZ employment. The line represents the linear regression line and the gray area the 95 percent confidence interval.

The impact of the immigration shock on industry growth with industry-CZ employment being the unit of analysis is reported in the upper part of Table 1. The labor supply shock is measured by the computed change in labor supply, $\ln \tilde{L}_o$, in columns (1)-(4) and by the observed change in immigration share, $\tilde{\mu}_o$, in columns (4)-(8). Column (1) presents the 2SLS results in absence of any controls, while column (2) controls for trends in industry and regional output by including 2-digit industry and CZ pair fixed effects.

As pointed out above, see Section 3.2, a potential concern is that language intensity and industry growth are otherwise related. We therefore include pre-sample characteristics of the industry and its workforce. In column (3) we add pre-sample industry controls in order to account for differences across industries in terms of e.g. openness and technology, while in column (4) we add pre-sample workers control to account for differences across industries in the skill composition of the labor force.[16] The 2SLS estimates show that, as predicted by theory, the labor supply increase led to substantial employment growth in industries that were initially intensive in the use of occupations that experienced a large immigration shock. The empirical results are robust to the inclusion of industry and CZ trends as well as industry

[16]The industry controls are initial log value added, log employment, log average wages, the share of exports in total sales, the share of imports in total costs and the share of wages in total costs. The workers control is the initial share of workers with a completed high school education averaged across firms in a 3-digit industry-CZ pair. All variables are calculated based on 2003 values.

and worker controls.

According to the model, the estimated slope coefficient κ^* equals the structural parameter $1/(\kappa+1)$. The estimated values of κ^* in Table 1 column (1)-(4) are therefore too large given the model restriction that $\kappa > 1$. One interpretation of this result is that final demand is more elastic than what the model allows for.[17]

Using the change in the immigrant share as the supply shock, the estimated coefficients are very much in line with the baseline results, confirming strong employment growth in immigrant intensive industries.

Table 1: Immigration and Employment Growth. 2SLS Estimates.

Dependent variable: $\ln \hat{L}_i$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum_o \lambda_{io} \ln \tilde{L}_o$	.81	3.47^a	3.75^a	3.74^a				
	(1.78)	(1.20)	(1.22)	(1.27)				
$\sum_o \lambda_{io} \tilde{\mu}_o$					.22	2.44^a	2.57^a	2.59^a
					(.49)	(.85)	(.83)	(.87)
Industry controls	No	No	Yes	Yes	No	No	Yes	Yes
Worker controls	No	No	No	Yes	No	No	No	Yes
Industry (2-digit)-CZ FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
				1st Stage Estimates				
$\sum_o \lambda_{io} \mathbb{L}_o$	$-.01^a$	$-.03^a$	$-.03^a$	$-.03^a$	$-.05^a$	$-.05^a$	$-.04^a$	$-.04^a$
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Number of observations	2,835	2,835	2,835	2,835	2,835	2,835	2,835	2,835

Note: Robust standard errors clustered by 2-digit industry-CZ in parentheses. Changes refer to the time period 2004 to 2013. The unit of observation is a 3-digit industry (NACE)-CZ pair. Industry controls are: Log value added, log employment, log average wages, the share of exports in total sales, the share of imports in total costs, and the share of wages in total costs (2003 values). The workers control is the share of workers with a completed high school education or higher (2003 values, averaged across firms in an industry). Models are weighted by industry-CZ log employment. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

Our theory suggests that industry size adjusts because average wage costs are changing, see Proposition 2. We proceed by estimating the impact of the immigration shock on the industry wage costs per employee and report 2SLS results in Table 2. Similarly to in Table 1, the labor supply shock is measured by the weighted change in the occupational supply based on $\ln \tilde{L}_o$, in columns (1)-(4) and by means of the observed change in immigration

[17]One could potentially extend the model to allow for more elastic demand. However, this extension does not deliver analytical solutions for the main testable predictions of the model.

share, $\tilde{\mu}_o$, in columns (5)-(8). Average wages in an industry are defined as the total wage bill of the industry relative to the number of employees with industry-CZ being the unit of analysis. As above, we report results with and without fixed effects and controls. We find that the immigration shock led to reduced wage growth in the industries most intensive in the use of occupations that experienced a large labor supply shock. The result is robust to the inclusion of industry and worker controls. Using the change in the immigrant share as an alternative measure of the supply shock produces slightly smaller point estimates, while the qualitative results remain the same.

Table 2: Immigration and Industry Wage Growth. 2SLS Estimates.

Dependent variable: $\ln \hat{W}_i$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sum_o \lambda_{io} \ln \tilde{L}_o$	-2.04^a	-.95^b	-1.60^a	-1.61^a				
	(.62)	(.45)	(.49)	(.51)				
$\sum_o \lambda_{io} \tilde{\mu}_o$					-.56^a	-.67^b	-1.10^a	-1.11^a
					(.15)	(.32)	(.33)	(.35)
Industry controls	No	No	Yes	Yes	No	No	Yes	Yes
Worker controls	No	No	No	Yes	No	No	No	Yes
Industry (2-digit)-CZ FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
				1st Stage Estimates				
$\sum_o \lambda_{io} \mathbb{L}_o$	-.01^a	-.03^a	-.03^a	-.03^a	-.05^a	-.05^a	-.04^a	-.04^a
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Number of observations	2,835	2,835	2,835	2,835	2,835	2,835	2,835	2,835

Note: Robust standard errors clustered by 2-digit industry and CZ in parentheses. Changes refer to the time period 2004 to 2013. The unit of observation is a 3-digit industry (NACE)-CZ pair. Industry controls are: Log value added, log employment, log average wages, the share of exports in total sales, the share of imports in total costs, and the share of wages in total costs (2000 values). The workers control is the share of workers with a completed high school education or higher (2003 values, averaged across firms in an industry). Models are weighted by industry-CZ log employment. ^{a} $p< 0.01$, ^{b} $p< 0.05$, ^{c} $p< 0.1$.

Economic Magnitudes. What are the economic magnitudes of the migration shock? Splitting industries into percentiles according to their exposure to the labor supply shock, we get that $\sum_o \lambda_{io} \ln \tilde{L}_o$ is .14 and .22 for the $10th$ and $90th$ percentile industry, respectively. Based on our estimates, this suggests that the migration shock led to roughly 30 percent higher growth in industry employment in the most versus least affected industries.[18] As for

[18] Calculated as $(.22 - .14) \times 3.74$ based on the results in column (4) in Table 1. As an alternative, we also calculated the least and most affected industries holding the native population constant ($\hat{L}_N = 1$). This yields roughly the same magnitudes.

the impact on wages, splitting industries into percentiles as above, we find that the most affected ($90th$ percentile) industries faced 13 percent lower growth in average wage costs compared to the least affected ($10th$ percentile).[19] Over the sample period, the average of $\ln W_i$ increased nominally by .40 log points. Therefore, although relative wages declined, even the most affected industries experienced wage growth.

We conclude that the migration shock led to economically large industry adjustments. Industries intensive in the use of occupations especially affected by immigration grew significantly faster. Our results show that these adjustments coincided with changes in relative wage costs across industries. The estimated magnitudes on industry wage costs and employment indicate that occupational mobility is relatively modest. We investigate this further in Appendix A.4.

6 Mechanisms: Occupation-level Evidence

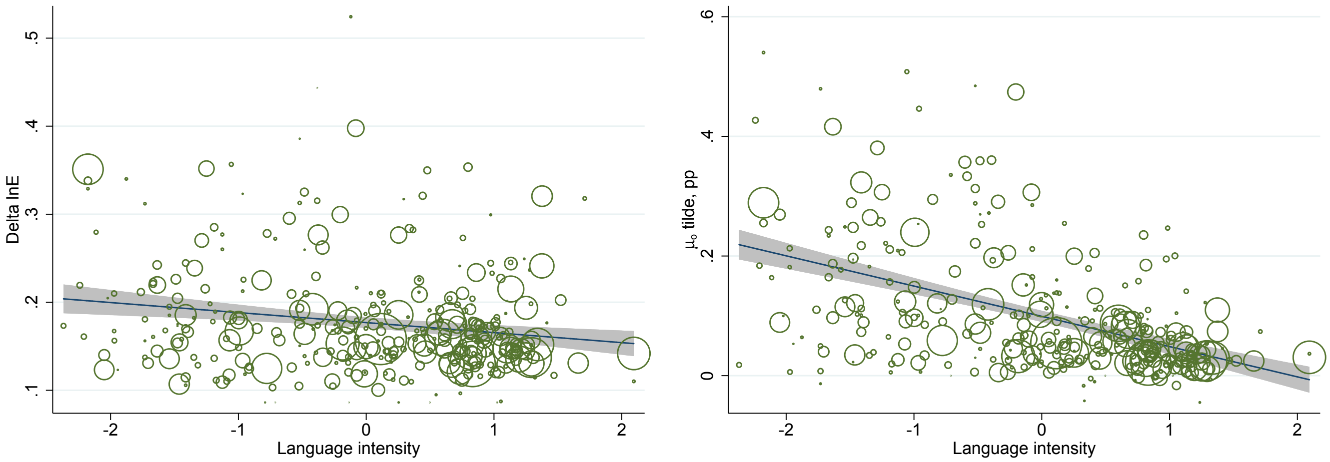
According to the model, absent aggregate income growth, occupational wage growth is simply inversely proportional to occupation labor supply, $\hat{w}_o = \hat{Y}/\hat{L}_o$, see equation (14). We therefore expect occupation-level wage adjustments in response to the labor supply shock. Using the same labor supply shock variables as in Section 3.1, we estimate the impact on occupational average wages.

The left panel of Figure 4 illustrates the first stage regression, i.e. the relationship between the labor supply shock (vertical axis) and the instrument (horizontal axis), using our baseline measure, $\ln \tilde{L}_o$ (left panel), as well as the alternative immigrant share measure, $\tilde{\mu}_o$ (right panel). In both cases, the instrument is highly correlated with the labor supply shock. According to our estimates, the change in the immigrant share, $\tilde{\mu}_o$, is 11 percentage points higher in language intensive versus not intensive occupations (comparing the 90th versus 10th percentile of language intensity).

We calculate mean wages by occupation o and commuting zone r and regress the 2004-2013 change, $\Delta \ln w_{or}$, on the labor supply shock variables. Our framework predicts that the wage response should be identical for natives and immigrants. Therefore, we also regress mean wages for natives and immigrants, respectively, on the labor supply shock variables. Table 3 shows the results. All specifications include CZ fixed effects, effectively controlling for trends in regional wage growth. As above, we also control for the initial share of workers with a completed high school education or higher. Columns (1)-(3) use $\ln \tilde{L}_o$ as the labor supply shock variable, whereas columns (4)-(6) use $\tilde{\mu}_o$ as the labor supply shock variable. In all cases, we find that occupational wages fall as a response to the immigration shock.

[19] Calculated as $(.22 - .14) \times (-1.61)$ based on the results in column (4) in Table 2.

Figure 4: Occupation-level. 1st Stage.



Note: The left figure shows a scatter plot between $\mathbb{L}_o$ on the x-axis and $\ln \tilde{L}_o$ on the y-axis, where $\tilde{L}_o = \mu_{Fo}\hat{L}_F + (1-\mu_{Fo})\,\hat{L}_N$. The right figure shows a scatter plot between $\mathbb{L}_o$ on the x-axis and observed $\tilde{\mu}_o$ on the y-axis. The unit of observation is 4-digit occupation codes. The size of the circles represent occupation employment. The line represents the linear regression line and the gray area the 95 percent confidence interval.

Importantly, the impact on wages for natives and immigrants are roughly similar with both specifications (comparing columns (2)-(3) and (5)-(6)).

The point estimates are comparable to the results from the industry-level analysis in Table 2, consistent with the predictions of the model. Splitting occupations into percentiles as above, we find that the most affected ($90th$ percentile) occupations faced 21 percent lower wage growth compared to the least affected ($10th$ percentile) occupations.[20]

[20]Calculated as $(.25 - .12) \times (-1.62)$ based on the results in column (1) in Table 3.

Table 3: Immigration and Occupation Wage Growth. 2SLS estimates.

Dep. variable: $\Delta \ln \hat{w}_o$	(1) All	(2) Natives	(3) Immigrants	(4) All	(5) Natives	(6) Immigrants
$\ln \tilde{L}_o$	-1.62^a	-1.20^a	-1.48^b			
	(.41)	(.43)	(.65)			
$\tilde{\mu}_o$				-.44^a	-.33^a	-.41^b
				(.11)	(.12)	(.18)
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
	1st Stage Estimates					
$\mathbb{L}_o$	-0.01^a	-0.01^a	-0.01^a	-0.05^a	-0.05^a	-0.05^a
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Number of observations	10,238	10,070	4,934	10,238	10,070	4,934

Note: Standard errors clustered by CZ in parentheses. Changes refer to the time period 2004 to 2013. The unit of observation is occupation (4-digit)-CZ. The workers control is the share of workers with a completed high school education or higher (2003 values, across individuals in an occupation). Models are weighted by occupation-CZ log employment.^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

7 Robustness and Discussion of Assumptions

7.1 Falsification Test

A potential concern is that industries with low average language requirements (comparing across the 3rd digit within a 2-digit industry) are industries with in general higher employment growth than other industries. To address this concern, we perform a placebo test and regress 1999-2003 employment and wage growth on the 2004-2013 change in labor supply. Results are reported in Tables 4 and 5 for employment growth and wage cost growth respectively.The coefficients of interest are not significant, suggesting that there are no differential industry-specific pre-trends.[21]

[21] We cannot include pre-sample controls here because we do not have data on industry outcomes before 1999.

Table 4: Immigration and Industry Employment. Falsification Test.

Dependent variable: $\Delta \ln \hat{L}_i$ (1999-2003)	(1)	(2)
$\sum_o \lambda_{io} \ln \tilde{L}_o$ (2004-2013)	-1.52	1.12
	(1.47)	(1.13)
Pre-sample industry controls	No	No
Pre-sample worker controls	No	No
Industry (2-digit)-CZ FE	No	Yes
	1st Stage Estimates	
$\sum_o \lambda_{io} \mathbb{L}_o$	-.01^a	-.03^a
	(.00)	(.00)
Number of observations	3,469	2,769

Note: Robust standard errors clustered by 2-digit industry-CZ in parentheses. Changes refer to the time period 2004 to 2013 for the instrument and 1999 to 2003 for the dependent variable. The unit of observation is a 3-digit industry-CZ pair. Models are weighted by industry-CZ log employment.^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

Table 5: Immigration and Industry Wage growth. Falsification Test.

Dependent variable: $\ln \hat{W}_i$ (1999-2003)	(1)	(2)
$\sum_o \lambda_{io} \ln \tilde{L}_o$ (2004-2013)	-1.00	-1.18
	(.92)	(.72)
Pre-sample industry controls	No	No
Pre-sample worker controls	No	No
Industry (2-digit)-CZ FE	No	Yes
	1st Stage Estimates	
$\sum_o \lambda_{io} \mathbb{L}_o$	-0.01^a	-0.03^a
	(.00)	(.00)
Number of observations	3,469	2,769

Note: Robust standard errors clustered by 2-digit industry-CZ in parentheses. Changes refer to the time period 2004 to 2013 for the instrument and 1999 to 2003 for the dependent variable. The unit of observation is a 3-digit industry-CZ pair. Models are weighted by industry-CZ log employment.^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

7.2 Substitutability between Immigrants and Natives

The theoretical framework is based on the assumption that immigrants and natives are perfect substitutes within narrowly defined occupations, while the previous literature often points to imperfect substitutability between natives and migrants within similar skill groups (Manacorda et al., 2012 and Ottaviano et al., 2013). In this Section we provide empirical results supporting the assumption of perfect substitutability within occupations. First, going back to the occupation-level results in Table 3, we observe that the impact on mean occupational wages is similar for natives and immigrants. This is consistent with our model where the relative change in occupation wages is identical for natives and immigrants.[22] Second, we examine to what extent the wage level is different between natives and immigrants within occupations. To do so, we use individual-level data on wages for natives and immigrants for all full-time employees in 2014, and regress log wages on a dummy which takes the value one if the individual is an immigrant. Table 6 reports estimates of the immigrant-native log wage differentials. Columns (1)-(3) report results for males and (4)-(6) for females. Without any controls, the male wage gap is .29 log points (column 1). Controlling for age, experience and tenure, the wage gap drops considerably to .19 log points (column 2).[23] Adding 4-digit occupational fixed effects, the immigrant wage gap is zero (column 3). We also find a zero wage gap for females within occupations (column 6). Hence, our results lend empirical support to the assumption of perfect substitutability between natives and immigrants within occupations.

Table 6: Immigrant-Native Wage Gap

Dependent variable: Log wage		Men			Women	
	(1)	(2)	(3)	(4)	5)	(6)
Immigrant dummy	-0.286^a	-0.188^a	0.017	-0.216^a	-0.125^a	0.014
	(0.027)	(0.025)	(0.014)	(0.039)	(0.029)	(0.014)
Age, experience and tenure controls	No	Yes	Yes	No	Yes	Yes
4-digit occupation fixed effects	No	No	Yes	No	No	Yes
Number of observations	791,163	791,163	791,163	356,715	356,715	356,715

Note: Robust standard errors clustered by 4-digit occupation. Data set restricted to full time employees in year 2014. ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

[22] See also wage impact studies with labor demand based on a CES production function, e.g Manacorda et al. (2012).

[23] In previous studies based on a CES tree structure, the degree of substitutability is typically defined within skill groups defined by education and experience, Manacorda et al. (2012).

8 Real Wages and Welfare

While our reduced-form approach informs us about the impact of the immigration shock on relative occupation wages, industry costs and industry employment, it does not inform us about the impact of the immigration shock on the level of (real) wages and welfare. The reason for this is that the reduced form approach can only identify relative effects, i.e., the common effect of immigration across all occupations and industries is not identified. This section therefore provides a complementary model-based analysis of the immigration shock on occupation real wages and welfare.

We do so by calibrating the general equilibrium model and calculating the counterfactual impact of a labor supply shock, holding all other parameters constant. Inspecting the expressions from Section 2.4, the counterfactual equilibrium only requires data on (i) the initial income shares of each occupation, Y_o/Y, (ii) the initial industry expenditure shares, β_i, (iii) the initial factor intensity matrix ω_{io}, (iv) the initial immigrant/native shares μ_{go} and occupation shares Π_{go} and (iv) the aggregate changes labor supply $\hat{L}_F$ and $\hat{L}_N$. All these variables are directly observed in our data, see Table 7.

In addition, we require a value of the heterogeneity parameter κ. According to our model, the value of $\kappa + 1$ is the inverse of the estimated slope coefficients from Tables 1, 2 and 3 columns (1-4). The coefficient estimates implie that $\kappa + 1 < 1$ which is inconsistent with our model, i.e. the dispersion in preferences is higher than what the model allows for. In the baseline counterfactual, we therefore choose a small value of κ ($\kappa = 1.1$), but we also report sensitivity tests with larger values of κ.

We summarize the counterfactual results in Figure 5. The left panel of Figure 5 shows the density of real wage changes, $\hat{w}_o/\hat{P}$, across occupations. The 90th and 10th percentile real wage change is 1.03 and .94, respectively. Recall that according to the reduced form results on occupational wages from Table 3, the most affected occupations faced 18 percent lower wage growth compared to the least affected occupations. The counterfactual analysis therefore produces slightly smaller magnitudes compared to the reduced form results. The right panel shows the density of nominal output prices across industries. Some industry prices decline, as these industries are intensive in the use of immigrant occupations, whereas other prices increase, as these industries are intensive in the use of occupations with relatively scarce supply of workers.

Finally, recall that the expected change in utility for group g is $\hat{U}_g = \hat{\Phi}_g/\hat{P}$. According to our results, the expected welfare change is close to zero for natives and -2 percent for the existing immigrant population. Therefore, while real wages in some occupations decline substantially, natives offset the negative impact by switching to higher wage occupations.

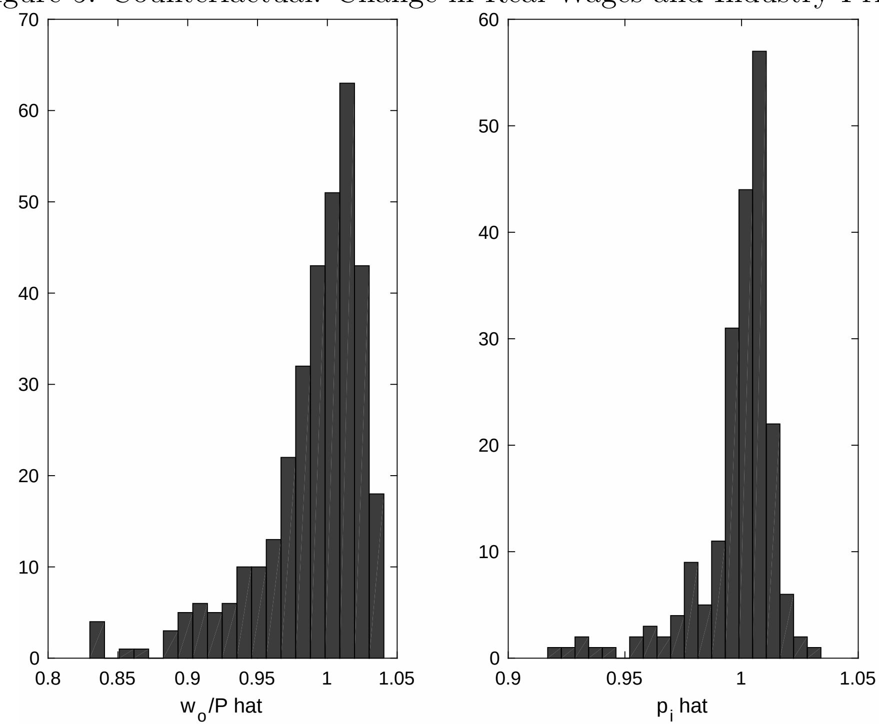
Immigrants, on the other hand, have fewer opportunities to switch to high wage occupations as their comparative advantage is concentrated in low wage occupations.[24]

Table 7: Parameter Values

Variable	
Y_o/Y	Income share of occupation o
β_i	Expenditure share on industry i
ω_{io}	Factor intensity matrix
μ_{go}	Native/immigrant shares, L_{go}/L_o
Π_{go}	Occupation shares, L_{go}/L_g
$\hat{L}_g$	Aggregate labor supply shock, $\hat{L}_F = 2.33$, $\hat{L}_N = 1.09$

All initial values refer to 2005 data.

Figure 5: Counterfactual. Change in Real Wages and Industry Prices



Note: The left figure shows the density of $\hat{w}_o/\hat{P}$ across 4-digit occupations. The right figure shows the density of $\hat{p}_i$ across 3-digit industries.

[24]Increasing the heterogeneity parameter κ to 2 produces $\hat{U}_N = 1$ and $\hat{U}_F = 0.985$ and the 90th and 10th percentile occupation real wage changes are 1.02 and 0.95, respectively.

9 Conclusions

We have investigated the impact of a major labor migration shock on industry employment, labor costs and occupational wages. We find that uneven sorting of immigrants and natives across occupations leads to differential growth of industries and wage costs. Immigration has a quantitatively large impact on the industry mix as sectors differ in their intensity in the use of immigrant occupations. Our results provide empirical support for the simplest possible, albeit, important, factor proportions story: Relative wages adjust to immigration and immigrant intensive industries grow more than other industries. Finally, we calibrate the general equilibrium model in order to assess the effect of immigration on real wages and welfare. The results from this quantitative simulation are broadly in line with the reduced form estimates. Furthermore, the welfare effect of the immigrant shock was close to zero for natives, but negative for the existing population of immigrants.

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Appendix

A Derivations

A.1 Solving the Model in Changes

Consider a shock to aggregate labor supply L_F and L_N, keeping all other parameters constant. Let $\hat{x} \equiv x'/x$ express the relative change in a variable, where x and x' denote the values in the initial and counterfactual equilibrium, respectively.

The relative change in earnings potential $\hat{\Phi}_g$ is

$$\begin{aligned}\hat{\Phi}_g^\kappa &= \frac{\sum_o A_{go} {w'}_o^\kappa}{\sum_o A_{go} w_o^\kappa} \\ &= \sum_o \frac{A_{go} w_o^\kappa}{\sum_o A_{go} w_o^\kappa} \hat{w}_o^\kappa \\ &= \sum_o \Pi_{go} \hat{w}_o^\kappa, \end{aligned} \tag{20}$$

where $\Pi_{go} = L_{go}/L_g$.

Using equation (10), the relative change in aggregate income is

$$\begin{aligned}\hat{Y} &= \sum_o \frac{w'_o L'_o}{\sum w_o L_o} \\ &= \sum_o \frac{w_o L_o}{\sum w_p L_p} \hat{w}_o \hat{L}_o \\ &= \sum_o \frac{Y_o}{Y} \hat{w}_o \hat{L}_o. \end{aligned} \tag{21}$$

From equation (7), the the relative change in occupation labor supply is

$$\begin{aligned}\hat{L}_o &= \sum_g \frac{\frac{A_{go} w_o^\kappa}{\Phi_g^\kappa} L_g}{\sum_g \frac{A_{go} w_o^\kappa}{\Phi_g^\kappa} L_g} \frac{\hat{w}_o^\kappa \hat{L}_g}{\hat{\Phi}_g^\kappa} \\ &= \sum_g \frac{\Pi_{go} L_g}{\sum_g \Pi_{go} L_g} \frac{\hat{w}_o^\kappa \hat{L}_g}{\hat{\Phi}_g^\kappa} \\ &= \hat{w}_o^\kappa \sum_g \mu_{go} \frac{\hat{L}_g}{\hat{\Phi}_g^\kappa}, \end{aligned} \tag{22}$$

where $\mu_{go} = L_{go}/L_o$.

Using equation (9), the relative change in nominal wages is

$$\hat{w}_o = \frac{\hat{Y}}{\hat{L}_o}. \tag{23}$$

Combining equations (21), (22) and (23),

$$\begin{aligned}
\hat{w}_o &= \frac{\sum_{o'} \frac{Y_{o'}}{Y} \hat{w}_{o'} \hat{L}_{o'}}{\hat{w}_o^{\kappa} \sum_g \mu_{go} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}}} \\
&= \frac{\sum_{o'} \frac{Y_{o'}}{Y} \hat{w}_{o'} \left(\hat{w}_{o'}^{\kappa} \sum_g \mu_{go'} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}} \right)}{\hat{w}_o^{\kappa} \sum_g \mu_{go} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}}}.
\end{aligned}$$

Rearranging,

$$\hat{w}_o^{\kappa+1} = \frac{\sum_{o'} \frac{Y_{o'}}{Y} \hat{w}_{o'}^{\kappa+1} \sum_g \mu_{go'} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}}}{\sum_g \mu_{go} \frac{\hat{L}_g}{\hat{\Phi}_g^{\kappa}}}.$$

The equilibrium $\hat{w}_o$ is a fixed point of the equation above.

Using equation (4), the relative change in industry employment is

$$\begin{aligned}
\hat{L}_i &= \frac{\sum_o \pi'_{io} L'_o}{\sum_o \pi_{io} L_o} \\
&= \sum_o \frac{\pi_{io} L_o}{\sum_p \pi_{ip} L_p} \hat{\pi}_{io} \hat{L}_o \\
&= \sum_o \frac{L_{io}}{L_i} \hat{\pi}_{io} \hat{L}_o.
\end{aligned}$$

Using the equilibrium expression for π_{io} in equation (3), we know that $\hat{\pi}_{io} = 1$. Therefore, we get

$$\hat{L}_i = \sum_o \lambda_{io} \hat{L}_o,$$

where $\lambda_{io} = L_{io}/L_i$.

A.2 The Estimation Equation

Using the log approximation $\ln(1+x) \approx x$ or $e^x \approx 1 + x$ repeatedly, we can express Proposition 1 as

$$
\begin{aligned}
\hat{L}_i &= \sum_o \lambda_{io} \hat{L}_o \\
&= \sum_o \lambda_{io} e^{\Delta \ln L_o} \\
&\approx \sum_o \lambda_{io} \left(1 + \Delta \ln L_o\right) \\
&= 1 + \sum_o \lambda_{io} \Delta \ln L_o
\end{aligned}
$$

or

$$
\begin{aligned}
\ln \hat{L}_i &= \ln \left(1 + \sum_o \lambda_{io} \Delta \ln L_o\right) \\
&\approx \sum_o \lambda_{io} \ln \hat{L}_o.
\end{aligned}
$$

A.3 Immigrant Share and Employment

This section shows that the change in the immigrant share can be used as a proxy for the change in total occupation employment when there if no native flight. Let $\Delta L_o = \Delta L_{Fo}$. The immigrant share is $\mu_{Fo} \equiv L_{Fo}/L_o$. Therefore, for marginal changes, the following must hold:

$$
\begin{aligned}
\Delta \mu_{Fo} &= \frac{L_o \Delta L_{Fo} - L_{Fo} \Delta L_o}{L_o^2} \\
&= \frac{\Delta L_{Fo}}{L_o} - \frac{L_{Fo}}{L_o} \frac{\Delta L_o}{L_o} \\
&= \frac{\Delta L_{Fo}}{L_o} \left(1 - \mu_{Fo}\right).
\end{aligned}
$$

The change in occupation employment L_o is then

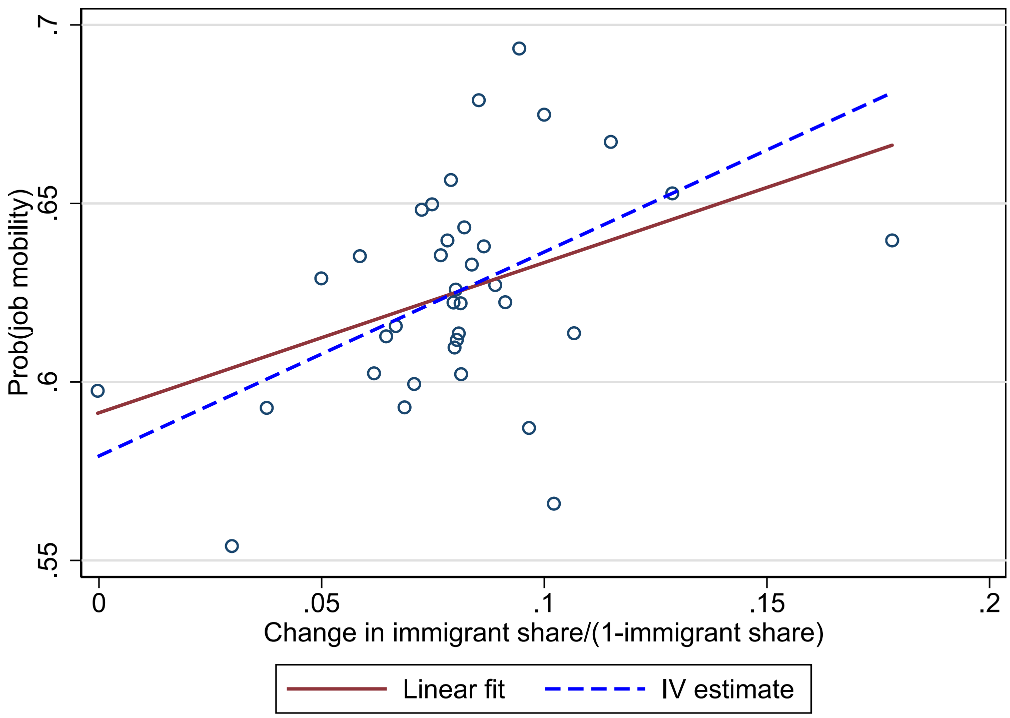
$$
\begin{aligned}
\hat{L}_o &= 1 + \frac{\Delta L_o}{L_o} \\
&= 1 + \frac{\Delta L_{Fo}}{L_o} \\
&= 1 + \frac{\Delta \mu_{Fo}}{1 - \mu_{Fo}},
\end{aligned}
$$

which can be approximated by $\ln \hat{L}_o \approx \Delta \mu_{Fo} / \left(1 - \mu_{Fo}\right)$.

A.4 Occupational Mobility

Recent studies have highlighted native job mobility, often involving occupational upgrading, as an important adjustment mechanism in explaining findings of modest and even positive effects of immigration on wages (e.g. Peri and Sparber, 2009). As we find substantial employment and wage adjustments from immigration into industry-CZ cells, we expect effects of immigration on native job mobility to be modest in our data. Defining job mobility as working outside the initial industry-by-CZ cell 10 years later, the average mobility rate among native, private-sector workers age 25-50 in 2004 is 62.6 percent in our data. Estimating a linear probability model of job mobility on the change in the immigrant share, including the exact same controls as in column (8) of Table 1, we next find the coefficient of the immigrant share variable to be 0.410 (s.e.= 0.192). This OLS estimate will be downward biased if favorable demand conditions (or productivity shocks) both recruit immigrants and induce natives to stay in their initial industry-by-CZ cell. When we reestimate the model using the IV strategy of Table 1, we obtain a 2SLS estimate that is slightly higher, 0.571 (0.491), but the estimate is no longer statistically significant. In economics terms, an increase in the immigrant share of 10 percentage points is predicted to raise the native mobility rate by 5.7 percentage points, or 9.1 percent of the sample average. We interpret this as evidence of modest occupational adjustments to migration shocks in our data. In Figure 6, we display the binned scatter plot of native job mobility versus the increase in the immigrant share, including predicted values from both the OLS and 2SLS models for illustrative purposes.

Figure 6: Occupational Mobility



B Additional Tables

Table 8: Immigration, Employment and Industry Wage Growth. OLS Estimates.

	(1)	(2)	(3)	(4)
Dependent variable: $\ln \hat{L}_i$				
$\sum_o \lambda_{io} \ln \tilde{L}_o$	-.08	-.22	-.15	-.20
	(.30)	(.50)	(.51)	(.52)
$\sum_o \lambda_{io} \tilde{\mu}_o$	-.32	.04	.35	.32
	(.23)	(.30)	(.30)	(.30)
Dependent variable: $\ln \hat{W}_i$				
$\sum_o \lambda_{io} \ln \tilde{L}_o$	-.08	-.34	-.60^a	-.59^a
	(.13)	(.23)	(.23)	(.23)
$\sum_o \lambda_{io} \tilde{\mu}_o$	-.08	.04	-.07	-.05
	(.09)	(.14)	(.14)	(.14)
Pre-sample industry controls	No	No	Yes	Yes
Pre-sample worker controls	No	No	No	Yes
Industry (2-digit)-CZ FE	No	Yes	Yes	Yes
Number of observations	3,554	2,835	2,835	2,835

Note: Robust standard errors clustered by industry-CZ in parentheses. Changes refer to the time period 2004 to 2013. The unit of observation is a 3-digit industry (NACE)-CZ pair. Industry controls are: Log value added, log employment, log average wages, the share of exports in total sales, the share of imports in total costs, and the share of wages in total costs (2003 values). The workers control is the share of workers with a completed high school education or higher (2003 values, averaged across firms in a 5-digit industry). ^{a} p< 0.01, ^{b} p< 0.05, ^{c} p< 0.1.

Table 9: Factor Intensity Matrix

	Professor or similar STYRK 2310			Sum
NACE803 “Higher education”	.52	.	.	1
NACE 751 “Administration of the state (..)	.06	.	.	1
NACE 732 “Research (..) on natural sciences and engineering”	.05	.	.	1

	Carpenter or similar STYRK 7421			Sum
NACE203 “Manufacture of builders’ carpentry and joinery”	.21	.	.	1
NACE205 “Manufacture of other products of wood (..)	.19	.	.	1
NACE454 “Building completion”	.15	.	.	1