The Labor Supply Curve is Upward Sloping: The Effects of Immigrant-Induced Demand Shocks*

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Abstract

What is the effect of immigration on native labor-market outcomes? An extensive literature identifies the differential impact of immigration on natives employed in jobs that are more exposed to immigrant labor (supply exposure). But immigrants consume in addition to producing output. Despite this, no literature identifies the impact on natives employed in jobs that are more exposed to immigrant consumption (demand exposure). We study native labor-market effects of supply and demand exposures to immigration. Theoretically, we formalize both measures of exposure and solve for their effects on native wages. Empirically, we combine employer-employee data with a newly collected dataset covering electronic payments for the universe of residents in Norway to measure supply and demand exposures of native workers to immigration over the period 2000-2015, surrounding EU expansions that begin in 2004. We find large, positive, and persistent differential effects of demand exposure on native worker income. Finally, we embed our qualitative theory into a quantitative framework, choose model elasticities to match our empirical estimates, and measure real wage changes for natives.

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1 Introduction

What is the effect of immigration on the evolution of wage income for native workers? This question motivates a large body of theoretical and empirical work. Much of this literature focuses on the impact of migrants as producers of output, identifying the differential impact of immigration across native workers employed in jobs that are more exposed to immigrant labor (supply exposure). But immigrants not only produce output, they also consume it. Despite this, no equivalent literature identifies the differential impact of immigration across native workers employed in jobs that are more exposed to immigrant consumption (demand exposure).

We study the effects of supply and demand exposures to immigration on native workers' labor-market income. Our key theoretical insight is straightforward. If immigrants' consumption patterns differ from natives', then an immigrant inflow increases demand for some goods more than others. This increases relative demand for native labor in these goods, which increases relative incomes of native workers employed there if native labor supply curves across sectors are upward sloping. Empirically, we combine employer-employee data with a newly collected dataset covering electronic payments for the universe of residents in Norway to measure supply and demand exposures to immigration across commuting zones and sectors. We study the impact of immigration on the Norwegian labor market over the period 2000-2015, the period surrounding EU expansions that begin in 2004. We find that natives employed in jobs with higher demand exposure to immigration experience large and persistent increases in their income relative to otherwise identical natives in less exposed jobs. Finally, we embed our qualitative theory into a quantitative model, choose model elasticities to match our empirical estimates, and study the impact of immigration into Norway on the levels of native real wages.

In Section 2, we present a theory of a local labor market with two factors (which we refer to as immigrant and native labor), constant returns to scale production functions that may differ across jobs (which we refer to as sectors), homothetic demand that may differ between immigrants and natives, and imperfectly elastic labor supply across sectors. We study how immigration differentially affects native wages across sectors. We argue that two forces are at play, which we refer to as supply and demand exposures. To gain intuition, it is useful to consider two extreme cases that isolate these forces.

In the first case, suppose immigrants and natives have common expenditure shares across sectoral output but different employment shares across sectors. In this case, *immigrant intensities of production* (defined as the share of the wage bill paid to immigrants within each sector) shape the impact of immigration on native workers in each sector.

We refer to these differences across sectors in native exposure to immigration—which are shaped by immigrant intensities of production—as supply exposure. Supply exposure is studied extensively in labor and international economics; see, e.g., Altonji and Card (1991), Card (2001), Friedberg (2001), Borjas (2003), Dustmann et al. (2016), and Burstein et al. (2020), among many others.

Whereas we incorporate supply exposure, our focus is on differences in immigrant and native consumer demands for sectoral output and how this shapes the impact of immigration on native wages. To gain intuition, suppose that the immigrant intensity of production is common across sectors (so that supply exposure is equalized) but that natives and immigrants have different expenditure shares across sectors. In this case, *immigrant intensities of consumption* (defined as the share of expenditure paid by immigrants within each sector) shape the impact of immigration on native workers in each sector. If an inflow of immigrants raises total expenditure of immigrants relative to natives within the local labor market, then the share of local spending within sectors that are immigrant intensive in consumption rises. This raises labor demand for native workers in these sectors relative to others, which in turn raises relative native wages there. We refer to these differences across sectors in native exposure to immigration—which are shaped by immigrant intensities of consumption—as demand exposure.

Section 2 formalizes this intuition, combines both types of exposure, and provides a theoretically consistent approach to measuring exposures. In an environment with two sectors and without imposing any functional forms, we show that changes in a sector's native (log) wage can be expressed as the sum of three terms: (i) a component that is common across sectors within the local labor market, (ii) a supply exposure component, and (iii) a demand exposure component. Supply exposure is the interaction between an immigrant-relative-to-native labor supply shock at the local labor market level and the sector's immigrant intensity of production within the local labor market. Demand exposure is the interaction between an immigrant-relative-to-native expenditure shock at the local labor market level and the sector's immigrant intensity of consumption within the local labor market. We show how underlying local elasticities shape the response of native wages to demand and supply exposures. Finally, we show that these two-sector, local results directly imply equivalent global results in a many-sector model given particular functional forms. This theory provides the first formalization of the effect of immigration on native labor-market outcomes via preference heterogeneity. It also helps guide our empirical investigation and interpret its results.

In Section 3, we describe our empirical context, datasets, and specification. We focus on the Norwegian labor market, which experienced an exceptionally large and rapid inflow of immigrants starting in the mid-2000s, with the share of migrants in the labor force growing from less than 8% to more than 14% percent in less than 10 years. This surge mostly resulted from European Union expansion in 2004 and 2007. The share of migrants from these new accession countries in Norway's labor force rose from less than 0.5% in 2005 to 4% in 2015.

Our empirical contribution rests on the ability to combine individual worker employment histories and tax income data with a newly collected dataset covering electronic payments for the universe of Norwegian residents beginning in 2006. The electronic payments data are provided by the Norwegian retail clearing institution, Nets Branch Norway, and cover all debit card payments via BankAxept and all online bank wire payments cleared via the Norwegian Interbank Clearing System (NICS). We show that aggregating this data yields measures of quarterly levels and growth rates of consumption that match National Accounts data very well. However, unlike National Accounts data, we observe the sector of expenditure, the location of expenditure, and the nationality of each consumer. Hence, we are able to construct immigrant intensities of consumption for each region-sector pair (defining region as commuting zones) as well as the immigrant-relative-to-native expenditure shock at the region level, the two components of demand exposure. Using the employment history data, we are similarly able to construct supply exposure.

Our empirical specification follows our theoretical predictions closely. We regress changes in individual native workers' incomes between 2004 and each year between 2000 and 2015 on a sector fixed effect, a local labor-market fixed effect, worker characteristics, and measures of supply and demand exposures, each constructed at the region-sector level. We instrument for both measures of exposure using a relatively standard instrument for supply exposure—the interaction between the lagged value of the immigrant intensity of production at the region-sector level and a Card instrument for the predicted inflow of immigrants at the region level—and a related instrument for demand exposure.

In Section 4 we present our empirical results. Our primary empirical contribution is to present the first evidence on how demand exposure shapes the earnings (real wage income) of native workers. Compared to similar individuals, a Norwegian employed in a region-sector with higher demand exposure experiences an increase in wage income between 2004 and each year thereafter. The effect starts small, peaks in 2014, and is relatively stable between 2009 and 2015. Our estimates imply that a worker's annual real earnings in 2015 would be about 8,000 krone higher if employed in 2004 in a region-sector with a one standard deviation higher measure of demand exposure, equivalent to 1.6% of annual average real earnings in 2003 of our estimation sample.

A natural concern is that regions and sectors with higher initial immigrant intensities of consumption may also differ in underlying trends. We show this is not the case. Another concern is that immigrant intensities of consumption and/or production are correlated with other pre-determined characteristics, and that these characteristics generate differential effects on incomes starting contemporaneously with the immigration shock. We find that our empirical results are stable when incorporating a wide range of additional controls. We additionally show that our empirical results are not driven by any one commuting zone or consumption category, and we find positive effects of demand exposure across alternative samples.

We present a set of additional empirical results on the underlying mechanism (in our theory) driving the relationship between demand exposure and native wages. We show that expenditure rises more within more demand-exposed region-sector pairs, as predicted by the theory. We also show that the impact of demand exposure on native wages is substantially and significantly larger in less-traded than within more-traded sectors, as predicted by our extended theory that incorporates trade.

Because our empirical analysis identifies only the *differential* effects on native real wage incomes of demand and supply exposures, we use an extended version of our model to quantify the impact of the immigrant inflow between 2003 and 2015 on the *levels* of native real wages in Section 5. We match model moments to our rich expenditure and income data and choose model elasticities to match our empirical findings via indirect inference.

We feed into the calibrated model the 130% national increase in immigrant employment between 2003 and 2015 and solve for the full general equilibrium response to this shock. The median real wage change—across commuting zone and consumption category pairs—is 2.8%. This effect masks substantial heterogeneity: the 10th and 90th percentiles are 1.6% and 4.3%. Finally, in addition to studying a range of sensitivity exercises, we quantify the importance of supply and demand exposures in obtaining these quantitative results. We do so by parameterizing restricted versions of the framework that abstract from one or the other exposure. We find that each exposure plays an important role in generating the model's real wage effects.

Relation to the literature. There is an extensive literature studying the impact of immigration on native wage incomes. Early work focuses on regional comparisons, answering the following question: Do native wages rise or fall in regions receiving relatively more immigrants? The canonical paper in this literature is Card (1990); see also Hunt (1992), Card (2009), Borjas (2017), and more recent extensions investigating adjustment mechanisms (e.g, Burchardi et al., 2019; Edo, 2020; Monras, 2020; Piyapromdee, 2021; Terry et al., Forthcoming).

One strand of the literature compares different groups of workers, defined by education and experience cells, assuming well integrated national markets (e.g., Borjas, 2003; Ottaviano and Peri, 2012). These papers answer the question: Which native workers complement or substitute foreign labor? Another strand of the literature compares labor-market outcomes across jobs and across region-job pairs, answering the question: Do native wages rise or fall in jobs in which immigrants are employed? Canonical papers in this literature include Altonji and Card (1991), Card (2001), Friedberg (2001), and Dustmann et al. (2016), while papers using firm-level data include Foged and Peri (2016), Doran et al. (2022), and Brinatti and Morales (2025).[1] In this space, our paper is most closely related to Burstein et al. (2020) in its approach and to Bratsberg and Raaum (2012) and Bratsberg et al. (2023) in its focus on Norway's experience following EU expansion. Both of these strands of the literature study what we refer to as supply exposure, emphasizing either competition or complementarity effects of foreign inflows on different types of native workers based on production functions at various levels of disaggregation: in aggregate, at the local level, within sectors, within firms, or some combination thereof. Some of these papers consider homogeneous labor and others heterogeneous labor that is classified into different factor types, but none introduces differential demand exposure across jobs.

Our contribution relative to these literatures is fourfold. First, theoretically we generalize the foundations of supply exposure, dropping functional forms; more importantly, we introduce demand exposure. Second, guided by our theory, we propose and implement an empirical research design that allows us to identify, for the first time, the impact of demand exposure on native wages. Third we show that, while omitting demand exposure could lead to biased estimates of supply exposure, in our empirical investigation demand and supply exposures at the region-sector pair (conditional on region and sector fixed effects) are not strongly correlated.[2] Finally, we quantify, for the first time, the real-wage implications of demand exposure using a quantitative model.

There is a distinct literature that centers on regional variation in migration (whether international or domestic) and how migrants affect aggregate regional labor supply and aggregate regional labor demand; see, e.g., Hong and McLaren (2015), Olney (2015), Albert and Monras (2022), and Badilla Maroto et al. (2024).[3] All these papers maintain,

[1] Some papers in this literature focus on the impact of supply exposure on outcomes distinct from native wages, including goods prices (e.g., Lach, 2007; Cortes, 2008) and technical change (e.g., Kerr and Lincoln, 2010; Lewis, 2011; Clemens et al., 2018; Peters, 2022).

[2] In this third contribution, our work is related to Dustmann et al. (2016) and Munoz (2023), who use commuters and "posted" workers respectively to identify the effect of supply exposure.

[3] This literature is related to theoretical insights in Borjas (2013), which argues that if immigrants spend a smaller share of their income locally than do natives, then immigration reduces the aggregate native wage by more. Our results relate to the differential impact of immigrants on natives across jobs.

however, the assumption that immigrants and natives have the same preferences over final goods, but that income spent locally may be affected by remittances or consumption/savings decisions. We instead focus on how migrants differentially affect demand across goods, for any given impact on aggregate labor supply and demand. In this respect, our contribution centers on variation in demand exposure across sectors, for which we find strong evidence in the data. There are a handful of papers that have identified migrants' and immigrants' distinctive consumption patterns; see Atkin (2016) and McCully et al. (2024). Relative to both of these literatures, we provide a theory for measuring demand and supply exposures and we identify their impacts on native labor-market outcomes.[4]

Finally, our formalization of demand exposure is most directly related to the international trade literature studying how demand differences across countries shape the pattern of trade and its effects on inequality; see, e.g., Costinot and Vogel (2010) and Caron et al. (2014). By emphasizing how changes in supply affect relative demand across goods, our paper is also related to work on the home market effect and directed technical change; see, e.g., Krugman (1980), Acemoglu (2002), and Costinot et al. (Forthcoming).

2 Theory

In this section we present a theoretical framework that guides our subsequent empirical and quantitative exercises. All derivations are provided in the Theoretical Appendix.

2.1 General environment

We consider a single closed economy populated by agents in two labor groups, indexed by g, whom we refer to as natives $g = n$ and immigrants $g = i$. The aggregate supply of each group g is exogenous and given by L^g.[5] Agents both produce and consume sectoral output, with sectors indexed by $s \in \mathcal{S}$. Agents within group g have common, homothetic preferences over sectoral output; but these preferences may differ across groups. All agents inelastically supply one unit of labor and choose in which sector to work. Output of sector s, Y_s, is a sector-specific constant returns to scale combination of employment of

[4]Our paper is also related to the literature studying the impact of tourism on local economic activity (e.g., Faber and Gaubert, 2019; Almagro and Domínguez-Iino, 2024; Allen et al., 2023).

[5]We apply this model across many regional labor markets indexed by r in our empirical analyses; we omit region subscripts here for notational simplicity. We additionally consider open economies and endogenous migration in the empirical and quantitative analyses.

each group g in its production, denoted by L_s^g.[6] Goods market clearing in the closed economy requires that total output equals total consumption, $Y_s = C_s$, where consumption in sector s is the sum of the consumption of natives and immigrants, $C_s = C_s^n + C_s^i$. Factor markets clear, so that $L^g = \sum_s L_s^g$ for each g. Agents within group g have individual preferences for working in each sector s, which implies that nominal wages for group g workers in each sector s, W_s^g, may vary across sectors. Each group has a balanced budget, with total income, $\sum_s W_s^g L_s^g$, equal to total expenditures, denoted by $X^g \equiv \sum_s P_s C_s^g$, where P_s is the price of sector s.

Our goal in what follows is to characterize the differential impact of changes in labor supplies of both immigrants and natives, $\ell^g \equiv d \log L^g$ for $g \in \{n, i\}$, on native wages, $w_s^n \equiv d \log W_s^n$, where we use lower-case variables to denote log changes in upper-case variables.

Defining immigrant intensities. In the analysis that follows, two equilibrium shares play a central role. We denote by

$$\theta_s^i \equiv \frac{L_s^i W_s^i}{L_s^i W_s^i + L_s^n W_s^n} \tag{1}$$

the share of labor payments in sector s that are paid to immigrants in the initial equilibrium; θ_s^n is defined equivalently for natives. Whereas θ_s^i is often referred to as the immigrant intensity of sector s, we refer to it as the *immigrant intensity of production* in sector s, in order to distinguish it from the following share. We denote by

$$\mu_s^i \equiv \frac{C_s^i}{C_s^i + C_s^n} \tag{2}$$

the share of expenditures (or consumption) in sector s that is spent by immigrants in the initial equilibrium; μ_s^n is defined equivalently for natives. We refer to μ_s^i as the *immigrant intensity of consumption* in sector s.

2.2 Analytic results

Here, we derive analytic expressions for the impact of immigration on native wages in a non-parametric environment with two sectors. We provide analytic extensions, including incorporating many sectors, below.

In this environment, there are three types of elasticities that play a role in the analysis. We define each of these elasticities locally, around an initial equilibrium.

[6] Although we abstract from capital, our results would be similar if the combination of immigrant and native labor represented by Y_s were combined with elastically-supplied capital in a Cobb Douglas production function (without imposing restrictions on the production function combining immigrant and native labor).

We denote by ρ the local elasticity of substitution in labor demand within sector s,

$$\ell_s^n - \ell_s^i = -\rho(w_s^n - w_s^i) \tag{3}$$

where ρ shapes firm substitution—for firms in sector s—between immigrant and native labor in response to a change in their relative wages within s.[7] We denote by η the local elasticity of substitution in consumption across sectors,

$$c_s^g - c_{s'}^g = -\eta(p_s - p_{s'}) \tag{4}$$

where η shapes consumer substitution between sectors in response to a change in relative sectoral prices. Finally, we denote by κ the local elasticity of substitution in labor supply across sectors,

$$\ell_s^g - \ell_{s'}^g = \kappa(w_s^g - w_{s'}^g) \tag{5}$$

where κ shapes labor reallocation between sectors in response to a change in relative wages. Given these definitions, we now turn to results, starting from a simple case where intuition is especially transparent before turning to the more general case. In extensions, we allow ρ to vary across sectors and η and κ to vary across groups.

A simple case. To build intuition and highlight the impact of demand exposure, suppose first that immigrants and natives are allocated identically across sectors ($\theta_s^i = \theta_{s'}^i$) and that preferences are Cobb-Douglas ($\eta = 1$).[8] In this case, the log change in the native wage in sector s relative to sector s' can be expressed as

$$w_s^n - w_{s'}^n = \frac{1}{1+\kappa} \underbrace{\left(x^i - x^n\right)\left(\mu_s^i - \mu_{s'}^i\right)}_{\text{demand exposure}} \tag{6}$$

Demand exposure depends on a region-specific shift and a region-and-sector-specific difference in shares, where $x^i - x^n$ is the aggregate change in immigrant-relative-to-native expenditure at the regional level and $\mu_s^i - \mu_{s'}^i$ is the difference in immigrant-intensities of consumption between sectors s and s'.

[7] There is some debate in the literature about whether immigrants and natives are perfect or imperfect substitutes; see, e.g., Borjas et al. (2012). Our results hold in the limit when ρ converges to infinity. Moreover, imperfect substitution at the sector level is consistent with perfect substitution at the task level in a framework in which sectoral output is produced from task output; see, e.g., Burstein et al. (2020).

[8] Here, we impose an assumption directly on endogenous variables: $\theta_s^i = \theta_{s'}^i$. A sufficient condition on primitives that generates this outcome is that there is neither productive comparative advantage nor differences in preferences for working in sectors across natives and immigrants. Appendix A.5 considers two additional simple cases featuring differences in supply exposure and no differences in demand exposure.

Intuitively, an increase in total immigrant-relative-to-native expenditure increases the share of expenditure in the sector with the higher immigrant intensity of consumption (the higher value of μ_s^i), which increases the relative demand for native labor in that sector. The elasticity of labor supply, κ, plays a central role in determining the impact of changes in relative demand for native labor on relative native wages across sectors. If $\kappa = \infty$, so that the relative supply curve of native labor across sectors is flat, then native wages must change equally across sectors. However, if the relative supply curve of native labor is upward sloping, $\kappa < \infty$, then an increase in total immigrant-relative-to-native expenditure will increase the native wage by more in the sector with the higher immigrant-intensity of consumption.

Whether immigrant inflows increase or decrease the expenditure of immigrants relative to natives depends on whether immigrants and natives are gross complements or substitutes in the aggregate factor demand system. This relationship between changes in immigrant and native populations and changes in immigrant and native expenditures is closely tied to the first stage of our empirical specification.[9]

The more general result. Now relax the previous restrictions, allowing immigrant and native allocations to differ across sectors and allowing η to differ from one. In the more general case, the intuition underlying equation (6) is preserved and the expression becomes

$$w_s^n - w_{s'}^n = \frac{1}{\eta + \kappa} \left\{ \underbrace{\Delta\left[x + (\eta - 1)p\right] \left(\mu_s^i - \mu_{s'}^i\right)}_{\text{demand exposure}} + \frac{\eta - \rho}{\kappa + \rho} \underbrace{\Delta\left[\ell - \kappa w\right] \left(\theta_s^i - \theta_{s'}^i\right)}_{\text{supply exposure}} \right\} \tag{7}$$

Relative to equation (6), there are three changes. First, the change in total immigrant-relative-to-native expenditure, $x^i - x^n$, in equation (6) is now net of changes in immigrant-relative-to-native price indices,

$$\Delta\left[x + (\eta - 1)p\right] \equiv \left(x^i + (\eta - 1)p^i\right) - \left(x^n + (\eta - 1)p^n\right)$$

in equation (7), where $p^g \equiv \sum_s (P_s C_s^g / X^g) p_s$ is the change in the price index for group g. Importantly, this shock remains common across sectors within the local labor market. Second, the role of η becomes explicit in determining the elasticity of the relative native wage across sectors with respect to a shift in the relative demand curve for native labor (the η in the $\eta + \kappa$ term multiplying both demand and supply exposure). Equation

[9] In practice, we find that an (exogenous) inflow of immigrants raises immigrant-relative-to-native expenditures, consistent with gross substitutability.

(7) clarifies that a necessary condition for higher demand exposure in sector s than s' to raise the relative wage of s is that the demand curve across sectoral output is downward sloping $\eta < \infty$; this is similar to the condition on the relative native supply curve across sectors discussed in the context of equation (6).

Third, there is a new term in the equation that captures the effect of supply exposure. As with demand exposure, supply exposure is the product of a region-specific shift and a region-and-sector-specific difference in shares, where

$$\Delta[\ell - \kappa w] \equiv \left(\ell^i - \kappa w^i\right) - \left(\ell^n - \kappa w^n\right)$$

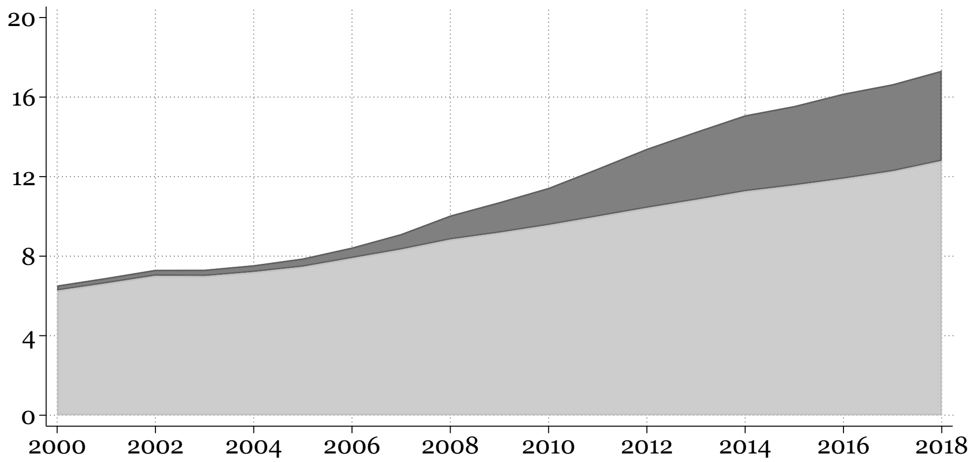
is the aggregate change in immigrant-relative-to-native employment net of changes in wage indices at the regional level, where $w^g \equiv \sum_s (L_s^g / L^g) w_s^g$ is the wage index for group g, and where θ_s^i is the immigrant-intensity of production in sector s. The effect of supply exposure depends on two forces: scale and substitution effects. With more immigrant workers, firms scale up production disproportionately in the sector that is immigrant intensive in production, increasing the demand for all inputs. At the same time firms substitute towards immigrant labor disproportionately in the sector that is immigrant intensive in production. Scale effects are governed by η. Higher substitutability across sectors in consumer demand induces consumers to switch more toward the sector with the larger price decline, which is the sector with the higher immigrant intensity of production. Substitution effects are governed by ρ, the elasticity of substitution between immigrants and natives in production. Equation (7) shows that an inflow of immigrants induces a shift in the relative demand curve for native labor towards or away from the immigrant-intensive in production sector depending on which of these two forces is stronger, i.e. depending on the sign of $\eta - \rho$. This is an application of the Hicks-Marshall laws of derived demand.

Further generalizations and additional results. In Appendix A.1 we provide graphical intuition for our analytic results.

In Appendix A.3 we further generalize the analytic results presented above by allowing the elasticity ρ to vary across sectors and the elasticities κ and η to vary across groups. This generalization leaves supply and demand exposures largely unchanged.

In Appendix A.4 we show that equations (6) and (7)—and their further generalizations described above—hold exactly in a many-sector extension of our analytic framework under the particular functional forms we impose in our quantitative model in Section 5. This many-sector parametric framework is the closed-economy version of the framework introduced by Burstein et al. (2020) and employed in Brinatti and Guo (2024), but extended to allow for differences across sectors in demand exposure. Finally, we extend the quan-

Figure 1: Immigrant and New Accession Share (in %) of the Norwegian Workforce



Notes: Dark grey plots 100 × number of 2004 and 2007 EU accession immigrants in the Norwegian labor force divided by the total number of individuals in the labor force for each year. Light grey plots the same calculation, but using non-EU accession immigrants in the numerator. Both are calculated for all employment relationships measured in November of each year.

titative model to incorporate trade in the Quantitative Appendix.

3 Empirical context, data, and specification

We describe the empirical context in Section 3.1, our data sources in Section 3.2, our empirical specification, instrumentation strategy, and measurement in Section 3.3.

3.1 Empirical context

We focus on the Norwegian experience in the 2000s, which provides an ideal empirical setting for two reasons. First, Norwegian data is exceptional, allowing us to measure immigrant intensities of consumption and production across sectors and commuting zones and allowing us to track individual workers' incomes over time, as we describe in Section 3.2. Second, Norway experienced a large and rapid increase in its immigrant population starting in the mid-2000s. The share of immigrants in the workforce rose from less than 8% to over 14% in less than ten years, as shown in Figure 1. We study the impact of this overall immigration shock on native Norwegian labor-market outcomes.

This immigration boom largely resulted from the European Union's expansion. In January 2004, the EU underwent its largest-ever enlargement, both in terms of the number of countries admitted and the total population added. Ten countries acceded in 2004: Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia. In January 2007, Bulgaria and Romania also joined. In what follows, we refer to these new entrants to the EU as the *new accession countries*. Norway, as a member of the European Economic Area—and therefore part of the EU single market—imposed only minimal restrictions on migration from these new member states (Dølvik and Eldring, 2008).

Indeed, while individuals from new EU accessions during the 2004-2009 transition period did not get full free movement rights immediately, the process was not difficult: they generally had to secure a residence/work permit tied to a concrete full time job offer before starting to work. Permits were conditional on the job meeting Norwegian-level pay and working conditions (documented by the employer). Once a worker had been legally employed for 12 months the special transitional restrictions no longer applied, and hence, migrants' access to the Norwegian labor market was unrestricted. This process explains why the increase in new EU accession migrants in the Norwegian *workforce* shown in Figure 1 only starts to become fully apparent in 2008 rather than a bit earlier. It is quite clear though, that new EU accession country migrants managed to enter and remain in the Norwegian labor market. In fact, by 2024, two of the new accession countries were among the three largest sources of Norway's immigrant population: Poland was the largest and Lithuania the third-largest. More broadly, the share of new accession migrants in Norway's labor force rose from less than 0.5% in 2005 to 4% in 2015, which is also shown in Figure 1.

Additional details on the Norwegian context. Norway's population is approximately 5.5 million, with the capital, Oslo, accounting for almost 20 percent. The Norwegian labor market is characterized by a combination of a generous unemployment insurance (UI) system and collective bargaining. The UI system compensates for nearly two-thirds of lost earnings and can be extended for up to two years. A majority of workers are covered by agreements negotiated between trade unions and employers. Approximately half of employees in the private sector benefit from tariff agreements under a two-tier bargaining system. Tariff wages are initially negotiated at the industry level and set centrally, after which they are supplemented by local adjustments bargained at the firm level. This local adjustment allows industry-specific wages to vary across regions in response to local demand conditions (and is the core of our theoretical model). This two-tier framework is regarded as a key factor contributing to Norway's relatively compressed wage structure. See Bhuller et al. (2022) for a detailed discussion.

3.2 Data

Employment, income, and worker characteristics data. The first key dataset contains administrative records on the universe of employment relationships from 2000.[10] This data provides us with measures of part-time and full-time employment status and five-digit industry codes.

We link this information to tax income data to measure annual wage income, which includes all income from any employer throughout the year, and is typically reported to the Tax Authority by employers. We winsorize income at the 99th percentile within each year and replace negative income (when a worker owes his or her employer money) with zero. We adjust this measure of income using the national consumer price index. The tax registers also provide information on each individual's residential municipality. In our empirical analysis, we define local labor markets using commuting zones. There are 46 commuting zones, which are defined using aggregate statistics linking workers' residential and employers' workplace municipalities, as described in Bhuller (2009).

We also link the employment data to population panel data using person identifiers, which allows us to measure worker-level background characteristics, including education levels and country of origin. In what follows, we consider a worker to be an immigrant if born outside Norway.

We use this individual dataset for two purposes, as we explain in more detail below: first, to compute labor supply exposure, and second, to construct some of our outcomes of interest.

Expenditure data. Our empirical contribution rests on the ability to combine employment histories with a newly collected dataset covering electronic payments for the universe of Norwegian residents beginning in 2006.[11] For this exercise we need two things. First, we need to compute immigrant intensities of consumption across consumption sectors and regions. Second, we need to determine the consumption sector of employment of each native worker in our employment data. We describe how we address these two points in what follows.

To construct immigrant intensities of consumption by region and consumption sector, we use data provided by the Norwegian retail clearing institution, Nets Branch Norway (henceforth referred to as Nets), which covers two data sources: (*i*) almost all debit card payments via BankAxept (*ii*) all online bank wire payments cleared via the Norwegian

[10] Before 2015, the data include employment relationships that had hours or income above a certain threshold. Thereafter, the data was reported monthly for every type of employment except self-employment.

[11] In Section 3.3, we discuss in detail how we address the fact that this dataset starts in 2006, whereas the first EU expansion occurred in 2004.

Interbank Clearing System (NICS).[12] BankAxept is the national payment system in Norway and is owned by Norwegian banks. Virtually all debit card payments in domestic physical stores are processed via BankAxept, whereas credit card payments, payments abroad, and online debit card payments are processed by VISA or Mastercard. NICS is the interbank clearing system for the Norwegian Krone (NOK). It is used by all banks operating in Norway and taking part in the Norwegian banking community's infrastructure for payments.[13]

BankAxept data allows us to link each card payment to the Merchant Category Codes (MCC) of the card terminal and with its associated zip code. We can then link MCCs to United Nation's 1999 COICOP categories based on a crosswalk constructed by Norges Bank. Furthermore, each debit card is associated to an individual, either native or foreign born. Hence, we use this dataset to compute immigrant and native debit card expenditures at the local level across COICOP categories.

We use a similar process for online bank wire payments. Specifically, in the bank wire transfer data we observe the recipient of each payment, which, if it is a business account, can be associated to the business industry NACE code and to the location of this business. We then use the Norges Bank crosswalk to map NACE codes into COICOP categories. And we use information on the sender of the bank wire transfer to determine if the payment was made by an immigrant or a native.[14]

In principle, we could define consumption sectors using either the 14 aggregate or the 58 disaggregate COICOP codes, directly defined by the UN. However, some categories are small; and for some it is difficult to determine whether an MCC or a NACE code should be associated to one or another COICOP category. As a result, we follow the approach developed by Norges Bank and use aggregate COICOP categories together with combinations of more disaggregated ones, something that we henceforth refer to as Consumption Categories (CCs). To understand this process, Table A1 in the Empirical Appendix lists all COICOP and CC categories in the raw data, side by side. Very often the Consumption Categories that we use in our analysis coincide with an aggregate COICOP category. Other times, a CC code coincides with a disaggregate COICOP. Finally, sometimes a CC is a combination of two or more disaggregate COICOPs. We additionally

[12] As explained in Ahn et al. (2024), the coverage of debit card payments in our micro-level data is almost perfect. There is, however, a small gap of about 13% at the beginning of the period, related to the closure of some accounts.

[13] Transaction via NICS includes all invoices paid using a "KID-number", which includes all invoices paid via "Efaktura" and "Avtale Giro."

[14] Table A2 in the Appendix provides examples of the mapping from NACE codes to Consumption Category codes, which are aggregations of COICOP codes, as explained below and in Appendix B.1. For example, "Manufacturing of other furniture" and "Wholesale of furniture" are both associated to "Furnishings."

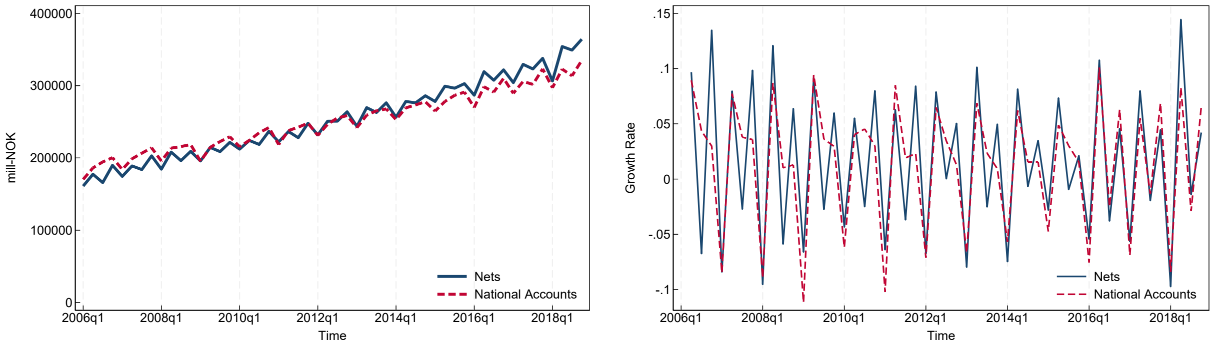
drop three categories, displayed in red. Two of these dropped categories do not fit the context of the theoretical framework: Payments to public institutions and Cash back. The third dropped category—Alcoholic beverages, tobacco and narcotics—has an immigrant intensity of consumption measured at the national level that is unstable across time, unlike every other consumption category, as shown in Figure A2 in the Empirical Appendix. This leaves us with 20 CC codes, displayed in the right-hand side of Table A1. See Section B.1 of the Empirical Appendix for additional details.

Three caveats are worth highlighting. First, we do not observe the sectoral allocation (the MCC code) of credit card expenditures. Credit card payments are observed in our data as payments of credit card bills received by banks and are included in the consumption category "Banks." To understand the extent to which credit card payments are or are not a large share of expenditure in Norway we can compare total credit card payments in 2006 to total household consumption. This ratio is 7 percent (Norges Bank, 2017), indicating that this allocation is unlikely to drive our results. Second, we do not directly observe cash payments. These are likely to be low in Norway as well. The earliest direct evidence for this are two surveys, one in 2007 and the other in 2017, providing estimates that imply cash represented less than 10% of total payments in Norway (Ahn et al., 2024; Norges Bank, 2023; Gresvik and Haare, 2008). Third, housing expenditures are both incomplete and primarily allocated across three separate consumption categories. We do not observe many house purchases in full, for example when part of the purchase is based on savings. The "Banks" category contains payments to the banks, including some mortgage payments and other forms of credit. We observe only a subset of rent payments. We do not observe housing rent paid to individuals. Housing rent paid to corporations is allocated to the consumption category "Services," since this contains real estate services. Finally, most construction-related expenditures (both in connection with housing and non-housing services) are allocated to "Utilities & Construction," (as shown in Table A3 in the Empirical Appendix).

Our data closely follows the estimation of Statistics Norway of aggregate expenditures, as shown Figure 2 and as shown in more detail in Ahn et al. (2024). The left panel of Figure 2 shows that our expenditure measure—aggregated across all consumption categories—tracks the quarterly level of consumption from the National Accounts very well. The right panel shows that the quarterly growth rate of our expenditure measure also strongly correlates (0.81) with the quarterly growth rate of consumption from the National Accounts.[15]

[15]National Accounts household consumption includes imputed housing consumption, for which there is no corresponding transaction. We subtract imputed housing consumption from the National Accounts. Imputed housing consumption is only available at the annual frequency. We assume that imputed housing

Figure 2: Nets Expenditure Data Compared with National Accounts Data.



Notes: The figures compare the levels (left panel) and quarterly growth rates (right panel) of total nominal consumption from our data and the National Accounts (including consumption abroad and excluding imputed housing consumption) over the period 2006-2018.

As mentioned above, for our empirical exercises we must also determine the extent to which a worker in our employment data was exposed to immigrant consumption. This requires mapping each 5 digit NACE code to a unique Consumption Category. To do so, we again use the Norges Bank's mapping from 5 digit NACE codes to CCs. This gives us an allocation of each worker in our employment data to a particular Consumption Category, which is linked to our expenditure data.

We highlight one feature of this mapping: a broad set of disaggregated NACE codes map into each CC code. Table A2 in the Empirical Appendix provides examples of this mapping, with which we intend to highlight a point that applies more broadly: the disaggregate 5-digit NACE employment industries that map into a given consumption category include production, wholesale, and retail industries. For example, the growing of grapes, the wholesale of fruit and vegetables, and their retail in specialized stores all map into the same consumption category: "Food and beverages." Also see Table A3, which provides additional details for one particular CC code.

3.3 Empirical specification

In this section we present our baseline estimation equation, describe how we measure each variable, outline the estimation sample, and present our identification strategy.

Estimation equation. The theory in Section 2 provides a useful guide for our empirical analysis. Our baseline empirical approach will follow equation (7) in most, but not all, respects. In our quantitative exercises, will run the same regression in model-generated data.

as a share of total housing-related consumption is fixed within the year to correct the quarterly series.

Relative to our theory, our empirical analysis differs in a few respects. First, we simplify the measure of demand and supply exposures. Instead of measuring $\Delta [x + (\eta - 1)p]$, we will instead focus exclusively on the differential change in expenditure of immigrants and natives, Δx, as in equation (6) where preferences are Cobb Douglas; similarly, instead of measuring $\Delta [\ell - \kappa w]$, we will instead focus exclusively on the differential change in employment of immigrants and natives, $\Delta \ell$.

Second, whereas our theory focused on a single closed economy, our empirical analysis will consider many such regional labor markets, indexed by r, which we will map to commuting zones. These regions will differ both in their region-specific values of Δx_r and $\Delta \ell_r$ and in their region-and-sector-specific initial immigrant intensities of consumption and production, the μ^i_{rs} and θ^i_{rs} terms. This is not outside the scope of our theory; it simply introduces region-specific indices.[16]

Third, whereas the dependent variable in equation (7) is the change in the native wage within each region-sector pair, in practice measured wages depend on the composition of workers employed there, which changes over time in response to shocks, generating endogeneity. In our empirical analysis, we instead compare the evolution of real incomes of otherwise identical individual native workers, indexed by j, who are initially employed in more and less (demand- and supply-) exposed region-sector pairs. In this, we follow an extensive literature using longitudinal worker data to estimate the effects of shocks on worker-level income; see, e.g., Jacobson et al. (1993), Autor et al. (2014), and Yagan (2019).[17]

We estimate two variants of the following individual-level regression

$$\Delta Income_{jt} = \delta_{r_j t} + \delta_{s_j t} + \beta^D_t \mu^i_{r_j s_j} \Delta x_{r_j} + \beta^S_t \theta^i_{r_j s_j} \Delta \ell_{r_j} + \gamma'_t K_j + \varepsilon_{jt} \tag{8}$$

an event-study and a difference-in-difference specification. In each specification, j indexes native individuals, r geographic regions, s sectors, and t time. In all specifications, we fix the commuting zone in which worker j resided, r_j, and the primary 5-digit NACE sector in which worker j was employed, s_j, in 2004. The time-varying region fixed effect, δ_{rt}, corresponds to the constant that is differenced out of both equations (6) and (7), where we compare wage changes across sectors in the same region. The time-varying sector fixed effect, δ_{st}, controls for national shocks to sectoral supply and demand. To understand

[16] Of course, as is always the case with cross-regional empirical designs, one might worry about interactions between regions, which are not specifically modeled in Section 2. We address these concerns empirically in Section 4.2 and quantitatively in Section 5.

[17] See Dustmann et al. (Forthcoming) for a discussion of the different interpretations and implications of estimation using individual panel data versus location panel data.

the roles of these two fixed effects, consider, for example, the impact of world oil prices, given the importance of oil production for the Norwegian economy. In years in which oil prices are high, workers living in local labor markets that specialize in its production may experience relative increases in income; and workers employed in industries that intensively use oil as an input may experience relative declines in income. These two effects will be absorbed by our region-time and, separately, sector-time fixed effects in equation (8). The vector K_j contains a set of observable individual characteristics, the returns to which may vary over time. We define this vector of worker controls as fixed-over-time indicators for characteristics of each worker as defined in 2004: ten income deciles, four education levels, and each 2004 age. Finally, $\mu^i_{rs}\Delta x_r$ and $\theta^i_{rs}\Delta \ell_r$ are measures of demand and supply exposure and $\Delta Income_{jt}$ is a measure of individual j's change in real income, all of which we describe in more detail below.

In all specifications, the coefficients of interest are β^D_t and β^S_t, which measure the (time-varying, in the event-study-style specification) effects of immigration on real wage income for natives who are initially employed in region-sector pairs with higher immigrant demand and supply exposures. Given how we measure exposures, in the event-study analyses these time-varying coefficients combine the impulse response to the immigration shock with the time-varying nature of the immigration shock. The differences-in-differences specifications, however, largely address this issue, instead measuring the medium-run response to the immigration shock.[18]

Measuring income changes. In our event-study-style framework, we separately estimate equation (8) for each year t between 2000 and 2015. In this specification, the dependent variable is the change in real wage income for individual j between 2004 and year t,

$$\Delta Income_{jt} \equiv Income_{jt} - Income_{j2004}$$

In our difference-in-difference framework, we estimate equation (8) for a single t and define the dependent variable as the average of worker j's real wage income between 2005 and 2015 minus real wage income in 2004,

$$\Delta Income_{jt} \equiv \frac{1}{11}\sum_{\tau=2005}^{2015} Income_{j\tau} - Income_{j2004}$$

To facilitate the parametrization of our quantitative model, in our difference-in-difference

[18] The estimated coefficients β^D_t and β^S_t do not directly recover structural elasticities. We will use the difference-in-difference versions of these moments to parametrize structural elasticities in our quantitative model using indirect inference.

framework we also estimate equation (8) defining the dependent variable using percent changes

$$\Delta Income_{jt} \equiv \left[\frac{1}{11}\sum_{\tau=2005}^{2015} Income_{j\tau} - Income_{j2004}\right] \Big/ Income_{j2004}$$

We additionally consider versions in which we measure income in the pre-shock period using the average of real income between 2000 and 2004, rather than in 2004 alone.

Measuring exposures. We measure supply exposure, $\theta^i_{rs}\Delta\ell_r$, as follows. The immigrant intensity of production in region r and sector s, θ^i_{rs}, is measured using data on employment from 2004; our instrument will use data on employment in 2003. The numerator is the employment in 2004 of immigrants who live in region r in 2004 and whose primary employment in 2004 is in 5-digit sector s. The denominator is the sum of immigrant and native employment, measured in the same way. A person is considered employed if he or she is at least 18 years old and works at least part time in 2004. We measure the region-specific immigration shock $\Delta\ell_r$ using the (midpoint) percent change in immigrant employment in commuting zone r relative to the (midpoint) percent change in native employment between 2003 and 2015. To facilitate the interpretation of coefficient estimates, we normalize supply exposure by its standard deviation.

We measure demand exposure, $\mu^i_{rs}\Delta x_r$, similarly. The immigrant intensity of consumption in region r and sector s, μ^i_{rs}, is measured using data on expenditure from 2007; our instrument will use data on expenditure in 2006. The numerator is the expenditure in 2007 at the point of purchase in region r of immigrants (regardless of where the immigrant lives) in the Consumption Category into which the 5-digit sector s maps. The denominator is the sum of immigrant and native expenditure, measured in the same way. We measure the region-specific immigration shock Δx_r using the (midpoint) percent change in commuting zone r in immigrant expenditures relative to the (midpoint) percent change in native expenditures between 2006 and 2015. To facilitate the interpretation of coefficient estimates, we normalize demand exposure by its standard deviation.

We highlight two related caveats about demand exposure. First, the value of the immigrant intensity of consumption, μ^i_{rs}, and its lagged value used in the instrument, $\mu^i_{rs,-1}$, are both measured using data in the period following the first part of EU expansion. Reassuringly, these region (CZ)-sector (CC)-specific measures of immigrant intensity of consumption are highly stable over time, as we show in Figure A3 in the Empirical Appendix. Second, the value of the shock Δx_r is also measured using data in the period following the first part of EU expansion. Our instrument will address this concern, replacing this change in expenditure between 2006 and 2015 using changes in (predicted) populations between 2003 and 2015.

Table 1: National Immigrant Consumption and Production Intensities

	Immigrant intensity of	
	A. Consumption	**B. Production**
1. Services	0.079	0.068
2. Electronics	0.066	0.067
3. Banks	0.064	0.030
4. Restaurants	0.063	0.215
5. Communication	0.063	0.081
6. Finance	0.061	0.039
7. Health	0.061	0.087
8. Clothing & Footwear	0.059	0.072
9. Furnishings & Household Equip.	0.058	0.059
10. Culture	0.056	0.065
11. Personal Effects	0.054	0.057
12. Personal Care	0.051	0.071
13. Insurance	0.050	0.037
14. Food & Beverage	0.050	0.072
15. Recreation	0.049	0.085
16. Hotels	0.048	0.181
17. Transport	0.047	0.059
18. Utilities & Construction	0.046	0.066
19. Motor vehicles	0.039	0.039

Notes: Immigrant intensity of consumption in column A is measured using spending of all residents in 2006. Immigrant intensity of production in column B is measured using employment in 2003, with shares taken across all employees who work in 5-digit NACE codes that map into a consumption category in this table. Statistics are calculated at the national level.

Table 1 displays immigrant intensities of consumption and production across the 19 CCs included in our baseline analysis (of our 20 CCs, we exclude Education for reasons described below), measured at the national level, where sectors are ordered by national immigrant intensity of consumption. We highlight four features of this data. First, there is substantial variation in both measures, although the coefficient of variation across sectors in the national immigrant intensity of production is almost three times greater than in the national immigrant intensity of consumption. Second, the correlation between the two measures is very low; see Figure A5 in the Empirical Appendix. Third, in Section B.2 of the Empirical Appendix we show that immigrant and native expenditure shares across sectors differ primarily because they have different preferences (demand shifters across sectors) rather than because preferences are non-homothetic and they have different incomes. This may result from the fact that the wage distribution is quite compressed in Norway. Finally, the immigrant intensity of production in the "Utilities & Construction"

CC code is approximately the median across CC codes; this may be surprising given the importance of immigrant labor in construction in some contexts. This results from the fact that this CC code contains a broad range of 5-digit NACE codes, some of which have very high immigrant intensities of production (e.g., Industrial cleaning at approximately 38%) and some very low (e.g., Construction of motorways, etc. at approximately 2%); see Table A3 in the Empirical Appendix for details. Importantly, in our empirical analysis, we measure the immigrant intensity of production at the 5-digit NACE level rather than the CC code level.

Baseline estimation sample. Our baseline estimation sample includes native males. We restrict the baseline sample to males because women are more likely to work in the public sector, where wages are generally less flexible and, therefore, less responsive to local demand conditions (such adjustment is central to our theoretical framework). We further restrict the sample to those aged 30 to 50 in 2004, to include individuals who actively participate in the workforce over the full 2000-2015 sample period, being at least 26 years old in 2000 and no greater than 61 years old in 2015. We include in our sample only those individuals with at least two years of full-time employment in the five years between 2000 and 2004, where full-time employment is reported by the employer. We additionally restrict the sample to workers who have some employment income in 2004, so that we can assign workers a sector of employment, s_j in equation (8). We drop from the sample native workers who die or migrate away from Norway, thereby ensuring a sample that is balanced across our observation window of 2000-2015.

We additionally restrict our baseline sample to workers living outside of Oslo in 2004. The Oslo labor market is very large; it will, therefore, receive a very large weight in the worker-level regressions. Moreover, Oslo is a large outlier in terms of immigration, with substantially higher immigrant population shares than the rest of the country, even before the EU enlargement. Finally, we omit workers employed in the public sector and in the education sector in 2004, because wages in these sectors are not particularly responsive to local demand; hence, the model's mechanisms do not apply.[19]

We revisit these choices in sensitivity and robustness exercises. Table A5 in the Empirical Appendix presents summary statistics for our estimation samples.

Instrumental variable approach and exclusion restrictions. Our estimation equation is a generalized triple difference model, where each measure of exposure is the product of

[19] Wage setting in the education sector is centrally bargained, with two agreements, one for Oslo and one for the rest of the country to account for differences in costs of living. Since 2004, but not before, school administrators have some flexibility in adjusting wages to counter offers, by setting the wage within a wage range that is conditional on a job title. These wage ranges are often narrow, and are decided centrally. For details, see Report (2003) and Report (2024).

a local-and-sectoral immigrant intensity, μ_{rs} for demand and θ_{rs} for supply, and a local shock, Δx_r for demand and $\Delta \ell_r$ for supply. We instrument for both demand and supply exposures using a relatively standard approach, with the demand exposure IV being $\mu^i_{rs,-1}\Delta Pop^i_r$ and the supply exposure IV being $\theta^i_{rs,-1}\Delta Pop^i_r$.

The instrument lags both local-sectoral immigrant intensities by one year, replacing the 2004 value of θ^i_{rs} with its value in 2003, $\theta^i_{rs,-1}$, and the 2007 value of μ^i_{rs} with its value in 2006, $\mu^i_{rs,-1}$. The instrument also replaces local changes in expenditures for immigrants relative to natives between 2006 and 2015, Δx_r, and local changes in employment for immigrants relative to natives between 2003 and 2015, $\Delta \ell_r$, with a measure of the predicted change between 2003 and 2015 in the EU accession immigrant population within region r, denoted by ΔPop^i_r. This predicted change is constructed as in the traditional (leave-out) Card instrument and detailed in Appendix B.3. We use EU accession immigrants rather than all immigrants because non-EU accession immigrants (e.g., Swedes) are particularly responsive to local labor demand; however, this choice is not particularly consequential, as we show below. Each of these choices helps alleviate concerns of attenuation bias. Moreover, because predicted changes in population are constructed over the 2003-2015 period, this alleviates concerns that the Δx_r shock is measured starting in 2006.

Whereas we use these instruments in our baseline because the supply exposure instrument is standard in the literature (and the demand exposure instrument is its natural analogue), in practice we'll show that identification arises largely from the lagged immigrant intensities alone. That is, our first stage is as strong and our second stage almost identical if we instrument using $\theta^i_{rs,-1}$ and $\mu^i_{rs,-1}$ alone.[20]

A natural concern in our context is that region-sector pairs with higher initial immigrant intensities of consumption or production (after residualizing on controls) differ from those with lower initial immigrant intensities in underlying trends. In Section 4.2 we test for this possibility and find no evidence that the estimated effects of immigration are simply the continuation of pre-existing trends.

Another natural concern is that the initial immigrant intensities are themselves correlated with other pre-determined region-sector characteristics, and that these characteristics generate differential effects on incomes across region-sector pairs starting contemporaneously with the immigration shock. We test if a range of region-sector characteristics are correlated with our demand and supply exposure instruments, conditional on the baseline controls in equation (8). Specifically, at the individual j level, we regress the in-

[20] A central concern—in the Bartik literature—with using region-industry shares as instruments is that unobserved shocks to specific industries may influence regional outcomes through those same exposure shares. However, in our context we are not aggregating up to the regional level and we explicitly control for sector-time effects.

Table 2: First-Stage Regression Results

	Demand Exposure			Supply Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
Demand Exposure IV	0.692	0.692	0.692			-0.003
	(0.096)	(0.096)	(0.097)			(0.010)
Supply Exposure IV			0.009	0.805	0.805	0.805
			(0.006)	(0.024)	(0.024)	(0.024)
SW F stat	51.5	51.4	59.1	1116.9	1116.3	1136.8
Worker Controls	No	Yes	Yes	No	Yes	Yes

Notes: Columns 1-3 display the first-stage regression predicting demand exposure and 4-6 the first-stage regression predicting supply exposure. Demand exposure is $\mu^i_{rs}\Delta x_r$, supply exposure is $\theta^i_{rs}\Delta\ell_r$, and their instruments are $\mu^i_{rs,-1}\Delta Pop^i_r$ and $\theta^i_{rs,-1}\Delta Pop^i_r$. All specifications include sector fixed effects and region fixed effects. Columns 2, 3, 5, and 6 additionally include worker-level controls (K_j). Columns 1, 2, 4, and 5 each include only the corresponding instrument whereas columns 3 and 6 include both instruments. There are 247,842 observations in all specifications. Robust standard errors are clustered at the CZ-CC level.

strument for demand exposure (and, separately, supply exposure) on region effects (δ_r), sector effects (δ_s), individual controls (K_j), and a broad range of region-sector controls. On the employment side these additional controls are defined in the year 2003 at the CZ-sector (5-digit) level and include the share of employees with college education, the share of employees who are female, the share of employees older than 40, the total region-sector wage bill, and the share of the regional wage bill in that sector. On the expenditure side these additional controls are defined in the year 2006 at the CZ-CC level and include the share of expenditure by those with a college education, the share of expenditure by females, the share of expenditure by residents older than 40, total expenditure at the region-sector level, and the share of regional expenditure in that sector.

Table A6 in Appendix B.5 shows the results of these balance tests. We see that while most of our additional controls are uncorrelated with either demand or supply exposures, some are and a joint F-test rejects the null that each instrument is jointly unrelated to the additional controls (conditional on baseline controls). To mitigate endogeneity concerns, in Table A7 we replicate our baseline analysis adding these additional controls one and at time and jointly. Our baseline results are not sensitive to any of these alternatives.

4 Empirical results

4.1 First-stage results

Table 2 displays results from estimating the first stage. As is true throughout the paper, we present robust standard errors clustered by commuting zone-consumption category pair. Since the sample, controls, measures of exposure, and instruments are all fixed over time, the first stage is common across years. Hence, reported results are invariant to the year t used in estimation. Because we have two endogenous variables, we always report first-stage SW F statistics.

In column 1 of Table 2 we regress individual-level demand exposure on its instrument, region fixed effects, and sector fixed effects. The demand-exposure instrument strongly and positively predicts demand exposure.[21] In column 2 we additionally include the vector of worker controls, K_j in equation (8). This leaves first-stage results unchanged. In column 3 we additionally include the supply-exposure instrument. The demand-exposure instrument continues to strongly and positively predict demand exposure whereas the supply-exposure instrument does not predict demand exposure. Columns 4-6 replicate this analysis, but display the prediction of supply exposure. Results are broadly similar. The supply-exposure instrument strongly and positively predicts supply exposure, the demand-exposure instrument does not predict supply exposure, and the first-stage SW F statistic for supply exposure is large.

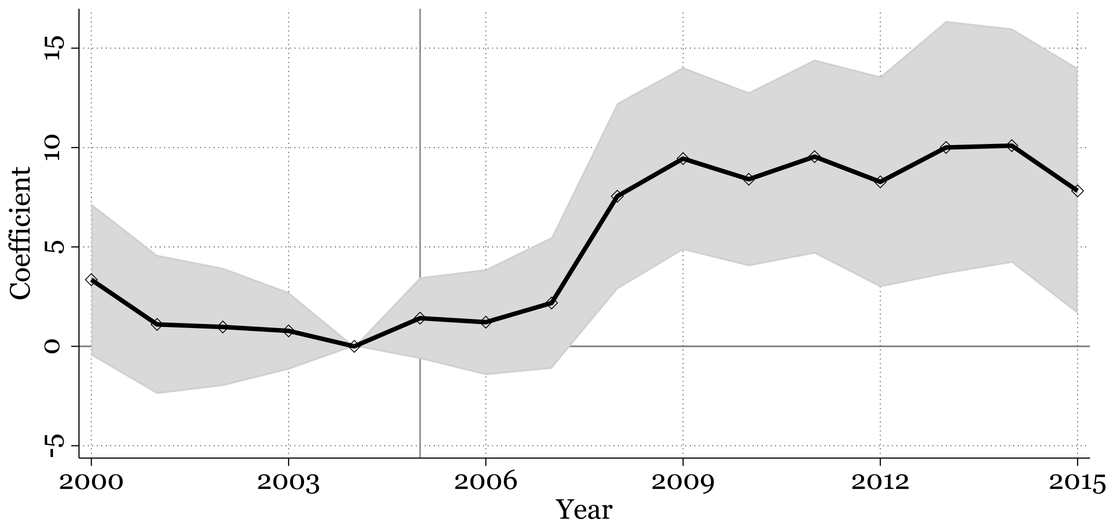
4.2 Main empirical results

In what follows, we present results on the impact of demand exposure on the evolution of native wages. Although regressions include supply exposure, we defer discussing the impact of supply exposure on the evolution of native wages given that these results are less novel.

Figure 3 presents our central empirical result. It shows how demand exposure, $\mu^i_{rs}\Delta x_r$, shapes the earnings trajectories of native Norwegian workers. It plots the 2SLS estimate of β^D_t from equation (8) for each t as well as the corresponding 95% confidence interval. Compared to similar individuals, a Norwegian employed in a region-sector with higher demand exposure experiences a positive increase in wage income between 2004 and all subsequent years. This effect starts very small and statistically insignificant, yet grows over time. This is broadly consistent with the flow of migrants displayed in Figure 1, although with a particularly substantial increase in 2008. The effect peaks in 2014 and is relatively stable between 2009 and 2015.

[21] In columns 1, 2, 4, and 5 the reported first-stage SW F statistic is equivalent to the KP F statistic, because we predict a single endogenous variable in each.

Figure 3: The Impact of Demand Exposure on the Evolution of Native Earnings



Notes: This figure reports the 2SLS estimates for each t of β_t^D in equation (8)—in which (normalized) supply and demand exposure are each instrumented—and the corresponding 95% confidence interval estimated in the baseline sample. Robust standard errors are clustered at the CZ-CC level.

To quantify the implications of demand exposure, we consider the impact of increasing a worker's 2004 demand exposure by one standard deviation. All else equal, the worker's annual real earnings would have increased by approximately 8,000 krone more between 2004 and 2015 (recall that the dependent variable is measured in thousands of krone). This represents about 1.6% of the average of 2003 real earnings of workers in our sample (which is 474,730 krone, reported in the first row of Table A5). Since estimated effects are similar over the period 2009-2015, this entails a similar increase in earnings for all such years.

A natural concern is that regions and sectors with higher initial immigrant intensities of consumption differ from those with lower initial immigrant intensities of consumption in underlying trends. Figure 3 investigates this possibility and provides no evidence of pre-existing differential trends. Workers in region-sector pairs that have higher demand exposure in the period 2003-2015 experience neither higher nor lower earnings growth over the period 2000-2004.

In Table 3, we instead explore the impact of demand exposure on the difference between average real wage income per year over the post-shock period of 2005-2015 and over the pre-shock period. We measure changes in real wage incomes in levels in columns 1 and 2 and in percent in columns 3 and 4. In columns 1 and 3 we measure real income in the pre-shock period using 2004 alone whereas in columns 2 and 4 we measure it using

Table 3: The Impact of Demand Exposure on Average Native Real Wage Income Per Year

	Levels Difference		Percent Difference	
	(1)	(2)	(3)	(4)
Demand Exposure	6.91	5.66	1.31	1.02
	(1.76)	(1.93)	(0.54)	(0.43)
Pre-shock 2004	X		X	
Pre-shock 2000-04		X		X
Average	88.3	117.9	23.1	29.0

Notes: This table reports the 2SLS estimate of β^D in equation (8) in which the dependent variable is measured as the change in average earnings per year over the post-shock period 2005-2015 relative to the pre-shock period. The difference in average earnings is measured in levels in columns 1 and 2 in percentage points in columns 3 and 4. The average income across 2005-2015 is compared to 2004 income in columns 1 and 3 and is compared to the average income across 2000-2004 in columns 2 and 4. Average refers to the average of the dependent variable. There are 247,842 observations in each specification. Robust standard errors are clustered at the CZ-CC level.

average real wage income over the period 2000-2004.[22]

Across all specifications, we find that a Norwegian employed in a region-sector with higher demand exposure experiences a positive and statistically significant increase in average real wage income (compared to a less-exposed worker) over the years 2005-2015. Using the column 1 specification, a native worker would have earned 6,910 krone more per year over the period 2005-2015 if employed in 2004 in a region-sector with a one standard deviation higher level of demand exposure. This is approximately 8% of the average growth in average earnings in the post-shock years compared to 2004 (which is 88,300 krone, reported in the final row of Table 3). Using the column 3 specification, the percent increase in average earnings over the period 2005-2015 relative to 2004 caused by moving to a region-sector with a one standard deviation higher value of demand exposure in 2004 is approximately 1.3%.

Sensitivity. Here, we describe four sets of robustness tests, each of which is presented formally in Appendix B.5.

First, we show that our results are not driven by any one consumption category or any one commuting zone. Specifically, we estimate the difference-in-difference specification shown in column 1 of Table 3, but do so omitting each CC (and all of the 5-digit NACE codes contained therein), one at a time. We then do the same thing, but omitting each CZ, one at a time. Figure A6 shows the resulting two histograms of these estimates. Results tightly cluster around our baseline estimate of 6.91.

Second, we show that our results are unlikely to be driven by endogeneity induced

[22]We winsorize percent real wage changes at the 99th percentile in the analysis reported in columns 3 and 4.

by omitted variable bias. Specifically, we again estimate the difference-in-difference specification shown in column 1 of Table 3, but add the additional region-sector controls displayed in the balance table (Table A6). Table A7 displays results, showing that our baseline results are unaffected by the inclusion, either individually or jointly, of the additional controls described in Section 3.3.

Third, we show that our results hold within alternative estimation samples. We separately extend the sample to include women, to include workers employed in education, and to include workers who live in Oslo. Alternatively, we restrict the sample to the subset of natives who have college educations and to the subset who do not. Table A8 displays results. While the quantitative impact of demand exposure varies across samples, across each sample we find that workers who are more exposed to immigration via the demand exposure channel experience larger increases in wage income.

Fourth, we show that instrumenting using only lagged immigrant intensities yields a strong first stage and almost identical baseline results. Table A9 compares the baseline first stage to an alternative in which both supply and demand exposures are predicted by the lagged immigrant intensities alone, $\theta^i_{rs,-1}$ and $\mu^i_{rs,-1}$. In the first stage, the resulting SW F stats remain large and the alternative demand exposure instrument predicts demand exposure (but not supply exposure) while the alternative supply exposure instrument predicts supply exposure (but not demand exposure), as in our baseline reported in Table 2. Table A10 then replicates our difference-in-difference specification of column 1 of Table 3, but using the alternative instruments. Estimated coefficients are very similar to their baseline values. These results suggest that identification comes from baseline differences in immigrant intensities of consumption and production, residualized of CZ and sector fixed effects and individual controls.

4.3 Additional results

Here, we describe four sets of additional results, each of which is presented formally in Appendix B.6.

Mechanism. In our theoretical framework, the mechanism driving the impact of demand exposure on native wage incomes is simple. An inflow of immigrants causes an increase in expenditure in sectors in which the immigrant intensity of consumption is higher. This increase in expenditures causes an increase in native wages. We have already documented the empirical link between demand exposure and native wage income. Here, we test the underlying mechanism, estimating a version of our baseline regression, but replacing the change in native wage income with the change in expenditure. Specifically,

Table 4: The Impact of Demand Exposure and Tradability

Effect of immigrant-induced demand exposure in more and less traded sectors

	All sectors	Less tradable sectors	More tradable sectors
	(1)	(2)	(3)
Demand Exposure	6.91	9.87	-6.27
	(1.76)	(2.10)	(5.85)

Notes: Column 1 replicates column 1 of Table 3. Columns 2 and 3 divide the baseline sample into two disjoint sets, those employed in less traded 5-digit sectors (190,750 observations) in column 2 and those in more traded 5-digit sectors in column 3 (57,092 observations).

we estimate at the region-sector level

$$\Delta \log X_{rst} = \delta_r + \delta_s + \beta_t^D \mu_{rs}^i \Delta x_r + \beta_t^S \theta_{rs}^i \Delta \ell_r + \varepsilon_{rs} \tag{9}$$

where X_{rst} is expenditure in region r and sector s at time t and where s is now defined at the CC level, which is the sectoral aggregation at which we observe expenditures. We measure and instrument for demand exposure exactly as in our baseline specification and construct more aggregated versions of supply exposure and its instrument (at the CC level instead of the 5-digit industry level). We measure the change in expenditures various ways and consider both event-study and difference-in-difference specifications, weighting observations by employment in each case. Table A11 and Figure A7 display results. We observe an increase in expenditures in more demand-exposed region-sector pairs, as predicted by the theory.

Trade. Our baseline theoretical framework in Section 2 models each local labor market as a fully closed economy. There are (at least) two important ways in which Norwegian regions interact.

First, native Norwegians may migrate across regions in response to immigration. Native migration is incorporated explicitly into our theoretical framework; but it is modeled as an exogenous shock rather than an endogenous response to immigration. However, in our empirical implementation we address this issue by instrumenting for the change in immigrant-relative-to-native employment, $\Delta\ell_r$, and expenditure, Δx_r. Hence, we identify the causal effects of immigration and native migration on the evolution of native earnings, in accordance with our theoretical results.

Second, Norwegian labor markets trade both intra- and internationally. Our theory does not directly incorporate goods trade. However, we build on Burstein et al. (2020), which focuses on how tradability shapes labor-market adjustment to immigration (via supply exposure) and shows that in more traded sectors, the relevant elasticity of substitution in consumption across sectors, our η, is endogenously higher, all else equal. What are the implications of this for the differential effect of demand exposure? Intuitively, η shapes the elasticity of the relative demand curve for native labor (see Appendix A.1), with a higher value reducing the impact of a shock to the relative native labor demand curve on relative native wages (see equation 7). This suggests that the estimated coefficient on demand exposure should be smaller when estimated within the set of more-traded sectors than when estimated within the set of less-traded sectors, all else equal, a hypothesis we test explicitly in an extension of our quantitative framework.

To define sectoral tradability, we start by constructing a measure of trade across each of 13 aggregated NACE industries using the maximum of EU industry imports and exports relative to EU industry GDP. This yields a ranking of tradability with three clear outliers as shown in Table A12: wholesale and retail trade, manufacturing, and mining and quarrying. We classify a worker as employed in a tradable sector if he is employed in a 5-digit NACE code within any of these three aggregate NACE industries.

Given this split of workers into more and less traded sectors, we revisit the baseline difference-in-difference specification of column 1 of Table 3. Table 4 displays results of this exercise. Column 1 replicates the baseline result on the full estimation sample, whereas columns 2 and 3 estimate the same specification, but separating the baseline sample of column 1 into two disjoint sets: workers employed in 2004 in less tradable sectors in column 2 and in more tradable sectors in column 3. Differences in point estimates are consistent with the above intuition. The estimated effect of demand exposure is greater within less tradable sectors (which is positive and significant) than the baseline effect estimated on all sectors, which is in turn greater than the estimated effect within more tradable sectors (which is negative although very imprecise). Although the coefficient in column 3 is very imprecise, we can reject equality of the coefficients in columns 2 and 3. Table A14 provides a number of robustness exercises, across which the ranking of point estimates remains robust.

Employment vs. wages. Our theory assumes full employment and that changes in native wage incomes are driven by changes in wages, rather than employment. In practice, our empirical results on wage incomes do not distinguish between these two. In Table A15 we show that our empirical effects appear to be driven by changes in income conditional on employment rather than by changes in employment. This is an imperfect test for two reasons. First, our measure of employment is coarse: we consider a worker to be employed in a given year if his wage income is positive.[23] Second, our sample is highly attached

[23] We do not observe hours worked until 2015; otherwise, we only observe part-time and full-time employment status.

to the labor market: the average number of years between 2005 and 2015 employed by workers in our sample is 10.5 out of a possible 11.[24]

Supply exposure. While we have controlled for supply exposure in our previous results, we have emphasized demand exposure to this point because our primary contributions are introducing, identifying, and quantifying the effects of demand exposure. Table A17 replicates Table 3, but reports the difference-in-difference estimates of β^S in addition to β^D, both when included together and when including each of them separately.[25] We find that more supply-exposed workers experience relatively smaller increases in their wage incomes over time. Figure A9 replicates Figure 3, but reports the event-study estimates of supply exposure instead of demand exposure. As is the case for demand exposure, we find that the decline in native wages in more supply-exposed region-sector pairs following 2004 is not merely a continuation of pre-existing trends. However, unlike the case for demand exposure, we find that there are pre-trends for supply exposure, with workers in more supply exposed region-sector pairs experiencing (relative) wage increases leading into 2004 and then, after 2004, wage declines.

Although supply exposure exhibits differential trends, the residualized variation in demand exposure is orthogonal to supply exposure, as shown in Figure A8, and the estimated effect of demand exposure is unchanged when excluding supply exposure, as can be seen in Table A17. This implies that violations of parallel trends for supply exposure do not contaminate identification of β^D.

5 Quantification

Our empirical analysis identifies the *differential* effects on native real wage incomes of demand and supply exposures. Here, we quantify the impact of the immigrant inflow between 2003 and 2015 on the *levels* of native real wages. Our approach is to parametrize a quantitative model, then feed into that model one shock (the national change between 2003 and 2015 in the employment of immigrants) and solve for the implied native real wage change in each region-sector pair. In what follows, we describe the framework, its

[24] Some papers in the immigration literature study the effects of migration on employment, see for example Dustmann et al. (2016). Other papers focus on the estimation of the effect of various shocks on real incomes, see for example Dustmann et al. (Forthcoming) and Autor et al. (2014), which estimate the effects of commuters and of import competition, respectively. Given our individual level administrative data, which captures workers while employed, and the fact that we do not have precise measures of the number of hours worked, we follow the empirical approach in Autor et al. (2014), also explored in the context of commuters in Dustmann et al. (Forthcoming), by tracing real income effects, and then separating these effects into years employed and average income while employed.

[25] For completeness, we report both demand and supply exposure estimates in all Appendix tables.

parameterization, and quantitative results in a baseline in which regions do not trade. In the Quantitative Appendix we present the more general model and its parameterization including trade; we additionally provide quantitative results in the case of trade.

5.1 Model assumptions

Relative to the model of Section 2, here we consider a framework featuring many sectors (instead of two), many regions (instead of one), and endogenous migration across regions (instead of exogenous). We achieve these generalizations at the cost of imposing strong functional form restrictions. Here, we outline the quantitative model. Model details are presented in Section C.1 of the Quantitative Appendix.

Preferences across sectoral output are CES, with elasticity of substitution across sectors s given by η and with preference shifters potentially varying across rsg (region, sector, and group). Sectoral production functions are also CES, with elasticity of substitution between native and immigrant workers given by ρ and with productivity shifters potentially varying across rsg.

Each agent chooses the rs pair to live and work. Utility is given by the product of real income (which is common across all group g agents choosing rs) and an idiosyncratic preference for living and working in each rs pair (which varies across agents). These idiosyncratic preferences are themselves drawn from a Fréchet distribution with shape parameter κ and with scale parameters potentially varying by rg (i.e., there are region-group specific amenities). We characterize the general equilibrium in Section C.2 in the Quantitative Appendix.

5.2 Parametrization

We parametrize the model defining regions as CZs and sectors as CCs. We use the more aggregated CC-level sectoral codes (rather than 5-digit NACE) because this is the level at which expenditure is observed.[26]

To parametrize the model, we express the equilibrium equations in changes in Section C.3. The parameters of this system in changes are those we require to conduct our quantification. We separate these parameters into a set of equilibrium shares and primitive elasticities. Here, we offer a brief overview of the model's parametrization. We provide details in Section C.4 in the Quantitative Appendix.

[26] In practice, we can infer 5-digit NACE expenditures under reasonable restrictions, which would allow for a more disaggregated parametrization.

Equilibrium shares. We require the immigrant intensity of production and two related shares: the share of all wage income that group g in region r earns within sector s and the share of group g labor within region r that is employed in sector s. These shares differ because wages are not equated across sectors. We also require the share of group g labor that lives in region r. Finally, we require two pieces of data on expenditure. First, we require the immigrant intensity of consumption (μ^i_{rs}), which we made use of in our empirical analyses. Second, we require the share of all expenditure by group g within region r that is spent on sector s. We can construct each of these shares directly given our labor income, expenditure, and employment data.[27]

Primitive elasticities. The elasticities we require are κ (the elasticity of labor supply across sectors and regions), η (the elasticity of demand across sectors in consumption), and ρ (the elasticity of demand across native and immigrant labor within sectors). To obtain these elasticities, we take the following approach.

We start by fixing the values of the three elasticities above. We then feed into our quantitative model three sets of shocks: (i) a change in employment for each group at the national level (one for each g), (ii) a change in region-group amenities (one for each rg pair), and (iii) a change in region-group productivities (one for each rg pair). We choose (i) to exactly match the national change in immigrant and native employment observed between 2003 and 2015. We choose (ii) and (iii) to match exactly the immigrant-relative-to-native labor supply change at the local labor market level and the immigrant-relative-to-native expenditure change at the local labor market level. That is, we exactly match the values of $\Delta\ell_r = \ell^i_r - \ell^n_r$ and $\Delta x_r = x^i_r - x^n_r$ that enter into the construction of demand and supply exposures in our empirical analysis. Given our parametrization of initial equilibrium shares, this implies that the shocked model exactly matches demand exposure in our empirical analysis and exactly matches a more aggregated measure of supply exposure (at the CC instead of the 5-digit NACE level).

Given the guess for elasticities and these shocks, we solve for the model-implied change in native real wages in each region-sector, measured in percent terms

$$\Delta Income_{rs} = \frac{(W^n_{rs})' - W^n_{rs}}{W^n_{rs}}$$

as in our difference-in-difference percent specification displayed in columns 3 and 4 of

[27] To make the data and model consistent, in Section C.4 we begin by adjusting the expenditure data to ensure that expenditure and income are consistent with the model, given that labor is the unique factor of production in the model and the regional economy is closed to trade. These adjustments—and the construction of equilibrium shares that follows—differ in the open-economy version of the model, and are also described in Section C.4.

Table 3; we can solve the model in changes for the percent change but not the level change. We also solve for the log change in expenditures, $\Delta \log X_{rs}$, in model-generated data.

We then estimate equations (8) and (9) in model-generated data, normalizing demand and supply exposures by their standard deviations (which are equivalent in the model and the data given the way we calibrate the shocks to (i)-(iii) described above) as in the empirical analysis. Finally, we iterate over the primitive elasticities to best match the empirical results for the impact of demand and supply exposures on income (displayed in columns 3 and 4 of Table 3 for demand exposure and Table A16 for supply exposure), as well as the impact of demand and supply exposures on expenditure (the demand exposure coefficient is displayed in column 2 of Table A11); we minimize the sum of square deviations of each of the four estimates.[28] This approach yields the following parameter values: $\kappa = 0.05$, $\rho = 1.55$, and $\eta = 1.43$.[29] Table 5 displays the resulting regression coefficients in model-generated data and the corresponding empirical targets.

Table 5: Model-Generated and Empirical Moments

Moments	Model-generated	Empirical targets
Demand exposure in income regression	1.12	1.16
Supply exposure in income regression	−0.43	−0.47
Demand exposure in expenditure regression	0.01	0.05
Supply exposure in expenditure regression	0.03	0.02

Notes: The first and second columns display estimated coefficients in model-generated data and the corresponding empirical targets, respectively. The empirical target in the first (second) row displays the average of coefficients on demand (supply) exposure in columns 3 and 4 of Table 3 (Table A16). The empirical target in the third row displays the coefficient on demand exposure in column 2 of Table A11. The empirical target in the fourth row is not reported in any table.

5.3 Quantitative Results

We feed into the calibrated model a single shock: the percent national increase in immigrant employment between 2003 and 2015 of approximately 130%, as shown in Figure 1. We then solve for the full general equilibrium response to this shock. Panel A of Fig-

[28]Empirically, in the income change regression we estimate these specifications setting 2004 as the base period and the average of 2000-2004 as the base period. In our quantification, we take the averages of these empirical results as our targets.

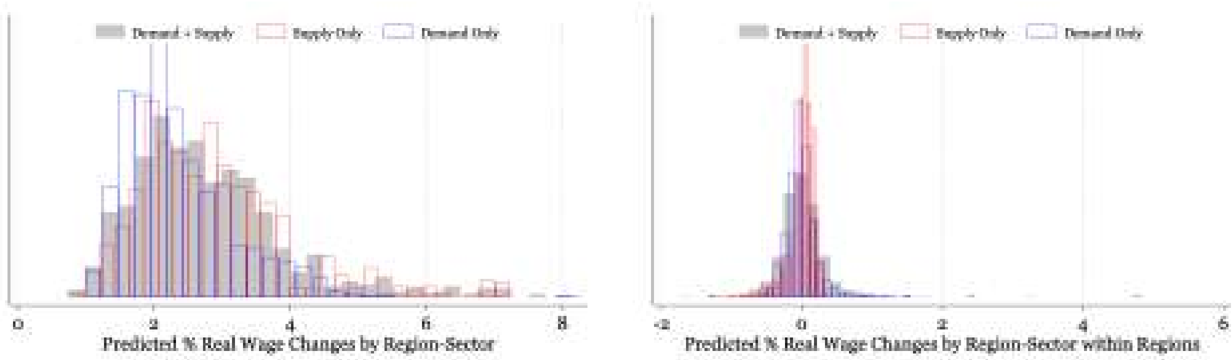
[29]We do not require the more restrictive assumption that $\kappa > 1$, which is required for there to be a finite solution to the expected value of $\varepsilon(\omega, r, s)$ conditional on agent optimization. Such a finite solution matters only for the calculation of a particular social welfare function, not for welfare (see Kim et al., 2020), output or changes in real wages (given that ε is a preference shifter), or any choices agents actually make. This low value of κ is also consistent with little native labor reallocation in response to immigration (not reported in the paper). This is perhaps driven by the generous nature of the Norwegian welfare state.

ure 4 reports the histogram of native real wage changes (reported in percent) across all region-sector pairs. The median real wage change is 2.8%. This effect masks substantial heterogeneity: the 10th and 90th percentiles are 1.6% and 4.3%. The commuting zone with the largest effects is Oslo, which is an outlier in terms of migration; the commuting zone with the smallest effects is Gudbrandsdalen, which is in the middle of Norway and experiences relatively little migration.

Figure 4: Model-Predicted Native Real Wage Changes

Panel A: Full Distribution

Panel B: Within-Region Variation



Notes: This figure reports the predicted percent real wage changes induced by overall immigration to Norway over the period 2003 to 2015 by three different models: a model with both demand and supply exposure, a model with only demand exposure, and a model with only supply exposure. Panel A reports the overall variance in predicted percent real wages, while panel B reports only the within region, across sectors, variation.

This variation in real wage changes is caused both by differences in immigrant flows across regions and by differences in supply and demand exposure within regions. To show within-region variation in real wage changes, we residualize predicted real wage changes on a regional fixed effect. Panel B of Figure 4 reports the resulting within-region variation in real wages. Comparing across figures, we see that a larger share of the model-predicted variation in real wage changes arises from differences in exposures across regions rather than within.

To what extent is the variation in real wage changes arising from differences in supply or demand exposure? To answer this question, we take a particular approach, conducting two alternative model parameterizations. In one, we parameterize model shares without using data on different employment shares of natives and immigrants within regions; this corresponds to a model in which there are no differences in supply exposure within regions (but there are across regions). In the other, we parameterize model shares without using data on different expenditure shares of natives and immigrants within regions; this corresponds to a model in which there are no differences in demand exposure within regions (but there are across regions).

Panels A and B of Figure 4 also display results of these alternative parameterizations. Differences within regions in both demand and supply exposures are important for driving our quantitative results. However, supply exposure appears slightly more important. We find that the model with (within-region) supply exposure differences alone accounts for between 56% and 69% of the overall predicted real wage change, with the model with (within-region) demand exposure differences alone accounting for between 31% to 44%, respectively. We describe this variance decomposition in Section C.5 of the Quantitative Appendix.

Additional quantitative analyses. We conduct two types of additional analysis in Section C.5 of the Quantitative Appendix. First, we conduct sensitivity analyses using our baseline quantitative framework under alternative parameter values, choosing $\kappa = 2$, $\rho = 4.6$ and $\eta = 1.65$, as in Burstein et al. (2020). With a higher value of ρ, we both decrease the average increase in native real wages (and some native workers experience real wage declines) and we increase the relative importance of supply exposure, as described in the Quantitative Appendix.

Second, we use a generalized version of the framework that incorporates trade across regions. Here, we find that the differential impact of demand exposure is largely confined to less traded sectors, consistent with our empirical results in Table 4. However, we also show that quantitative differences in the impact of supply exposure in the model-generated data are inconsistent with our empirical findings.

6 Conclusions

What is the effect of immigration on native labor-market outcomes? In this paper we introduce demand exposure, formalize it, measure it in the Norwegian context, estimate its differential effects on native Norwegian worker incomes, and quantify its impact on native worker real wages.

To make progress on this issue, we present a theoretical framework in which the immigrant intensities of production and consumption may vary across jobs. We solve analytically for the differential effects of immigration on native wages across jobs that are more supply exposed and/or more demand exposed. These theoretical results guide our measurement of supply and demand exposures in the data as well as our empirical strategy to identify their effects.

Empirically, we focus on the evolution of native Norwegian workers' wage income surrounding a large and rapid inflow of immigrants. We combine employer-employee data with a newly collected dataset covering electronic payments for the universe of residents in Norway to measure supply and demand exposures. We find large, positive, and persistent differential effects of demand exposure: increasing a native worker's demand exposure in 2004 by one standard deviation increases the worker's annual real earnings by approximately 8,000 krone in 2015, equal to approximately 1.6% of the sample average earnings in 2003. We also find moderate, negative differential effects of supply exposure. While our empirical results identify differential effects across natives employed in more and less supply and demand exposed jobs, they do not measure the change in real wages induced by immigration.

Finally, we embed these mechanisms into a quantitative framework to measure the impact of immigration on native real wages. In our baseline parameterization, we find that the large inflow of immigrants between 2003 and 2015 increased the median real wage (across region-sector pairs) by 2.8%. However, the effects are substantially larger in regions with large inflows of immigrants and in sectors with especially high demand and low supply exposures.

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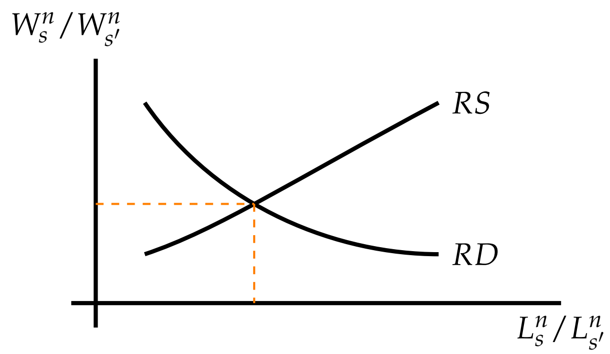
APPENDIX

A Theoretical appendix

A.1 Graphical intuition

Here, we provide graphical intuition for the structure of our analytic results on the impact of immigration on the relative wage of native workers across sectors. Relative native wages across sectors equate the relative demand for native labor and the relative supply of native labor across sectors, as displayed in Figure A1, where RD is the inverse demand for native labor by producers in sector s relative to s' and RS is the inverse supply of native labor to sector s relative to s', both as a function of the relative native wage in the two sectors.[30] The relative employment and wage of natives across sectors are determined by the intersection of these two curves.

Figure A1: Graphical Representation of the Determination of Relative Native Wages



Notes: Relative native wages across sectors, $W_s^n/W_{s'}^n$ are determined by the intersection of the (inverse) relative demand curve RD and relative supply curve RS across sectors.

An immigrant inflow leaves the RS curve unchanged at fixed native preferences, but shifts the RD curve. Suppose that the local elasticity of the RD curve in the initial equilibrium is η and of the RS curve is κ. Then the impact of a small change in the immigrant population on the relative wage of natives across sectors is given by

$$\frac{d\log\left(W_s^n/W_{s'}^n\right)}{d\log L^i} = \frac{1}{\eta+\kappa}\frac{d\log RD}{d\log L^i}$$

where $d\log RD/d\log L^i$ is the elasticity of the shift of the RD curve with respect to the immigrant population. In our framework, η is the elasticity of demand across sectors,

[30] RS is the supply of native labor to sector s relative to s' as a function of the relative native wage in the two sectors. It is not the aggregate supply of native labor relative to immigrant labor.

which also equals the elasticity of the native relative demand curve; and κ is the elasticity of the relative supply of natives across sectors. Moreover, in our framework, the elasticity of the shift in the *RD* curve is given by the sums of the demand exposure and supply exposure terms. Hence, to understand the impacts of demand and supply exposures on relative wages, it is sufficient to understand their impacts on the shift in the relative demand curve for native labor.

Consider demand exposure first. To gain intuition, suppose that the immigrant intensity of production is common across sectors (so that supply exposure is equalized) but that natives and immigrants have different preferences (so that they have different expenditure shares across sectors). Without loss of generality, suppose that the immigrant intensity of consumption is higher in sector s than in s'. In this case, the relative demand for native labor dedicated to satisfy immigrant consumption is shifted to the right of the relative demand for native labor dedicated to satisfy native consumption; i.e., at a given relative wage for natives across sectors, satisfying immigrant demand across sectors requires relatively more natives employed in sector s than s' compared to satisfying native demand. The *RD* curve in Figure A1 is a weighted average of the two. If immigration raises total expenditures of immigrants relative to natives, then it raises the relative weight that the aggregate *RD* curve places on the relative demand for native labor dedicated to satisfy immigrant consumption, and hence shifts the relative demand for native labor to the right. As a result, the relative wage of natives in s increases if the *RS* curve is upward sloping.

Consider supply exposure second. To gain intuition, suppose that the immigrant intensity of consumption is common across sectors (so that demand exposure is equalized) but that natives and immigrants have different relative productivities (or amenities) associated with working in different sectors (so that they have different employment shares across sectors). In this case, the aggregate *RD* curve is the same as the relative demand for native labor dedicated to satisfy either native or immigrant consumption. The impact of an inflow of immigrants on the location of the *RD* curve then boils down to the two competing forces we describe in Section 2.2—scale and substitution—and the difference in the immigrant intensity of production.

A.2 System in changes

Here we provide a partial characterization of the equilibrium system of equations, in log changes, in response to changes in labor supplies, ℓ^g. The goods-market clearing condition can be expressed as

$$y_s = c_s \tag{10}$$

Constant returns to scale production implies that the change in the production of sector s is given by

$$y_s = \sum_g \theta_s^g \ell_s^g \tag{11}$$

and the zero profit condition in the production of each sector can be expressed as

$$p_s = \sum_g \theta_s^g w_s^g \tag{12}$$

where θ_s^g is the initial share of total costs in the production of sector s that is paid to group g workers, defined for immigrants in equation (1). The change in the consumption of sector s can be expressed in terms of the changes in consumption by each group g as

$$c_s = \sum_g \mu_s^g c_s^g \tag{13}$$

where μ_s^g is the share of total consumption of sector s in the initial equilibrium that is consumed by group g workers, defined for immigrants in equation (2). Finally, the labor-market clearing condition yields

$$\ell^g = \sum_s \Pi_s^g \ell_s^g \tag{14}$$

where $\Pi_s^g \equiv L_s^g / L^g$ is the initial share of g employment within sector s.

A.3 Proofs in the non-parametric, two-sector setting

Deriving equations (6) and (7). Here, we prove results in the non-parametric setting. We start from an initial equilibrium and feed in changes in labor supplies, ℓ^g. In this proof we allow ρ to vary across sectors and denote its value in sector s by ρ_s, since this does not complicate the proof. Specifically, replace equation (3) with the following generalization

$$\ell_s^n - \ell_s^i = -\rho_s (w_s^n - w_s^i) \tag{15}$$

From budget balance, $X^g = \sum_s P_s C_s^g$, we have

$$x^g = \sum_s \zeta_s^g (p_s + c_s^g)$$

where $\zeta_s^g \equiv P_s C_s^g / X^g$ is the share of group g's spending on sector s. This is equivalent to

$$x^g - p^g = \sum_s \zeta_s^g c_s^g$$

where $p^g \equiv \sum_s \zeta_s^g p_s$ is the local change in group g's price index. The previous expression, the definition of η in equation (4) imposing $\eta^g = \eta$, and the two-sector assumption yield

$$c_s^g = x^g - p^g + \eta \zeta_{s'g} p_{s'} - \eta \zeta_{s'g} p_s$$

Adding and subtracting $\eta \zeta_s^g p_s$ from the right-hand side yields

$$c_s^g = -\eta p_s + (\eta - 1) p^g + x^g \tag{16}$$

From labor-market clearing and the two-sector assumption, we have

$$\ell^g = \sum_s \Pi_s^g \ell_s^g = \Pi_{s'g}(\ell_{s'}^g - \ell_s^g) + \ell_s^g$$

where $\Pi_s^g \equiv L_s^g / L^g$ denotes the initial share of employment of g in sector s. Substituting in from the definition of κ in equation (5), imposing $\kappa^g = \kappa$, and rearranging yields

$$\ell_s^g = \Pi_{s'g} \kappa (w_s^g - w_{s'}^g) + \ell^g$$

Adding and subtracting $\Pi_s^g \kappa w_s^g$ to the right-hand side of the previous expression yields

$$\ell_s^g = \kappa w_s^g - \kappa w^g + \ell^g \tag{17}$$

where we define $w^g \equiv \sum_s \Pi_s^g w_s^g$ as the local change in group g's wage index.

For any sector s, equation (15) and equation (17) yield

$$w_s^n - w_s^i = \frac{\kappa}{\kappa + \rho_s} \Delta \left[\frac{\ell}{\kappa} - w \right] \tag{18}$$

where $\Delta \left(\ell / \kappa - w \right) \equiv \ell^i / \kappa - w^n - \left(\ell^n / \kappa - w^i \right)$. Equations (10), (11), and (13) yield

$$\ell_s^n - \theta_s^i (\ell_s^n - \ell_s^i) = \sum_g \mu_s^g c_s^g$$

The previous expression and equation (16) yield

$$\eta p_s = \sum_g \mu_s^g \left[(\eta-1)p^g + x^g\right] - \left[\ell_s^n - \theta_s^i(\ell_s^n - \ell_s^i)\right] \tag{19}$$

The previous expression, equation (3), and equation (18), yield

$$p_s = \frac{1}{\eta}\sum_g \mu_s^g[(\eta-1)p^g + x^g] - \frac{\kappa\rho_s}{\eta}\frac{\Delta\left[\ell/\kappa - w\right]}{\kappa+\rho_s}\theta_s^i - \frac{1}{\eta}\ell_s^n \tag{20}$$

Equations (12) and (18) yield

$$\begin{aligned} p_s &= \sum_g \theta_s^g w_s^g = (1-\theta_s^i)w_s^n + \theta_s^i w_s^i = w_s^n - \theta_s^i(w_s^n - w_s^i) \\ &= w_s^n - \frac{1}{\kappa+\rho_s}\theta_s^i \Delta\Big[\ell - \kappa w\Big] \end{aligned}$$

The previous expression, equation (20), and equation (17) yield

$$w_s^n = \frac{1}{\eta+\kappa}\sum_g \mu_s^g\left[x^g + (\eta-1)p^g\right] + \frac{\Delta\Big[\ell-\kappa w\Big]}{\kappa+\rho_s}\frac{\eta-\rho_s}{\eta+\kappa}\theta_s^i - \frac{1}{\eta+\kappa}(\ell^n - \kappa w^n)$$

which can be expressed as

$$w_s^n = \alpha + \frac{1}{\eta+\kappa}\left\{\Delta\Big[x + (\eta-1)p\Big]\mu_s^i + \frac{\eta-\rho_s}{\kappa+\rho_s}\Delta\left[\ell-\kappa w\right]\theta_s^i\right\}$$

where $\Delta\Big[x+(\eta-1)p\Big] \equiv \Big(x^i + (\eta-1)p^i\Big) - \Big(x^n + (\eta-1)p^n\Big)$ and where

$$\alpha \equiv \frac{1}{\eta+\kappa}\left[x^n + (\eta-1)p^n - \ell^n + \kappa w^n\right]$$

To obtain equation (6), suppose that $\rho_s = \rho$ and $\theta^i = \theta_s^i$ for each s and that $\eta = 1$. With common values of ρ_s and θ_s^i across sectors, the supply exposure term can be moved into the constant, α. Additionally with $\eta = 1$ we obtain equation (6). To obtain equation (7), impose only that $\rho_s = \rho$ for each s. □

Results in the two-sector, fully general non-parametric setup. Here, we generalize equations (4) and (5) to allow η and κ to vary across groups g, generalize equation (3) to allow ρ to vary across sectors (which we allowed in the proof above), and derive a generalization of equation (7).

As above, we define ρ_s using equation (15). We denote by η^g group g's local elasticity of substitution in consumption across sectors,

$$c_s^g - c_{s'}^g = -\eta^g (p_s - p_{s'}) \tag{21}$$

where η^g shapes consumer substitution between sectors—for consumers in group g—in response to a change in sectoral prices. Finally, we denote by κ^g group g's local elasticity of substitution in labor supply across sectors,

$$\ell_s^g - \ell_{s'}^g = \kappa^g (w_s^g - w_{s'}^g) \tag{22}$$

where κ^g shapes labor allocation between sectors—for workers in group g—in response to a change in their wages.

Following the same steps as in the derivation of equations (16) and (17), we obtain

$$c_s^g = -\eta^g p_s + (\eta^g - 1) p^g + x^g \tag{23}$$

and

$$\ell_s^g = \kappa^g w_s^g - \kappa^g r^g \tag{24}$$

where we define

$$r^g \equiv w^g - \frac{1}{\kappa^g} \ell^g$$

The system of equations is then (15), (10) - (13), (23), and (24).

From equation (24), of which there are four, we can solve for each w_s^g as a function of the corresponding ℓ_s^g,

$$w_s^g = \frac{1}{\kappa^g} \ell_s^g + r^g \tag{25}$$

Together with the previous expression, equation (12), of which there are two, allows us to solve for each p_s as a function of ℓ_s^n and ℓ_s^i,

$$p_s = \frac{1}{\kappa^n} \theta_{sn} \ell_s^n + \frac{1}{\kappa^i} \theta_s^i \ell_s^i + \theta_{sn} r^n + \theta_s^i r^i$$

Together with the previous expression, equation (23), of which there are four, yields a solution for each c_s^g as a function of ℓ_s^n and ℓ_s^i,

$$c_s^g \left(\ell_s^n, \ell_s^i \right) = -\eta^g \left(\frac{1}{\kappa^n} \theta_{sn} \ell_s^n + \frac{1}{\kappa^i} \theta_s^i \ell_s^i \right) - \eta^g \left(\theta_{sn} r^n + \theta_s^i r^i \right) + (\eta^g - 1) p^g + x^g$$

This leaves us with four unknowns: l_s^g for each sg pair. Equation (15) and the previous expressions yield

$$\ell_s^i = \ell_s^n + \rho_s \frac{1}{\kappa^n} \ell_s^n - \rho_s \frac{1}{\kappa^i} \ell_s^i + \rho_s (r^n - r^i)$$

and solving for ℓ_s^i, we obtain

$$\ell_s^i = \left(\frac{\kappa^i}{\kappa^i + \rho_s} \right) \left(\frac{\kappa^n + \rho_s}{\kappa^n} \right) \ell_s^n + \left(\frac{\kappa^i \rho_s}{\kappa^i + \rho_s} \right) (r^n - r^i)$$

which leaves us with two unknowns, l_{sn} for each s. Equations (10), (11), and (13), together with the above expressions, yield

$$\ell_s^n = \frac{\kappa^n \kappa^i \left(\overline{\eta}_s - \rho_s \right) \Delta \left[\frac{1}{\kappa} \ell - w \right]}{(\kappa^n + \nu_s)(\kappa^i + \rho_s)} \theta_s^i + \frac{\kappa^n \Delta \left[x + (\eta - 1) p \right]}{\kappa^n + \nu_s} \mu_s^i + \frac{\kappa^n}{\kappa^n + \nu_s} \left[x^n + (\eta^n - 1) p^n - \overline{\eta}_s r^n \right]$$

where

$$\overline{\eta}_s \equiv \mu_s^n \eta^n + \mu_s^i \eta^i \tag{26}$$

is a weighted average of the native, η^n, and immigrant, η^i, elasticities of substitution in consumption, with weights given by the share of expenditure in sector s spent by natives, μ_s^n, and immigrants, μ_s^i, respectively; where

$$\nu_s \equiv \left(\frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i \right) \rho_s + \left[1 - \frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i \right] \overline{\eta}_s \tag{27}$$

is similarly a weighted average of ρ_s and $\overline{\eta}_s$, with weights given by $\frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i$ and $1 - \frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i$, respectively; and where

$$\begin{aligned} \Delta \left[\frac{1}{\kappa} \ell - w \right] &= \left(\ell^i / \kappa^i - w^i \right) - \left(\ell^n / \kappa^n - w^n \right) \\ \Delta \Big[x + (\eta - 1) p \Big] &= \left(x^i + (\eta^i - 1) p^i \right) - \left(x^n + (\eta^n - 1) p^n \right) \end{aligned}$$

Substituting back in equation (25), we obtain

$$w_s^n = \alpha_s + \frac{1}{\nu_s + \kappa^n} \left\{ \Delta \Big[x + (\eta - 1) p \Big] \mu_s^i + \frac{\kappa^i \left(\overline{\eta}_s - \rho_s \right)}{\kappa^i + \rho_s} \Delta \left[\frac{1}{\kappa} \ell - w \right] \theta_s^i \right\} \tag{28}$$

where

$$\alpha_s \equiv \frac{1}{\nu_s + \kappa^n} \left[x^n + (\eta^n - 1) p^n + \left(\kappa^n + \nu_s - \overline{\eta}_s \right) r^n \right] \tag{29}$$

Note that in the baseline cases, we had $\eta = \eta^n = \eta^i$. This implies that $\overline{\eta}_s = \eta$ in equation (26). We also had $\kappa = \kappa^n = \kappa^i$. This implies that $\nu_s = \overline{\eta}_s$ in equation (27). Together, these restrictions imply $\nu_s = \overline{\eta}_s = \eta$.

Relaxing the baseline restrictions leaves supply and demand exposures largely unchanged. However, it alters their implications for relative wages both because all elasticities are heterogeneous across sectors and, more importantly, because the term α from equation (7) becomes a sector-specific term α_s in equation (28). In practice, the estimating equation in this case would feature four separate shocks (to immigrant employment and expenditure and to native employment and expenditure) rather than two shocks (combining immigrant and native employments and immigrant and native expenditures).

A.4 Proofs in the many-sector setting

Consider a setting with arbitrarily many sectors in which consumption aggregators for each group g are constant elasticity of substitution (CES) with elasticity of substitution η and in which idiosyncratic amenity draws (which multiply real consumption in the individual's utility function) for working in each sector s for each individual in group g are distributed Fréchet with shape parameter κ.

In this framework, equations (6), (7), and (28) continue to hold. These results follow as direct corollaries of our previous results. The intuition is straightforward. The proofs in the two-sector, non-parametric setting only make use of the two-sector assumption in two places: *(i)* in deriving equation (16) (the relationship between changes in consumption in a given sector, the price change in that sector, and the group-specific price index) and *(ii)* in deriving equation (17) (the relationship between changes in labor allocation in a given sector, the wage change in that sector, and the group-specific wage index). The parametric assumptions of CES consumption aggregators and Fréchet distributed amenity draws directly imply these equations in the many-sector setting.

Note that results in the more general cases considered in Section A.3 also hold here for the same reason.

A.5 Additional simple cases

In the main text we provided intuition for the effect of demand exposure by discussing a simple case of our more general framework. Here, we provide similar exercises for supply exposure.

Supply exposure in Econ 101. Our general model captures the simplest way the past literature has modeled the effects of immigration. To show this, we assume away differences in demand exposure ($\mu^i_s = \mu^i_{s'}$) and assume the native population does not change

($\ell^n = 0$), as in that past literature. We additionally assume that immigrants and natives are the same factor of production (e.g., $\rho \to \infty$), that immigrants do not work in sector s', and that native workers do not reallocate across sectors ($\kappa = 0$). Then, our main result collapses to:

$$w_s^n - w_{s'}^n = -\frac{1}{\eta}\theta_s^i \ell^i = -\frac{1}{\eta}\frac{L_s^i W_s}{(L_s^i + L_s^n)\, W_s}\frac{dL_s^i}{L_s^i} = -\frac{1}{\eta}\frac{dL_s^i}{L_s^i + L_s^n} = -\frac{1}{\eta}\frac{dL_s^i}{L_s}$$

This equation show how, in this very special case, immigration moves natives wages along the (inverse) labor demand curve ($1/\eta$).[31]

Supply exposure with heterogeneous labor. Much of the existing literature has departed from assuming that labor is homogeneous. Some papers delineate workers into imperfect substitutes across education cells (Katz and Murphy, 1992), others across education and experience cells (Card and Lemieux, 2001), and others along other relevant dimensions. Within the immigration literature, Ottaviano and Peri (2012) argue that immigrants and natives are imperfect substitutes even within narrow categories. Irrespective of what defines different factors of production, if there are differences in the distribution of immigrants and natives over characteristics that define different factors of productions, we can consider that natives and immigrants are imperfect substitutes (at least locally). To capture how past literature has thought about immigrant effects on the labor market, we can assume that immigrants and natives are a different factor of production ($\rho < \infty$) and that immigrants and natives have the same preferences over final goods ($\mu_s^i = \mu_{s'}^i$). In this case, our result collapses to:

$$w_s^n - w_{s'}^n = \frac{\eta - \rho}{(\eta + \kappa)(\kappa + \rho)} \Delta \left[\ell - \kappa w\right] (\theta_s^i - \theta_{s'}^i)$$

This equation highlights that immigration affects native labor in more relative to less immigrant-intensive sectors through two mechanisms: scale and substitution. An increase in immigrants lowers immigrant wages relative to native wages. On the one hand, this reduction induces substitution away from native labor towards immigrant labor within sectors, and more so in the higher θ_s^i sector. On the other hand, the same reduction in immigrant wages reduces costs and, therefore, expands production disproportionately in the higher θ_s^i sector. The strength of substitution is determined by ρ and of scale by η. Which mechanism dominates is an empirical question.[32]

[31] Note that if $\kappa > 0$ then we would need to replace $1/\eta$ by $1/(\eta + \kappa)$.

[32] This formula was derived and extended in Burstein et al. (2020) to incorporate differences in tradability across sectors, where—in an open economy—more traded sectors endogenously have higher values of what we refer to as η.

B Empirical appendix

B.1 Details on expenditure data

Additional details on sectoral aggregation. Table A1 displays the raw COICOP sectoral aggregation of the Nets expenditure data, including a COICOP category 13 that captures all payments to banks, and provides guidance on how we use COICOP categories to create Consumption Categories, the consumption categories that we use in our analysis.A few things are worth highlighting.

First, we refine the bank payment category (COICOP 13) by excluding payments likely associated with servicing mortgages or other investment-related debt. The remaining bank payments closely track aggregate statistics on credit card payments, indicating that this category captures payments of credit card bills, as explained in Ahn et al. (2024).

Second, we combine consumption categories 072 (Operation of personal transport equipment) and 073 (Transport service) into one (Transport); we combine 092 (Major durables for outdoor recreation), 093 (Other recreational items and equipment, gardens and pets), and 094 (Recreational and cultural services) into one (Recreation). And we combine 124 (Social protection) and 126 (Financial services) into one (Finance). These choices are made to combine small categories or those that are more difficult to allocate from the disaggregated employment data. We omit COICOP 14 (Payments to public institutions) and cash withdrawals. We also omit COICOP 10 (Education) from the labor market regressions, since incomes cannot adjust flexibly in this category.

We additionally omit COICOP 2 (Alcoholic beverages, tobacco and narcotics) because—unlike every other consumption category—its immigrant intensity of consumption measured at the national level is unstable across time, especially in the first years of the dataset, as shown in Figure A2. See also Figure A3 for the correlation of the immigrant intensity of consumption at the CZ-CC level in 2007 and both 2010 and 2015.

As a result of all these choices, we are left with the 20 Consumption Categories shown in the right hand-side part of Table A1. Table A1 provides the labels of the original COICOP categories and the long and short version labels of the Consumption Categories. For Tables 1, A2, and A13 we use the short version labels.

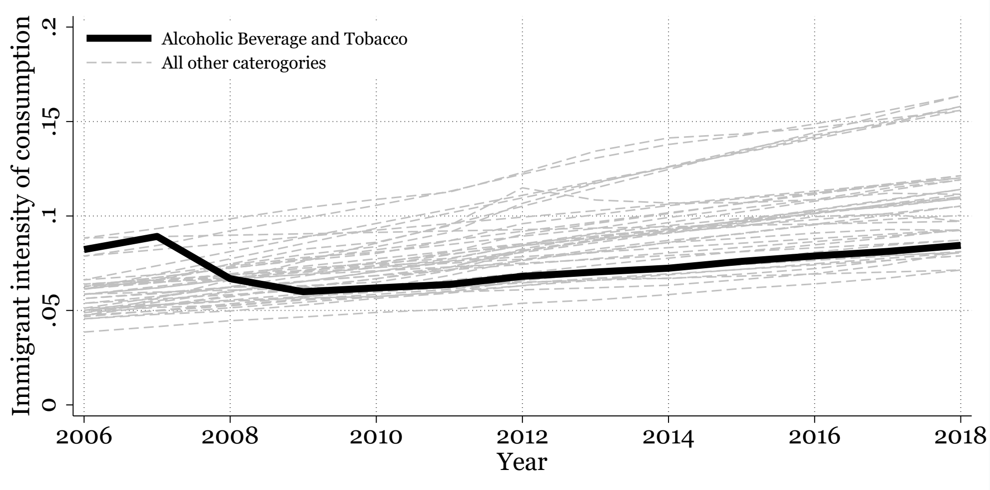
Table A1: Consumption Categories

	COICOP Category
1	Food and non-alcoholic beverages
2	Alcoholic beverages, tobacco and narcotics
3	Clothing and footwear
4	Utilities, electricity, gasoline, housing rent
5	Furnishings, household equip. and routine household maintenance
6	Health
7	Transport
071	Purchase of vehicles
072	Operation of personal transport equip.
073	Transport services
8	Communications
9	Recreation and culture
091	Audio-visual, photographic + information processing equip.
092	Major durables for outdoor recreation
093	Other recreational items and equipment, gardens and pets
094	Recreational and cultural services
095	Newspapers, books and stationery
10	Education
11	Restaurants and Hotels
111	Restaurants
112	Hotels
12	Miscellaneous services
121	Personal care
123	Personal effects
124	Social protection
125	Insurance
126	Financial services
127	Other services
13	Payments to banks (mortgage + credit)
14	Payments to public institutions (public)
cash	cash withdrawal

	Consumption Category
1	Food and non-alcoholic beverages ("Food & Beverages") (1)
3	Clothing and footwear ("Clothing & Footwear") (2)
4	Utilities, electricity, gasoline, housing rent ("Utilities & Construction") (3)
5	Furnishings, household equip. and routine household maintenance ("Furnishings & Household Equip.") (4)
6	Health ("Health") (5)
7	Transport
071	Purchase of vehicles ("Motor Vehicles") (6)
72-73	Other transport ("Transport") (7)
8	Communications ("Communications")(8)
9	Recreation and culture
091	Audio-visual, photographic + information processing equip. ("Electronics") (9)
92-94	Recreation ("Recreation") (10)
095	Newspapers, books and stationery ("Culture") (11)
10	Education ("Education") (12)
11	Restaurants and Hotels
111	Restaurants ("Restaurants") (13)
112	Hotels ("Hotels") (14)
12	Miscellaneous services
121	Personal care ("Personal Care") (15)
123	Personal effects ("Personal Effects") (16)
124+26	Finance ("Finance") (17)
125	Insurance ("Insurance") (18)
127	Other services ("Services") (19)
13	Payments to banks (mortgage + credit) ("Banks") (20)

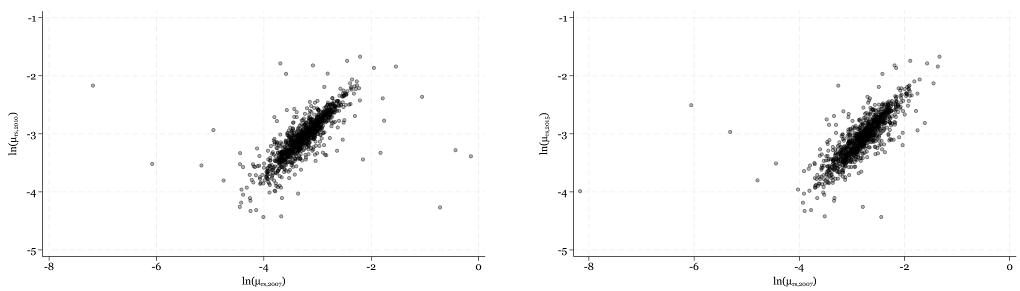
Notes: This table shows how Norges Bank aggregates some disaggregate COICOP categories into Consumption Categories and which COICOP categories are maintained as Consumption Categories, displayed in blue. In our exercise we drop three consumption categories, displayed in red. The Consumption Category column displays both the long category title and a short version used for the other tables of this paper.

Figure A2: Excluded Spending Category: Alcoholic Beverage, Tobacco and Narcotics



Note: The immigrant intensity of consumption of each consumption sector measured at the national level for each year from 2006 to 2018.

Figure A3: Correlation of CZ-CC Immigrant Intensities of Consumption Over Time



Note: These two graphs plot the relationship between the natural logarithm of the immigrant intensity of consumption at the CZ-CC level in 2007 and either 2010 (in the left panel) or 2015 (in the right panel). The figure uses the CC codes in our baseline estimation sample.

Details on concordance between Consumption Categories and 5-digit NACE. Table A2 provides examples of the concordance between 5-digit industry codes in the employment data and consumption categories. The purpose of the table is to highlight that the disaggregate employment industries that map into a given aggregate consumption sector include both production of products as well as wholesale and retail sale of these products.

Table A2: Examples of Concordance from 5-Digit Industries NACE to Consumption Categories

5-Digit Industry NACE	**Consumption Category**
Manuf. of other furniture	Furnishings & Household Equip.
Wholesale of furniture	Furnishings & Household Equip.
Retail sale of antiques	Furnishings & Household Equip.
Manuf. of paper stationery	Culture
Wholesale of books, newspapers, magazines	Culture
Retail sale of books in specialized stores	Culture
Book publishing	Culture
Growing of grapes	Food & Beverages
Wholesale of fruit + vegetables	Food & Beverages
Retail sale of fruit + vegetables in specialized stores	Food & Beverages
Taxi operation	Transport
Cableway transport and ski lifts	Transport
Passenger air transport	Transport

Notes: This table shows some examples of how Norges Bank maps 5 digit NACE codes into Consumption Categories.

Table A3: Largest 5-digit NACE codes assigned to the Consumption Category "Utilities & Construction" and Immigrant Shares

Industry	Immigrant share
Industrial cleaning	37.89%
Painting	15.08%
Joinery installation	8.35%
Manufacture of metal structures and parts of structures	7.29%
General construction of buildings	6.20%
Manufacture of other builders' carpentry and joinery	6.18%
Collection and treatment of other waste	5.39%
General construction of civil engineering works	4.27%
Wholesale of hardware, plumbing and heating equipment and supplies	3.86%
Installation of electrical wiring and fittings	3.20%
Production of primary aluminium	3.19%
Production of electricity	2.77%
Construction of motorways, roads, airfields and sport facilities	2.56%
Demolition and wrecking of buildings, earth moving	2.08%

Notes: This table computes the immigrant share in production, i.e., number of immigrants divided by total amount of workers, in the largest 5-digit NACE codes that are assigned to the Consumption Category "Utilities & Construction" using 2004 data.

B.2 Taste and income heterogeneity

Our theory in section 2 assumes that immigrants and natives have homothetic, but potentially different preferences. In practice, preferences are non-homothetic. Here, we study the extent to which immigrant and native expenditure shares differ in our data because they have different tastes (demand shifters) or because preferences are non-homothetic and they have different incomes.

Let total expenditure on sector s by a household j—who lives in commuting zone r_j and is a member of group g_j—be denoted by x_j. Suppose that

$$\log x_{js} = \mu_{s_j}^{g_j} + \alpha_s \log Income_j + \varepsilon_{js} \tag{30}$$

Here, $Income_j$ denotes the individual's income and α_s is a sector fixed effect. The product of these controls for sector-specific income elasticities of demand (that are common across groups, g). And μ_s^g is a group $\times$ sector fixed effect that allows for different demand shifters across sectors for natives and immigrants. We estimate the parameters of equation (30) using our individual-level expenditure data for the year 2006.

With the estimated coefficients we can compute total predicted expenditure of each individual on each sector as

$$\log \widehat{x}_{js} = \widehat{\mu}_{s_j}^{g_j} + \widehat{\alpha}_s \log Income_j$$

Differences in predicted expenditure in a sector across households reflects either preference heterogeneity (differences in $\widehat{\mu}_s^g$ across g) or differences in income (differences in $\log Income_j$). Hence, differences in immigrant intensities of consumption can be decomposed into differences in preferences or differences in the distribution of income across natives and immigrants.

We construct average predicted (log) expenditures of immigrants and natives on each sector s as

$$\log \widehat{x}_s^g = \frac{1}{|\mathcal{J}_g|} \sum_{j \in \mathcal{J}_g} \log \widehat{x}_{js} = \widehat{\mu}_s^g + \widehat{\alpha}_s \frac{1}{|\mathcal{J}_g|} \sum_{j \in \mathcal{J}_g} \log Income_j$$

where $\mathcal{J}_g$ is the set of individuals in group g and $|\mathcal{J}_g|$ is the number of these individuals. We can, therefore, decompose differences in average predicted log expenditures of immigrants and natives on each sector s at the national level into a component associated with taste differences and a component associated with income differences.

$$\log \widehat{x}_s^i - \log \widehat{x}_s^n = \underbrace{\widehat{\mu}_s^i - \widehat{\mu}_s^n}_{\text{taste differences}} + \underbrace{\widehat{\alpha}_s \left(\overline{Income}_i - \overline{Income}_n\right)}_{\text{income differences}} \tag{31}$$

Table A4: What Accounts for Variation in Immigrant Intensities of Consumption?

Fraction of expenditure differences explained by	
A. Taste Differences	**B. Income Differences**
0.885	0.115

Notes: Decomposing differences in the predicted average log expenditure of immigrants and natives across sectors into taste differences and income differences by projecting each of the two right-hand-side terms in equation (31) onto the left-hand side.

where $\overline{Income}_g \equiv \frac{1}{|\mathcal{J}_g|}\sum_{j\in\mathcal{J}_g}\log Income_j$ is the average log income of group g at the national level. Given the above identity, we can separately project each of the two right-hand-side terms onto the left-hand-side term. This provides an empirical decomposition of differences in $\log\widehat{x}_s^i - \log\widehat{x}_s^n$ across sectors into the preference-heterogeneity component and the income heterogeneity component.

Table A4 displays results. The vast majority of the variation between predicted immigrant and predicted native expenditure shares across sectors is driven by differences in tastes, rather than by differences in incomes.

B.3 Card instrument construction

Index each EU accession origin country by o. For each region r we predict the percent change in the EU accession immigrant population between 2003 and 2015 as

$$\Delta Pop_r^i \equiv \frac{\sum_o \frac{pop_{ro}^i}{pop_o^i}\Delta pop_{-ro}^i}{\frac{1}{2}\left(pop_r^i + \sum_o \frac{pop_{ro}^i}{pop_o^i}\Delta pop_{-ro}^i + pop_r^i\right)} \tag{32}$$

where pop_{ro}^i and $pop_o^i = \sum_r pop_{ro}^i$ are the initial 2003 populations of immigrants from origin o within region r and across all of Norway, $pop_r^i = \sum_o pop_{ro}^i$ is the initial 2003 population of immigrants within region r summed across all origins o, and Δpop_{-ro}^i is the change over time, between 2003 and 2015, in the national population of immigrants from origin o excluding region r. The numerator of the right-hand side of equation (32) is the predicted growth of the EU accession immigrant population within region r between 2003 and 2015. The denominator is the average of the initial 2003 population of EU accession country immigrants and the predicted population from these countries within region r in 2015, which is itself the sum of the initial population and its predicted growth.

B.4 Summary statistics

Table A5 displays summary statistics. Figure A4 displays maps of residualized demand exposure for two CCs. Figure A5 plots the correlation between immigrant intensities of consumption and production across CC measured at the national level.

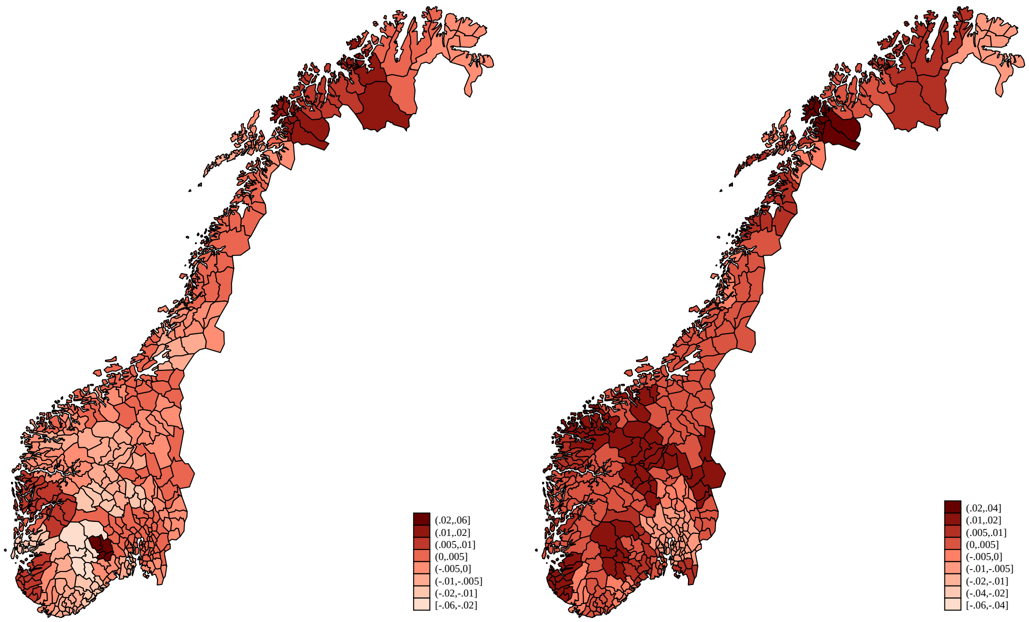
Table A5: Summary Statistics

	Male	Female	Include Educ.	Include Oslo	Exclude Manuf.
Income:					
Natives	474.73	342.03	474.47	500.75	472.26
Immigrants	435.60	338.05	436.60	448.17	435.13
New accession immigrants	473.40	358.98	464.01	495.01	475.41
Income, college graduates:					
Natives	587.35	400.90	565.93	622.08	579.42
Immigrants	530.07	402.76	519.07	550.00	531.55
New accession immigrants	570.05	433.28	529.76	587.16	567.32
Income, non-college graduates:					
Natives	440.41	314.81	439.33	453.59	436.07
Immigrants	383.67	291.40	382.76	390.11	374.74
New accession immigrants	394.50	288.23	392.64	398.16	391.24
Employment rate:					
Natives	0.96	0.96	0.96	0.96	0.96
Immigrants	0.92	0.94	0.93	0.93	0.92
New accession immigrants	0.94	0.92	0.95	0.96	0.93
Employment rate, college graduates:					
Natives	0.97	0.95	0.97	0.97	0.97
Immigrants	0.94	0.95	0.95	0.94	0.94
New accession immigrants	0.95	0.94	0.96	0.96	0.95
Employment rate, non-college graduates:					
Natives	0.96	0.96	0.96	0.96	0.96
Immigrants	0.92	0.93	0.92	0.92	0.91
New accession immigrants	0.93	0.91	0.93	0.95	0.92
Non-college graduate share:					
Natives	0.77	0.68	0.72	0.72	0.75
Immigrants	0.65	0.58	0.61	0.64	0.61
New accession immigrants	0.55	0.51	0.48	0.49	0.52

Notes: This table provides summary statistics for income (denominated in thousands of krone) and employment rates by education level for the various samples used in our empirical exercises. Statistics are computed for the year 2003. New accession immigrants are the subset of immigrants from countries joining the EU in 2004 and 2007. The new accession immigrants used to construct this table are those who lived in Norway in 2003, rather than those who enter after accession.

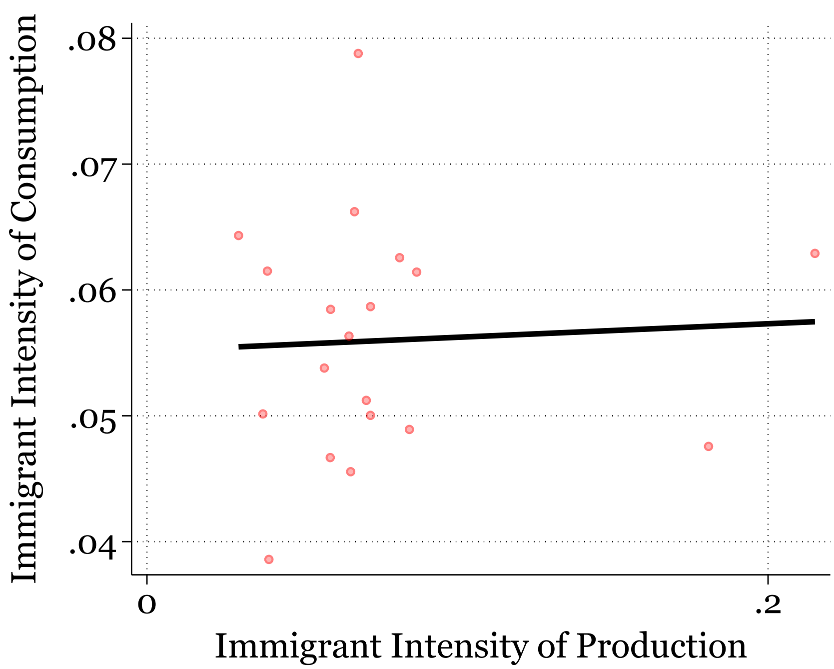
Figure A4: Maps of (Residualized) Demand Exposure

Panel A: Electronics | Panel B: Motor Vehicles



Note: These two maps show the residualized demand exposure measure for two sectors: "Electronics" and "Motor Vehicles."

Figure A5: Correlation between Immigrant Intensities of Consumption and Production

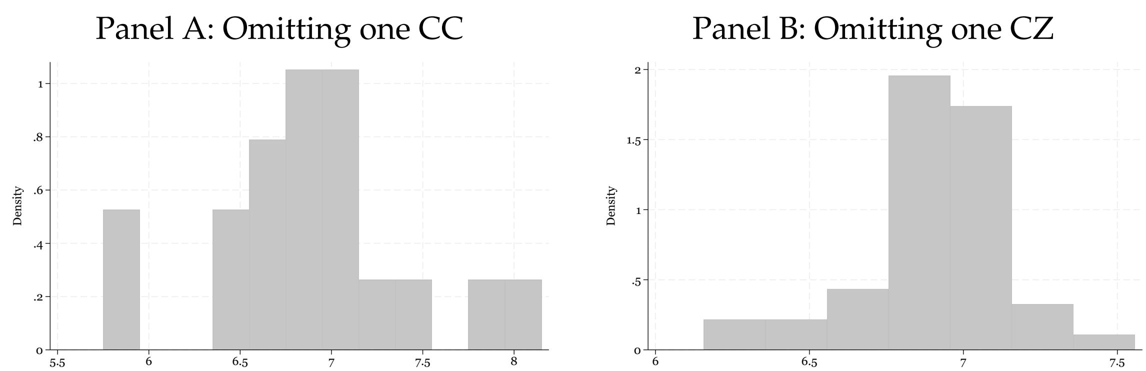


Note: This figure shows the correlation between the immigrant intensity of consumption (μ^i_s) and production (θ^i_s), both measured at the national level.

B.5 Details of empirical sensitivity analyses from Section 4.2

Results are not driven by any one CC or CZ. Here, we revisit the difference-in-difference specification shown in column 1 of Table 3 to show that our baseline estimates are not driven by any particular CC or CZ.

Figure A6: Histogram of the Impact of Demand Exposure omitting each CZ or CC



Note: The figure shows a histogram of estimated effects of demand exposure on native incomes using the specification of column 1 of Table 3, but omitting from the estimation sample either each CC sector, one at a time, or one CZ region, one at a time.

To do so, we estimate the difference-in-difference specification of equation (8) reported in column 1 of Table 3. Relative to the baseline, we drop all workers employed in a single CC from the regression sample, estimate the coefficient β^D associated with this sample restriction, and then iterate over each CC, storing 19 values of the regression coefficient. Panel A of Figure A6 reports the histogram of resulting estimates. We repeat this exercise, but iterating over dropping from the estimation sample workers in each CZ. Panel B reports the histogram of resulting estimates. In each panel, estimates are tightly bunched around our baseline value.

Including additional region-sector controls. Here, we revisit the difference-in-difference specification shown in column 1 of Table 3, but add the additional region-sector controls displayed in the balance table (Table A6).

Table A6: Balance table for different sets of controls

	Dependent Variable			
	Baseline Demand IV		Baseline Supply IV	
	coeff.	s.e.	coeff.	s.e.
Wage Share	0.45	(0.59)	0.63	(0.31)
Female Empl.	-0.01	(0.12)	0.43	(0.10)
College Empl.	0.19	(0.06)	0.55	(0.09)
Old Empl.	0.00	(0.04)	-0.38	(0.07)
Spend Share	1.47	(0.40)	0.18	(0.24)
Female Spend	2.04	(0.63)	-0.24	(0.20)
College Spend	1.24	(0.90)	0.32	(0.29)
Old Spend	-1.96	(0.66)	-0.09	(0.24)
Test for joint significance:				
F-statistic	5.03		10.14	
p-value	0.00		0.00	
N	247,320		247,320	
R-squared	.79		.543	

Notes: In this table the variables are: "Wage Share" is the share of the CZ wage bill in that 5-digit industry in 2003; "Female Empl." is the share of 5-digit industry x CZ employment by female workers in 2003; "College Empl." is the share of 5-digit industry x CZ employment by college educated workers in 2003; "Old Empl." is the share of 5-digit industry x CZ employment by workers older than 40 years old in 2003; "Spend Share" is the share of CZ expenditures in that CC in 2006; "Female Spend" is the share of CC x CZ expenditure by females in 2006; "College Spend" is the share of CC x CZ expenditure by the college-educated in 2006; "Old Spend" is the share of CC x CZ expenditure by older than 40 in 2006.

Table A7: The Impact of Demand Exposure, Different Sets of Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demand Exposure	6.91	6.88	6.89	6.79	6.90	6.80	6.38	7.32	7.40	6.99
	(1.76)	(1.76)	(1.80)	(1.75)	(1.76)	(1.78)	(1.71)	(1.64)	(1.72)	(1.58)
Supply Exposure	-2.14	-2.15	-2.02	-2.23	-2.09	-2.14	-2.11	-2.11	-2.14	-2.04
	(1.02)	(1.02)	(1.02)	(1.01)	(1.03)	(1.02)	(1.02)	(1.03)	(1.02)	(1.02)

Notes: Column 1, replicates column 1 of Table 3. Columns 2 to 11 in Panel A replicate column 1 of Table 3 adding different sets of controls: column 2 includes the share of the CZ wage bill in that 5-digit industry in 2003; column 3 includes the share of 5-digit industry x CZ employment by female workers in 2003; column 4 includes the share of 5-digit industry x CZ employment by college educated workers in 2003; column 5 includes the share of 5-digit industry x CZ employment by workers older than 40 years old in 2003; column 6 the share of CZ expenditures in that CC in 2006; column 7 includes the share of CC x CZ expenditure by females in 2006; column 8 includes the share of CC x CZ expenditure by the college-educated in 2006; column 9 includes the share of CC x CZ expenditure by older than 40 in 2006; column 10 includes all these controls together.

Table A7 displays results. Results are very stable across columns. In columns 2 to 9 we introduce each of the controls, one by one, displayed in Table A6. In column 10 we include all the controls at once.

Alternative estimation samples. Here, we revisit the difference-in-difference specification shown in column 1 of Table 3, but with different estimation samples. Table A8 displays the resulting estimates.

Table A8: The Impact of Demand Exposure, Alternative Samples

	(1)	(2)	(3)	(4)	(5)
Demand Exposure	3.54	3.00	16.33	7.46	5.33
	(1.08)	(1.71)	(4.53)	(3.43)	(2.11)
Supply Exposure	-1.53	-1.56	-3.53	2.95	-3.79
	(0.82)	(0.99)	(1.02)	(2.25)	(1.06)

Notes: Columns 1 to 5 replicate column 1 of Table 3 on alternative samples. Column 1 includes females into the sample, column 2 includes workers in education, column 3 includes residents of Oslo in 2004 and controls for pre-trends following Freyaldenhoven et al. (Forthcoming), column 4 restricts the sample to College educated workers, and column 5 restricts the sample to Non-College educated workers.

In columns 1-3, we consider expanded estimation samples. In column 1, we extend the sample to include women. Women earn less income than men, which depresses the estimated coefficient. In column 2, we extend the sample to include workers employed in education. We do not expect our mechanism to apply in the education sector, given restrictions on wage setting described in footnote 19. In column 3, we extend the sample to include workers who live in Oslo. When we include these workers, we observe that there is a contraction of earnings in the pre period in more relative to less demand exposed sector-region pairs (a negative linear negative trend) and an expansion of earnings in the post period in more relative to less demand exposed sector-region pairs. Following Freyaldenhoven et al. (Forthcoming), we remove this linear pre-trend by estimating region-sector linear trends in pre-shock data, i.e., 2000-2004, from worker-level total income (in levels); we then use these estimates to predict the level of worker-level total income if total income would have followed the trends predicted by the 2000-2004 period. We then remove these predicted real incomes from the actual real incomes throughout the entire sample period, i.e., 2000 to 2015. This gives us our de-trended real incomes, which we use to compute differences in real incomes across periods.

In columns 4 and 5 we consider restricted estimation samples. Column 4 restricts the sample to native workers who have a college education. Column 5 restricts the sample to native workers who do not have a college education.

Alternative instruments. Here, we show that instrumenting using only lagged immigrant intensities yields a strong first stage and almost identical second-stage results.

Table A9: First-stage, Alternative Instruments

	Demand Exposure		Supply Exposure	
	(1)	(2)	(3)	(4)
Baseline Demand IV	0.69		-0.00	
	(0.10)		(0.01)	
Baseline Supply IV	0.01		0.81	
	(0.01)		(0.02)	
Immigrant Intensity in Consumption		0.44		-0.00
		(0.06)		(0.01)
Immigrant Intensity in Production		0.01		0.64
		(0.00)		(0.02)
SW F stat	59.1	58.7	1136.8	1115.7

Notes: This table shows first-stage regressions that predict demand exposure, in column 1 and 2, and supply exposure, in columns 3 and 4. Immigrant intensities are computed using the baseline period, 2003 for supply and 2006 for demand intensities.

Table A10: Effect of Demand Exposure, Alternative Instruments

	(1)	(2)
Demand Exposure	6.91	6.91
	(1.76)	(1.76)
Supply Exposure	-2.14	-2.14
	(1.02)	(1.03)

Notes: Column 1 replicates Column 1 of Table 3. Column 2 uses the immigrant intensity in consumption at baseline as an instrument, while keeping our baseline supply exposure instrument. Column 3 uses the immigrant intensity in consumption and production at baseline as an instruments.

Table A9 compares the baseline first stage to an alternative in which both supply and demand exposures are predicted by the lagged immigrant intensities alone, $\theta^i_{rs,-1}$ and $\mu^i_{rs,-1}$. There are two key results here. First, the SW F stats remain large and very similar to those in the baseline first stage. Second, the alternative demand exposure instrument predicts demand exposure but not supply exposure, and vice versa, exactly as in our baseline first stage.

Table A10 then replicates our difference-in-difference specification of column 1 of Table 3 (in column 1) and displays results of the same specification but using the alternative instruments (in column 2). The estimated coefficients and their standard errors are almost identical.

B.6 Details of additional empirical results from Section 4.3

Here, we provide details of the additional empirical exercises outlined in Section 4.3. We include one additional empirical exercise in which we estimate our baseline difference-in-difference specification on endogenous subsamples defined by worker reallocation; we do not reference this in the main text, since this specification introduces endogeneity.

Mechanism. Here, we present estimates of equation (9) at the CZ-CC level. To do so, we construct more aggregate measures of supply exposure, at the CZ-CC level instead of using 5-digit NACE industries (and more aggregate versions of the instrument for supply exposure). We weight observations by employment and construct robust standard errors clustered at the CZ-CC level. We define the change in expenditure in two ways:

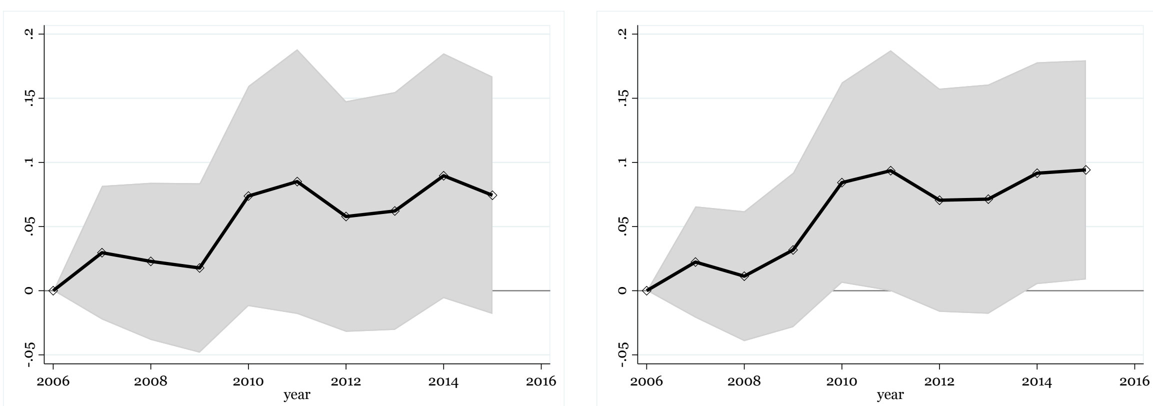
$$\Delta \log X_{rst} = \begin{cases} \log X_{rst} - \log X_{ms,2006} \\ \log \left(\frac{1}{9} \sum_{t=2007}^{2015} X_{rst} \right) - \log X_{ms,2006} \end{cases}$$

In the first, we use the log difference in expenditures between year t and the year 2006. In the second, we use the difference between log of average of expenditures between 2007 and 2015 and the log of expenditures in 2006. We consider both omitting Oslo from the estimation sample and including it. In all cases we include the education sector, since the reason for omitting it from the baseline analysis is that wages do not adjust, not because expenditure does not adjust.

Figure A7: Impact of Demand Exposure on the Evolution of Expenditures

Panel A: Omit Oslo

Panel B: Include Oslo



Note: This figure reports the 2SLS estimates associated with demand exposure (controlling for supply exposure) of the event-study specification of regression (9), together with the corresponding 95% confidence interval. Each region-sector pair is weighted by employment. Robust standard errors are clustered at the CZ-CC level.

Figure A7 displays the event-study estimates and 95% confidence intervals. Table A11

Table A11: The Impact of Demand Exposure on Expenditures

	Omit Oslo		Include Oslo	
	(1)	(2)	(3)	(4)
Demand Exposure	0.07	0.05	0.09	0.06
	(0.05)	(0.04)	(0.04)	(0.03)
Terminal year	2015	average	2015	average

Notes: This table reports the 2SLS estimates associated with demand exposure (controlling for supply exposure) of the difference-in-difference specification of regression (9). Columns 1 and 2 omit Oslo from the estimation sample whereas columns 3 and 4 include it. Columns 1 and 3 define the terminal year in $\Delta \log X_{rst}$ as 2015 whereas columns 2 and 4 use the average across 2007 and 2015. Each region-sector pair is weighted by employment. Robust standard errors are clustered at the CZ-CC level.

displays the difference-in-difference estimates. In Table A11, we report results using 2015 as the terminal year in constructing $\Delta \log X_{rst}$ and using the average across 2007 to 2015. Across specifications, we observe an increase in expenditures in more demand-exposed region-sector pairs.

Trade. Here, we provide details of the exercise displayed in Table 4 and then outline a set of robustness exercises.

To define sectoral tradability, we start by constructing a measure of trade across each of 13 aggregated NACE industries, indexed by i, using the following statistic:

$$\text{Trade}_i = \frac{\max\{\text{EU imports}_i, \text{EU exports}_i\}}{\text{EU GDP}_i}$$

where imports are calculated as imports into the EU from non-member states and exports are calculated similarly. Data is sourced from EUROSTAT using the NACE Rev 2. industry classification for the year 2023. Table A12 displays the 13 NACE codes and the resulting trade measures and classification.

We classify a worker as employed in a more tradable sector if his 5-digit NACE code is contained within wholesale and retail trade, manufacturing, or mining and quarrying. Table 4 displays the baseline difference-in-difference estimate in column 1, whereas columns 2 and 3 estimate the same specification, but separating the baseline sample of column 1 into two disjoint sets: workers employed in 2004 in less tradable sectors in column 2 and in more tradable sectors in column 3.

Here, we additionally consider a set of robustness exercises, defining sectors as tradable or not differently. Table A14 reports results, with Panel A reporting results estimated within non-tradable sectors and Panel B reporting results estimated within tradable sectors. The first column replicates the results from Table 4.

Table A12: Trade to GDP Ratios by NACE Sector

NACE code	(max(M, X) / GDP) x 100	Tradable
Wholesale and retail trade; repair of motor vehicles and motorcycles	85.57	Yes
Manufacturing	49.24	Yes
Mining and quarrying	32.63	Yes
Electricity, gas, steam and air conditioning supply	12.63	No
Transportation and storage	10.84	No
Water supply; sewerage, waste management and remediation activities	7.61	No
Agriculture, forestry and fishing	6.65	No
Professional, scientific and technical activities	6.06	No
Administrative and support service activities	5.07	No
Information and communication	3.48	No
Construction	2.34	No
Financial and insurance activities	2.05	No
Real estate activities	0.31	No

Notes: This table reports the baseline classification of aggregate NACE sectors into tradable and non-tradable based on the maximum between EU imports and exports relative to sectoral output.

Table A13: More and Less Tradable Consumption Categories for Robustness Exercises

More tradable CCs	Share of Employment in tradable NACE (%)	Less tradable CCs	Share of Employment in tradable NACE (%)
Motor Vehicles	100.00	Finance	0.00
Electronics	100.00	Hotels	0.00
Personal Effects	100.00	Insurance	0.00
Furnishing & Household Equip.	98.50	Banks	0.00
Culture	97.59	Restaurants	0.00
Food & Beverages	86.16	Services	0.15
Clothing & Footwear	83.16	Communications	6.33
Personal Care	75.33	Health	14.77
Utilities & Construction	41.41	Recreation	23.82
		Transport	31.20

Notes: This table reports the share, within each CC code, of employment in 2004 in tradable NACE sectors, using our baseline definition of tradable aggregate NACE sectors.

In the first robustness, we define consumption categories as more or less tradable as follows. As above, define the same three aggregate NACE codes as tradable. We then construct the share of workers—at the national level—employed in tradable aggregate NACE codes within each CC using employment in 2004. We then construct the median share across CCs in this share (weighting by employment) and allocate a CC to more tradable if and only if its share is above this median. Table A13 reports the national tradable share of employment for each CC following this approach. Column 2 of Table A14 reports results of replicating Table 4 but dividing CCs by tradability in this way. Column 3 then replicates column 2, but defining a CC's tradability separately within each CZ based on the employment mix of that CC in that CZ across the aggregate NACE codes.

Table A14: The Impact of Exposures using Alternative Definitions of Tradability

Panel A: Effect of demand exposure in non-tradable sectors

	Baseline			Baseline + Goods			Goods vs. Services		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demand Exposure	9.87	8.01	8.23	10.06	8.01	8.24	8.35	7.31	8.83
	(2.10)	(1.81)	(1.92)	(2.17)	(1.81)	(1.92)	(1.84)	(1.88)	(2.12)
Supply Exposure	-1.84	-2.22	-1.11	-1.81	-2.22	-1.24	-1.84	-1.82	-1.82
	(1.54)	(1.28)	(1.53)	(1.55)	(1.28)	(1.55)	(1.38)	(1.65)	(1.57)

Panel B: Effect of immigrant-induced demand exposure in tradable sectors

	Baseline			Baseline + Goods			Goods vs. Services		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demand Exposure	-6.27	7.82	0.47	-6.75	7.82	0.33	-2.44	1.88	3.69
	(5.85)	(11.78)	(6.81)	(5.81)	(11.78)	(6.83)	(6.67)	(7.20)	(6.10)
Supply Exposure	-2.30	-2.26	-3.29	-2.39	-2.26	-3.10	-2.41	-2.21	-2.05
	(1.29)	(1.59)	(1.36)	(1.30)	(1.59)	(1.37)	(1.52)	(1.28)	(1.35)

Notes: Panel A, column 1, replicates column 2 of Table 4. Panel B, column 1, replicates column 3 of Table 4. In Panels A and B, columns 1-3 classify the 13 aggregate NACE industries into tradables and non-tradables as in the baseline. Column 2 classifies a worker as employed in a tradable CC if the share of employment at the national level in that CC that is in one of the three traded NACE codes is above the (employed-weighted) median employment share in tradable NACE codes across CCs. Column 3 replicates this, but defines CC tradability at the regional level using regional employment shares. Columns 4 to 6 and columns 7 to 9 repeat the exercises shown in columns 1 to 3, but changing the tradable, non-tradable classification of aggregate NACE codes. Columns 4 to 6 consider as tradable the three baseline NACE industries, but also include all goods-producing aggregate NACE codes. Columns 7 to 9 classify aggregate NACE industries as tradable and non-tradable splitting between goods- and service-producing aggregate industries.

Columns 4-6 repeat the exercises in columns 1-3, but alter the allocation of aggregate NACE codes to more and less tradable, by including all goods-producing aggregate codes into the tradable set, in addition to the 3 codes used in columns 1-3. Columns 7-9 repeat the exercises in columns 1-3, also altering the allocation of aggregate NACE codes to more and less tradable, by allocating goods-producing aggregate NACE codes to more tradable and service-producing aggregate NACE codes to less tradable, irrespective of the trade data.

Across all specifications, the demand exposure coefficient estimated within the less-tradable sectors is larger than that estimated within all sectors, which is in turn larger than that estimated in the more-tradable sectors. We note that the supply exposure coefficient is never significantly different between the two, both in Table 4 or the robustness in Table A14. Nevertheless, the ranking of the supply exposure point estimates across more- and less-traded sectors is inconsistent with the predictions of our quantitative model.

Table A15: Impact of Exposures on Employment and Income Conditional on Employment

	2005-2015 Effect		Placebo	
	Years Emp	Avg Income | Emp	Years Emp	Avg Income | Emp
	(1)	(2)	(3)	(4)
Demand Exposure	0.01	7.72	0.00	1.08
	(0.01)	(2.58)	(0.00)	(1.38)
Supply Exposure	0.00	-1.79	-0.00	-1.03
	(0.01)	(1.64)	(0.00)	(0.79)
Average	10.5	65.0	3.9	-27.8
Observations	247842	246951	247842	247506

Notes: Columns 1 and 3 estimate a version of equation (8) in which the dependent variable is the number years of with positive wage income between 2005 and 2015 (in column 1) and between 2000 and 2004 (in column 3). Columns 2 and 4 estimate a version of equation (8) in which the dependent variable is the difference between average income across years with positive wage income between 2005 and 2015 and wage income in 2004 (in column 2) and average income across years with positive wage income between 2000 and 2003 and wage income in 2004 (in column 4). Average refers to the average of the dependent variable in the corresponding sample. Robust standard errors are clustered at the CZ-CC level.

Employment vs. wages. Table A15 displays results of estimating the difference-in-difference specification of equation (8), as in column 1 of Table 3, but replacing the change in income with a measure of the change in years employed and a measure of the change in income conditional on employment. Specifically, in column 1, the dependent variable is the sum of years employed for individual j summed across the 11 years from 2005 through 2015. In column 2, the dependent variable is the average real wage income of individual j across the subset of years between 2005 and 2015 in which j was employed (whereas the dependent variable used in column 1 of Table 3 is the average taken across all years between 2005 and 2015, whether or not the individual was employed). We define worker j as being employed in year t if his wage income is positive. Finally, columns 3 and 4 replicate this analysis, but focusing on the pre-shock period.

Supply exposure. Table A16 replicates the specification of column 1 of Table 3, but reports the difference-in-difference estimates of β^S in addition to β^D. Workers in more supply-exposed region-sectors in 2004 experience a relative decline in their wage incomes in response to immigration. Table A17 replicates the column 1 specification of Table A16, but also reports estimates of β^S and β^D when omitting either demand exposure (in column 1) or omitting supply exposure (in column 2). Estimates of either exposure is almost identical in our baseline (displayed in column 3) and when omitting the other measure of exposure. Figure A8 shows that this results from the fact that the residualized variation in demand exposure is orthogonal to residualized variation in supply exposure. Specifically,

Table A16: The Impact of Exposures on Average Native Real Wage Income Per Year

	Levels Difference		Percent Difference	
	(1)	(2)	(3)	(4)
Demand Exposure	6.91	5.66	1.31	1.02
	(1.76)	(1.93)	(0.54)	(0.43)
Supply Exposure	-2.14	-1.13	-0.62	-0.31
	(1.02)	(1.10)	(0.34)	(0.29)
Pre-shock 2004	X		X	
Pre-shock 2000-04		X		X
Average	88.3	117.9	23.1	29.0

Notes: This table replicates the specifications of Table 3, but reports the 2SLS estimate of β^S and β^D.

Figure A8 plots the correlation between predicted demand exposure and predicted supply exposure from the first stage, after residualizing these of each of the other covariates included in equation (8): sector fixed effects, CZ fixed effects, and individual controls.

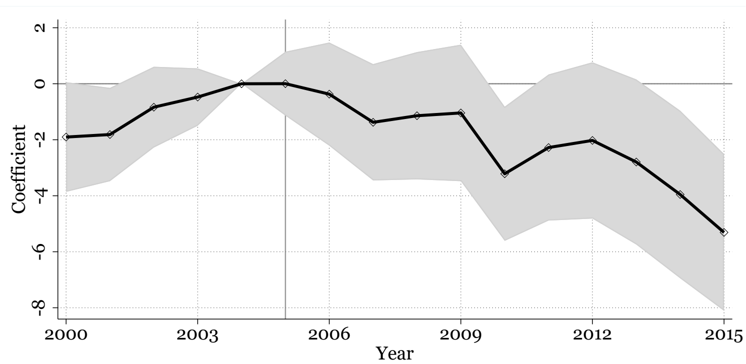
Table A17: Impact of Exposures on Income when Omitting Other Measure of Exposure

	(1)	(2)	(3)
Supply Exposure	-2.02		-2.14
	(1.04)		(1.02)
Demand Exposure		6.97	6.91
		(1.74)	(1.76)

Notes: Column 1 omits from our baseline specification Demand Exposure. Column 2 omits from our baseline specification Supply Exposure. Column 3 replicates Column 1 of Table 3..

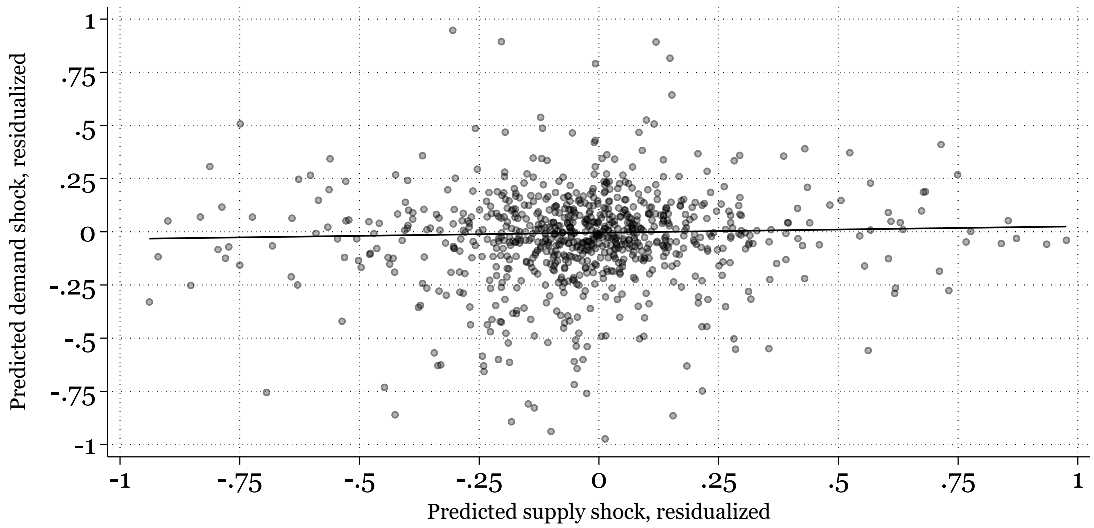
Finally, Figure A9 replicates Figure 3, but reports the event-study estimates of supply exposure instead of demand exposure.

Figure A9: The Impact of Supply Exposure on the Evolution of Native Earnings



Note: This figure replicates Figure 3, but reports the coefficient on supply exposure, β_t^S.

Figure A8: Correlation Between Demand and Supply Exposures



Note: The figure shows a scatter plot of predicted demand and supply exposures (from the first stage), residualized on sector fixed effects, region fixed effects, and the vector of individual controls.

Effects estimated in distinct (endogenous) subsamples. In our main analyses, we have identified the effects of demand and supply exposures on samples defined by predetermined characteristics, in the interest of avoiding endogeneity. However, it might be of interest to see how these empirical effect sizes differ from those estimated across workers who do not reallocate (across either region or sector), those who do reallocate across only regions, and those who reallocate across only sectors. Table A18 presents the results of this exercise.

Table A18: Effect of Exposures in Various Samples Defined by Reallocations

	Baseline	Stayers	Δ Region	Δ Sector
	(1)	(2)	(3)	(4)
Demand Exposure	6.91	3.95	24.14	5.27
	(1.76)	(2.03)	(10.32)	(2.61)
Average in 2015	88.3	114.6	131.0	56.3
Observations	247842	127051	6792	104405

Notes: This table replicates column 1 of Table 3. Column 1 is our baseline sample whereas columns 2-4 are selected subsamples: the column 2 sample is the set of workers who are employed in the same sector and living in the same region in 2015 as in 2004, the column 3 sample is the set of workers who are employed in the same sector and living in a different region in 2015 than in 2004, and the column 4 sample is the set of workers who are employed in a different sector (including non-employment) and living in the same region in 2015 as in 2004. Average reports the average value of the dependent variable in the corresponding sample.

C Quantitative appendix

C.1 Quantitative model

Here, we present a generalized version of the quantitative model in which regions may trade with each other. The quantitative model used in the baseline simply imposes the restriction that all inter-regional trade costs are infinite.

There are a finite number of regions, indexed by $r \in \mathcal{R}$. Workers are either immigrant or native, indexed by $g = \{i, n\}$. There is a continuum of workers with a given nativity, g, indexed by $\omega \in \Omega^g$ with measure $L^g = |\Omega^g|$. Each worker observes an idiosyncratic preference shifter, $\varepsilon(\omega, r, s)$, for each region-sector pair rs. This is distributed Fréchet with shape parameter $\kappa > 0$ and with amenity shifter, U_r^g, for each group g across each region r.[33] A worker's utility is the product of her real wage and her amenity shifter.

After drawing all amenity shocks, each worker makes a choice of which region in which to live and which sector in which to work. Let Ω_{rs}^g denote the set of workers who chose rs and denote by L_{rs}^g its measure. Let $L_r^g = \sum_s L_{rs}^g$ denote the measure of group g workers in region r.

Each region produces one version of a non-traded final good for each of the two groups of labor, g, combining the services of all sectors,

$$C_r^g = \left(\sum_{s \in \mathcal{S}} \left(\widetilde{\mu}_{rs}^g \right)^{\frac{1}{\eta}} \left(C_{rs}^g \right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \text{ for all } r,$$

where C_r^g is the absorption (and production) of the final good in region r for the consumption of group g, C_{rs}^g is the absorption of sector s in region r in the consumption of group g, and $\eta > 0$ is the elasticity of substitution between sectors in the production of the final good for both groups. The absorption of sector s in region r by group g is itself an aggregator of the services of sector s across all origins,

$$C_{rs}^g = \left(\sum_{j \in \mathcal{R}} \left(C_{jrs}^g \right)^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}} \text{ for all } r, s,$$

where C_{jrs}^g is the absorption within region r by group g of region j's output of sector s and where $\alpha > \eta$ is the elasticity of substitution between origins for a given sector for both

[33] We do not require the more restrictive assumption that $\kappa > 1$, as described in footnote 29. Additionally, our approach implies that a single elasticity, κ, shapes both sectoral and regional reallocations. It is straightforward to introduce different elasticities across regions and sectors.

groups.

Sector s in region r produces output by combining immigrant and domestic labor,

$$Q_{rs} = A_{rs} \left(\left(A^i_{rs} L^i_{rs} \right)^{\frac{\rho-1}{\rho}} + \left(A^n_{rs} L^n_{rs} \right)^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \text{ for all } r, s \tag{33}$$

where L^g_{rs} is the mass of group g workers employed in sector s in region r; A_{rs} and A^g_{rs} are the systematic components of productivity of all workers and of any group g worker, respectively, in this sector and region; and $\rho > 0$ is the elasticity of substitution between immigrant and domestic labor within each sector.

The services of a sector can be traded between regions subject to iceberg trade costs, where $\tau_{rjs} \geq 1$ is the cost for shipments of sector s from region r to region j and we impose $\tau_{rrs} = 1$ for all regions r and sectors s. The quantity of sector s produced in region r must equal the sum of absorption (and trade costs) across destinations,

$$Q_{rs} = \sum_{g} \sum_{j \in \mathcal{R}} \tau_{rjs} C^g_{rjs} \text{ for all } r, s \tag{34}$$

Of course, labor market clearing implies

$$L^g = \sum_{r \in \mathcal{R}} \sum_{s} L^g_{rs}.$$

We assume trade is balanced in each region and all markets are perfectly competitive.

C.2 Equilibrium characterization

Final-good profit maximization in region r implies

$$C^g_{rs} = \widetilde{\mu}^g_{rs} \left(\frac{P^c_{rs}}{P^g_r} \right)^{-\eta} C^g_r \tag{35}$$

where

$$P^g_r = \left(\sum_{s \in \mathcal{S}} \widetilde{\mu}^g_{rs} \left(P^c_{rs} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{36}$$

denotes the final good price for group g, and where P^c_{rs} denotes the absorption price of sector s in region r (which is common across groups). Optimal regional sourcing of sector

s in region j implies

$$C^g_{rjs} = \left(\frac{\tau_{rjs} P_{rs}}{P^c_{js}}\right)^{-\alpha} C^g_{js} \tag{37}$$

where

$$P^c_{rs} = \left(\sum_{j\in\mathcal{R}} \left(\tau_{jrs} P_{js}\right)^{1-\alpha}\right)^{\frac{1}{1-\alpha}} \tag{38}$$

and where P_{js} denotes the output price of sector s in region j. Equations (34), (35), and (37) imply

$$Q_{rs} = \left(P_{rs}\right)^{-\alpha} \sum_g \sum_{j\in\mathcal{R}} \widetilde{\mu}^g_{js} \left(\tau_{rjs}\right)^{1-\alpha} \left(P^c_{js}\right)^{\alpha-\eta} \left(P^g_j\right)^{\eta} C^g_j \tag{39}$$

Profit maximization in the production of sector s in region r implies

$$P_{rs} = \frac{1}{A_{rs}} \left(\left(W^i_{rs}/A^i_{rs}\right)^{1-\rho} + \left(W^n_{rs}/A^n_{rs}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}} \tag{40}$$

and

$$L^g_{rs} = \left(A_{rs} A^g_{rs}\right)^{\rho-1} \left(\frac{W^g_{rs}}{P_{rs}}\right)^{-\rho} Q_{rs}, \tag{41}$$

Budget balance for each group g in each r requires[34]

$$\sum_s L^g_{rs} W^g_{rs} = P^g_r C^g_r \text{ for all } r, g \tag{42}$$

Worker $\omega \in \Omega^g$ chooses the rs pair that maximizes real wage income W^g_{rs}/P^g_r, multiplied by the systematic amenity value U^g_r, and the idiosyncratic amenity value $\varepsilon\left(\omega, r, s\right)$, maximizing $\left(W^g_{rs}/P^g_r\right) \times U^g_r \times \varepsilon\left(\omega, r, s\right)$. Idiosyncratic worker amenities imply that the mass of group g workers who work in sector s within region r is

$$L^g_{rs} = \frac{\left(W^g_{rs}\right)^{\kappa}}{\sum_{j\in\mathcal{S}} \left(W^g_{rj}\right)^{\kappa}} L^g_r \tag{43}$$

[34] This equation is equivalent to the more disaggregated budget balance for each group g in rs, since consumption of this group in r is simply $\frac{L^g_{rs} W^g_{rs}}{\sum_{s'} L^g_{rs'} W^g_{rs'}} C^g_r$.

and that the mass of group g choosing region r is given by[35]

$$L_r^g = \frac{\left(\frac{U_r^g}{P_r^g}\left[\sum_{s\in\mathcal{S}}\left(W_{rs}^g\right)^{\kappa}\right]^{\frac{1}{\kappa}}\right)^{\kappa}}{\sum_{r'\in\mathcal{R}}\left(\frac{U_{r'}^g}{P_{r'}^g}\left[\sum_{s\in\mathcal{S}}\left(W_{r's}^g\right)^{\kappa}\right]^{\frac{1}{\kappa}}\right)^{\kappa}} L^g \tag{44}$$

An equilibrium is a vector of prices $\left\{P_r^g, P_{rs}, P_{rs}^c\right\}$, wages $\left\{W_{rs}^g\right\}$, quantities produced and consumed $\left\{C_r^g, C_{rs}^g, C_{rjs}^g, Q_{rs}\right\}$, and labor allocations $\left\{L_{rs}^g, L_r^g\right\}$ for all regions r, sectors s, and worker groups g that satisfy (35)-(44).

C.3 System in changes

In the estimation, we shock aggregate factor supplies of natives and immigrants, L^g for each g, the values of regional amenities for each group, U_r^g for each rg pair, and the values of regional productivities for each group, A_r^g (where $A_{rs}^g \equiv A_r^g \widetilde{A}_{rs}^g$) for each rg pair. Here, we express the system in changes shocking of these. In the counterfactuals, we only shock the supply of immigrants, holding all other parameters else fixed. Hence, in the counterfactuals we simply fix a subset of the parameters.

We define $\widehat{X} = X'/X$, where X' is the value of either any parameter or equilibrium outcome in the new equilibrium and X is its value in the initial equilibrium. The underlying shocks we feed into the system are $\widehat{L}^g$, $\widehat{U}_r^g$, and $\widehat{A}_r^g$. Starting from the equations in Section C.2, we obtain

$$\widehat{C}_{rs}^g = \left(\frac{\widehat{P}_{rs}^c}{\widehat{P}_r^g}\right)^{-\eta} \widehat{C}_r^g \tag{45}$$

$$\widehat{P}_r^g = \left(\sum_{s\in\mathcal{S}} S_{rs}^{eg}\left(\widehat{P}_{rs}^c\right)^{1-\eta}\right)^{\frac{1}{1-\eta}} \tag{46}$$

where

$$S_{rs}^{eg} \equiv \frac{\widetilde{\mu}_{rs}^g\left(P_{rs}^c\right)^{1-\eta}}{\sum_{s'\in\mathcal{S}}\widetilde{\mu}_{rs'}^g\left(P_{rs'}^c\right)^{1-\eta}}$$

equals the share of all expenditure by group g within region r that is spent on sector s. That is, the numerator is g's expenditure in region r on s and the denominator is g's

[35]If the elasticity across regions differs from that across sectors, the outmost κ in the numerator and denominator would be adjusted.

expenditure in region r. We have

$$\widehat{C}^{g}_{rjs} = \left(\frac{\widehat{P}_{rs}}{\widehat{P}^{c}_{js}}\right)^{-\alpha} \widehat{C}^{g}_{js} \tag{47}$$

$$\widehat{P}^{c}_{rs} = \left(\sum_{j\in\mathcal{R}} S^{m}_{jrs} \left(\widehat{P}_{js}\right)^{1-\alpha}\right)^{\frac{1}{1-\alpha}} \tag{48}$$

where

$$S^{m}_{jrs} \equiv \frac{\left(\tau_{jrs}P_{js}\right)^{1-\alpha}}{\sum_{j'\in\mathcal{R}}\left(\tau_{j'rs}P_{j's}\right)^{1-\alpha}}$$

equals the share of all expenditure on sector s within r that is sourced from region j. That is, the numerator is region r's expenditure on sector s that is sourced from region j and the denominator is region r's expenditure on sector s across all sources. We also have

$$\widehat{Q}_{rs} = \left(\widehat{P}_{rs}\right)^{-\alpha} \sum_{g}\sum_{j\in\mathcal{R}} S^{xg}_{rjs} \left(\widehat{P}^{c}_{js}\right)^{\alpha-\eta} \left(\widehat{P}^{g}_{j}\right)^{\eta} \widehat{C}^{g}_{j} \tag{49}$$

where

$$S^{xg}_{rjs} \equiv \frac{\widetilde{\mu}^{g}_{js}\left(\tau_{rjs}\right)^{1-\alpha}\left(P^{c}_{js}\right)^{\alpha-\eta}\left(P^{g}_{j}\right)^{\eta} C^{g}_{j}}{\sum_{g'}\sum_{j'\in\mathcal{R}}\widetilde{\mu}^{g'}_{j's}\left(\tau_{rj's}\right)^{1-\alpha}\left(P^{c}_{j's}\right)^{\alpha-\eta}\left(P^{g'}_{j'}\right)^{\eta} C^{g'}_{j'}}$$

is the share of all output (in units or equivalently value) produced in region r sector s that is shipped to region j for group g. We also have

$$\widehat{P}_{rs} = \left(\theta^{i}_{rs}\left(\frac{\widehat{W}^{i}_{rs}}{\widehat{A}^{i}_{r}}\right)^{1-\rho} + \left(1-\theta^{i}_{rs}\right)\left(\frac{\widehat{W}^{n}_{rs}}{\widehat{A}^{n}_{r}}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}} \tag{50}$$

where θ^{i}_{rs} is defined as in Section 2.1: the share of all labor payments in region r and sector s that are paid to immigrants. We also have

$$\widehat{L}^{g}_{rs} = \left(\widehat{A}^{g}_{r}\right)^{\rho-1}\left(\frac{\widehat{W}^{g}_{rs}}{\widehat{P}_{rs}}\right)^{-\rho} \widehat{Q}_{rs} \tag{51}$$

and

$$\sum_{s\in\mathcal{S}} S^{yg}_{rs}\widehat{L}^{g}_{rs}\widehat{W}^{g}_{rs} = \widehat{P}^{g}_{r}\widehat{C}^{g}_{r} \text{ for all } r, g \tag{52}$$

where

$$S_{rs}^{yg} \equiv \frac{L_{rs}^g W_{rs}^g}{\sum_{s'\in\mathcal{S}} L_{rs'}^g W_{rs'}^g}$$

is the share of all of the wage income that group g in region r earns within sector s. The numerator is g's labor income in sector s in region r. The denominator is g's total labor income in region r. Finally, we have

$$\widehat{L}_{rs}^g = \frac{\left(\widehat{W}_{rs}^g\right)^\kappa}{\sum_{j\in\mathcal{S}} \frac{L_{rj}^g}{L_r^g}\left(\widehat{W}_{rj}^g\right)^\kappa}\widehat{L}_r^g \tag{53}$$

where L_{rs}^g / L_r^g is the share of group g in region r that works within sector s and

$$\widehat{L}_r^g = \frac{\left(\frac{\widehat{U}_r^g}{\widehat{P}_r^g}\left[\sum_{s\in\mathcal{S}} \frac{L_{rs}^g}{L_r^g}\left(\widehat{W}_{rs}^g\right)^\kappa\right]^{\frac{1}{\kappa}}\right)^\kappa}{\sum_{r'\in\mathcal{R}} \frac{L_{r'}^g}{L^g}\left(\frac{\widehat{U}_{r'}^g}{\widehat{P}_{r'}^g}\left[\sum_{s\in\mathcal{S}} \frac{L_{r's}^g}{L_{r'}^g}\left(\widehat{W}_{r's}^g\right)^\kappa\right]^{\frac{1}{\kappa}}\right)^\kappa}\widehat{L}^g \tag{54}$$

where L_r^g / L^g is the share of group g in region r.

C.4 Parameterization

Normalizing expenditure data. Suppose we have expenditure and income measured at the same level of sectoral aggregation, s. In our quantification, this s is the CC level, to which we have aggregated the 5-digit NACE codes.

In the data, we observe labor income of each group g that lives in a given region r—wherever those people work—and works in a given sector s in the year 2004. Denote this by I_{rs}^g. In the data, we observe expenditure that is actually spent in each region r—wherever those people live—of each group g within each sector s in the year 2006. Denote this by $Exp_{rs}^{g,0}$.

In the model, whether there is trade or not (since trade is balanced), the relationship between expenditure and income satisfies three conditions:

i. expenditure of each group g of agents living in a region r equals their labor income in that region

ii. expenditure within each non-traded sector summed across all groups in a given region equals income summed across all groups within that region-sector

iii. expenditure within each traded sector summed across all regions and groups equals income within that sector

In the closed economy version of the model used in our baseline quantification, condition (iii) can be dispensed with (since no sectors are traded).

For many reasons, these conditions will not be satisfied in our data. When we calibrate the shares in the system in changes, these conditions must be satisfied. To satisfy them, we take the following iterative approach. In each iteration i, we proceed in two steps. First, we define

$$Exp_{rs}^{g,i_0} = \frac{\sum_{s'} I_{rs'}^{g}}{\sum_{s''} Exp_{rs''}^{g,i-1}} \times Exp_{rs,0}^{g,i-1}$$

which ensures that Exp_{rs}^{g,i_0} is consistent with group g in region r's total spending equalling its total income. Second, we use this value Exp_{rs}^{g,i_0} to define, for each non-traded sector $s \in \mathcal{S}_N$,

$$Exp_{rs}^{g,i} = \frac{\sum_{g'} I_{rs}^{g'}}{\sum_{g''} Exp_{rs}^{g'',i_0}} \times Exp_{rs}^{g,i_0} \quad \text{for each } s \in \mathcal{S}_N$$

and for each traded sector $s \in \mathcal{S}_T$,

$$Exp_{rs}^{g,i} = \frac{\sum_{g',r'} I_{r's}^{g'}}{\sum_{g'',r''} Exp_{r''s}^{g'',i_0}} \times Exp_{rs}^{g,i_0} \quad \text{for each } s \in \mathcal{S}_T$$

These two definitions ensure that region×sector spending equals region×sector income in the case of non-tradables and sector spending equals sector income in the case of tradables. We then check if

$$\sum_{s} Exp_{rs}^{g,i} = \sum_{s} I_{rs}^{g}$$

for each rg pair. If not, we continue to iteration $i+1$. After converging at the end of iteration i^*, define $E_{rs}^{g} = Exp_{rs}^{g,i^*}$. We use E_{rs}^{g} and I_{rs}^{g} as the raw data with which we construct shares in the parameterization.

Importantly, while we are adjusting expenditures to be consistent with the three conditions that must be satisfied in the model, we store $Exp_{rs}^{g,0}$ to define the μ terms that are not used in the construction of shares, but are used in regression analyses. This way, the μ terms used in the regression analysis exactly coincide in the model and the data.

Parameterizing shares in the baseline (no-trade) quantification. From Section C.3, the shares required to parameterize the model are: S_{rs}^{eg}, S_{jrs}^{m}, S_{rjx}^{xg}, θ_{rs}^{i}, S_{rs}^{yg}, L_{rs}^{g}/L_{r}^{g}, and L_{r}^{g}/L^{g}. However, in the no-trade version of the model, there are two substantial simplifications.

First,

$$S^m_{jrs} = \begin{cases} 1 & \text{if } j = r \\ 0 & \text{otherwise} \end{cases}$$

Second,

$$S^{xg}_{rjs} = \begin{cases} \overline{\mu}^g_{rs} & \text{if } j = r \\ 0 & \text{otherwise} \end{cases}$$

where $\overline{\mu}^g_{rs}$ is the version of μ constructed using the renormalized expenditure data rather than the value of μ constructed using the raw expenditure data. Given these simplifications, the shares are straightforward to construct given our data on incomes, I^g_{rs}, and (renormalized) expenditures (as described above), E^g_{rs}, and employment, L^g_{rs}. Specifically (omitting S^m_{jrs}, which is either 1 or 0), we have

$$\begin{aligned}
S^{eg}_{rs} &= E^g_{rs} \bigg/ \left(\sum_{s'} E^g_{rs'} \right) \\
S^{xg}_{rjs} &= \overline{\mu}^g_{rs} = E^g_{rs} \Big/ \left(E^i_{rs} + E^n_{rs} \right) \\
\theta^g_{rs} &= I^g_{rs} \Big/ \left(I^i_{rs} + I^n_{rs} \right) \\
S^{yg}_{rs} &= I^g_{rs} \bigg/ \left(\sum_{s'} I^g_{rs'} \right)
\end{aligned}$$

Finally, the two employment shares L^g_{rs}/L^g_r, and L^g_r/L^g are trivial.

Parameterizing shares in the extended quantification with trade. We also consider an extended model in which some sectors are not traded across regions (infinite trade costs, as in our baseline quantification) and others are traded freely across regions (trade costs of one). Here, we must adjust the shares S^m_{jrs} and S^{xg}_{rjs} constructed above for the subset of sectors s in which trade is free. In what follows, consider such a sector.

Consider first S^m_{jrs}. This equals expenditure in region r on sector s shipped from region j, E_{jrs}, divided by total expenditure in region r in sector s, E_{rs}. We directly observe E_{rs}, since $E_{rs} = E^i_{rs} + E^n_{rs}$. We now focus on measuring the numerator, E_{jrs}, which we do not directly observe. From equation (38), we have

$$P^c_{js} = \left(\sum_{r' \in \mathcal{R}} (P_{r's})^{1-\alpha} \right)^{\frac{1}{1-\alpha}} = P^c_s$$

This implies that the sectoral consumption price is equated across regions within a given tradable sector. Together with equation (36), we have

$$P_r^g = \left(\sum_{s \in \mathcal{S}} \widetilde{\mu}_{rs}^g \left(P_s^c\right)^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

Together with equations (35) and (37), we have

$$C_{jrs}^g = \left(\frac{P_{js}}{P_s^c} \right)^{-\alpha} \widetilde{\mu}_{rs}^g \left(\frac{P_s^c}{P_r^g} \right)^{-\eta} C_r^g$$

Hence, we obtain

$$E_{jrs}^g = \widetilde{\mu}_{rs}^g \left(P_{js}\right)^{1-\alpha} \left(P_s^c\right)^{\alpha-\eta} \left(P_r^g\right)^{\eta} C_r^g$$

Define $S_{jrs}^{gm} \equiv E_{jrs}^g / E_{rs}^g$ as the share of group g's consumption in region r in sector s that is sourced from region j. This can then be expressed as

$$S_{jrs}^{gm} = \frac{E_{jrs}^g}{\sum_{j'} E_{j'rs}^g} = \frac{\left(P_{js}\right)^{1-\alpha}}{\sum_{j'} \left(P_{j's}\right)^{1-\alpha}}$$

This is common across groups, which yields

$$S_{jrs}^m = \frac{\left(P_{js}\right)^{1-\alpha}}{\sum_{j'} \left(P_{j's}\right)^{1-\alpha}}$$

Hence, the import share in a given region-sector from a given origin is invariant to the importing region. This implies

$$S_{jrs}^m = S_{js}^m$$

where S_{js}^m is simply the total labor payments in region j and sector s relative to total labor payments in sector s summed across all regions

$$S_{jrs}^m = S_{js}^m = \frac{I_{js}}{I_s} \tag{55}$$

where $I_s \equiv \sum_r I_{rs}$ This is the equation with which we measure S_{jrs}^m (in a sector with trade).

Consider second S_{rjs}^{xg}. We can express this as

$$S_{rjs}^{xg} = \frac{E_{rjs}^g}{I_{rs}}$$

where we do not directly observe expenditure by group g in region j on sector s purchased from region r: E^{g}_{rjs}. However, we can re-express S^{xg}_{rjs} as

$$S^{xg}_{rjs} = \frac{E_{rjs}}{I_{rs}} \times \overline{\mu}^{g}_{js}$$

where $E_{rjs} = E^{i}_{rjs} + E^{n}_{rjs}$. While we do not directly observe E_{rjs}, we have already constructed $S^{m}_{rjs} = E_{rjs}/E_{js}$ above, which implies $E_{rjs} = S^{m}_{rjs} \times E_{js}$. Hence, we combine these to obtain

$$S^{xg}_{rjs} = S^{m}_{rjs}\frac{E_{js}}{I_{rs}} \times \overline{\mu}^{g}_{js}$$

which is the equation with which we measure S^{xg}_{rjs} (in a sector with trade).

C.5 Additional quantitative exercises

Variance decomposition. To quantify this, we regress native real wage changes in each rs pair from the full model, $\widehat{w}^{\text{full}}_{rs}$ on native real wage changes in the model with only demand exposure differences within region, $\widehat{w}^{\text{demand}}_{rs}$, on native real wage changes in the model with only supply exposure differences within region, $\widehat{w}^{\text{supply}}_{rs}$, both including and not including a region fixed effect

$$\widehat{w}^{\text{full}}_{rs} = \alpha + \left[\alpha_r\right] + \beta^{\text{demand}}\widehat{w}^{\text{demand}}_{rs} + \beta^{\text{supply}}\widehat{w}^{\text{supply}}_{rs} + \varepsilon_{rs}$$

From this regression, we generate a predicted real wage change from the full model,

$$\widehat{w}^{\text{full pred}}_{rs} = \widehat{\beta}^{\text{supply}}\widehat{w}^{\text{supply}} + \widehat{\beta}^{\text{demand}}\widehat{w}^{\text{demand}}$$

using the coefficient estimates, $\widehat{\beta}^{\text{supply}}$ and $\widehat{\beta}^{\text{demand}}$. We then decompose this prediction into a component arising from the model with differences in supply exposure alone and from the model with differences in demand exposure alone by regressing each component of the prediction on $\widehat{w}^{\text{full pred}}_{rs}$. By the properties of OLS, the two coefficients sum to one.

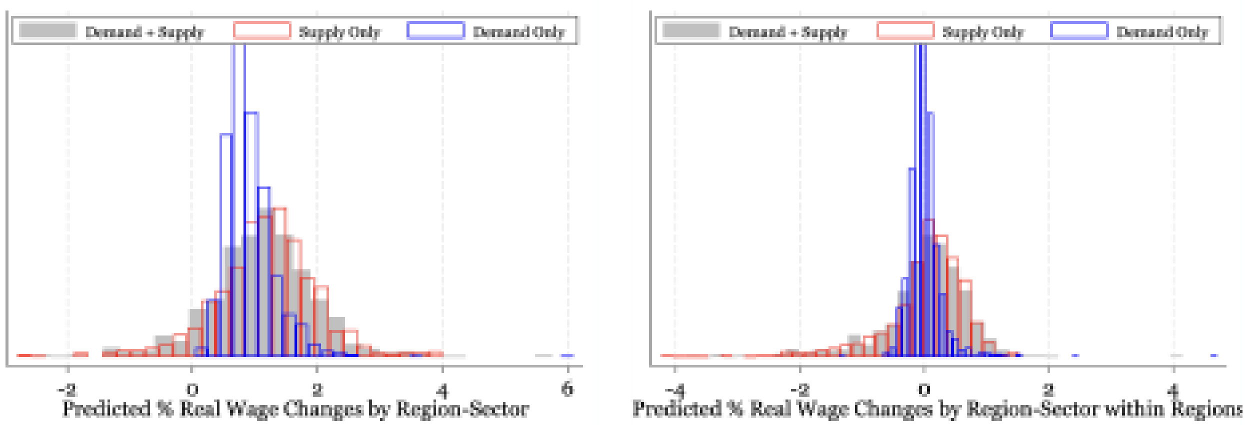
When we include regional fixed effects in the regression, α_r, the version of the model with only supply exposure differences accounts for 56% of the variance (and the version of the model with only demand exposure differences accounts for 44%). When we do not include regional fixed effects in the regression, the version of the model with only supply exposure differences accounts for 69% of the variance (and the version of the model with only demand exposure differences accounts for 31%).

Alternative parameter values. Here, we replicate our baseline quantitative analysis, but using alternative values of the elasticities, κ, ρ, and η. We take these alternatives from Burstein et al. (2020): $\kappa = 2$, $\rho = 4.6$, and $\eta = 1.65$. Figure A10 displays the distribution of changes in native real wages across region-sector pairs. The median real wage change is 1.1% (compared to 2.8% in our baseline). The 10th and 90th percentile changes in real wages are 0.1% and 2.1% (compared to 1.6% and 4.3% in our baseline).

Figure A10: Model-Predicted Native Real Wage Changes, Alternative Calibration

Panel A: Full Distribution

Panel B: Within-Region Variation



Notes: This figure reports the predicted percent real wage changes induced by overall immigration to Norway over the period 2003 to 2015 by three different models: a model with both demand and supply exposure, a model with only demand exposure, and a model with only supply exposure, calibrating elasticities following Burstein et al. (2020) instead of our empirical results. Panel A reports the overall variance in predicted percent real wages, while panel B reports only the within region, across sectors, variation.

The intuition for these alternative quantitative results is straightforward. First, by raising the value of $\kappa + \eta$, this alternative parameterization reduces the change in relative native wages induced by a given shock to the relative demand curve for native labor (as shown in equation 7 and as described in Section A.1). By raising ρ, we reduce $\eta - \rho$, which increases the impact of differences in supply exposure on the shift in the relative demand curve for native labor. Finally, by raising ρ, we also reduce the overall benefit to native workers of an increase in immigrant supply (in the absence of differences in supply or demand exposure). This explains why native workers can be harmed by immigration in this alternative parameterization.

Quantification with between-region trade. Here, we revisit our baseline counterfactual exercise, but in a version of the quantitative model in which a set of CC codes are freely traded (unlike the baseline quantification, where all CC codes are not traded) and the remaining CC codes remain non-traded. We allocate CC codes to traded and non-traded based on the fraction of workers in each CC that work in the three aggregate NACE codes we classify has highly traded, as described in Appendix B.6. We display the resulting traded and non-traded CC codes in Table A13. We show the results of estimating the baseline difference-in-difference specification on income separately within the CCs classified as traded and non-traded—using this definition—in column 2 of Table A14.

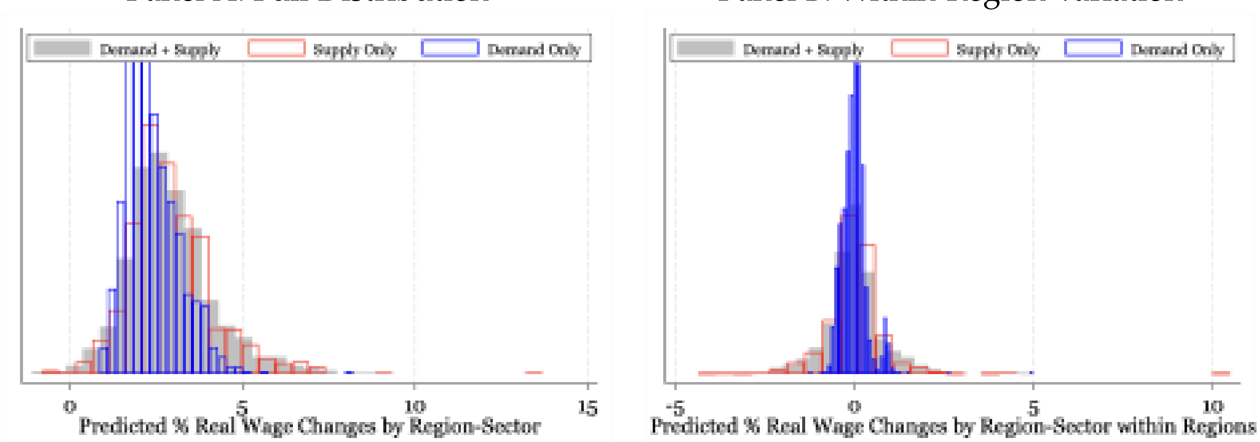
In this model, we calibrate shares in the traded sectors differently from in the non-traded sectors, as described in Section C.4. We fix elasticities at their baseline levels, but must now additionally choose a value for α, where $1 - \alpha$ is the trade elasticity. We choose $\alpha = 7$, to obtain a trade elasticity of 6.

We provide two sets of results. First, we show what these parameter values imply for estimates of the difference-in-difference specification of the income change regression, separately estimated within the sample of trade and non-traded CC codes. In the non-traded sample, we obtain a coefficient of 7.36 on demand exposure and of -0.48 on supply exposure. In the traded sample, we obtain a coefficient of 2.93 on demand exposure and of 4.37 on supply exposure. These results for demand exposure line up reasonably well with our empirical counterparts shown in Table A14. However, the gap between model-implied supply-exposure coefficients estimated in the traded and non-traded sectors does not line up well with differences in their empirical counterparts.

Second, we show what the model implies for native real wage changes across region-sector pairs in Figure A11.

Figure A11: Model-Predicted Native Real Wage Changes, Incorporating Trade

Panel A: Full Distribution Panel B: Within-Region Variation



Notes: This figure reports the predicted percent real wage changes induced by overall immigration to Norway over the period 2003 to 2015 using the model in which some sectors are freely traded and some are not traded. We use three alternative models: a model with both demand and supply exposure, a model with only demand exposure, and a model with only supply exposure. Panel A reports the overall variance in predicted percent real wages while panel B reports only the within region, across sectors, variation.