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? A massive 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 the native labor-market effects of supply and demand exposures to immigration. Theoretically, we solve for the native wage effects of immigration through both channels. 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 all native workers to immigration induced by the EU expansions in 2004 and 2007. We find large, positive, and persistent effects of demand exposure to EU expansion on native worker income.

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1 Introduction

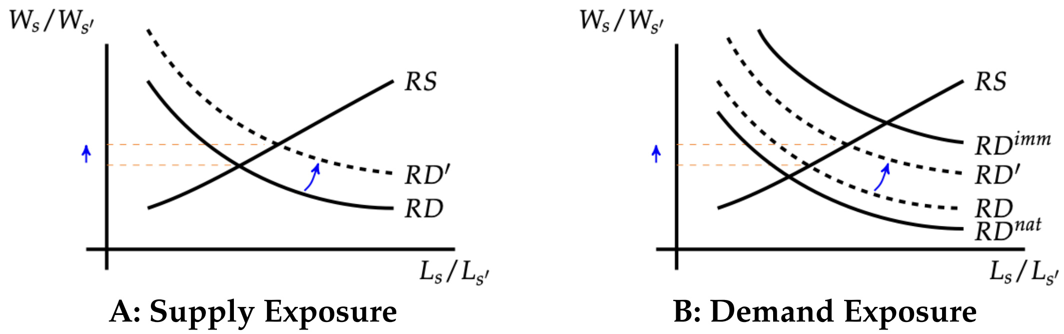
Summary. What is the effect of immigration on the evolution of labor income for native workers? This question motivates a massive body of theoretical and empirical work. Much of this literature focuses on identifying the differential impact of immigration across native workers employed in jobs that are 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. Theoretically, we solve for the effects of immigration in a non-parametric, two-sector economy (and in a semi-parametric, many-sector economy). We provide explicit definitions for each measure of exposure and show how underlying elasticities shape the impacts of each. For instance, if the native labor supply curve across jobs is upward sloping, then native wages rise relatively more in jobs that have higher demand exposure in response to an inflow of immigrants to the economy. Guided by our theory, 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 induced by EU expansions in 2004 and 2007 on the Norwegian labor market. Empirically, we find that natives employed in jobs that are more positively exposed on the demand side to immigration experience large and persistent increases in their income relative to otherwise identical natives in less exposed jobs.

Details. In Section 2, we present a theory 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 elastic labor supply across sectors that may differ between immigrants and natives. Importantly, native wages may vary across sectors within the local labor market.

We study how shocks to the aggregate supplies of immigrant and native labor differentially affect native wages across sectors. In response to an aggregate inflow of immigrant labor, changes in relative native wages across sectors must equate changes in relative native labor supplies and demands. To gain intuition for these wage responses, it is useful to consider two extreme cases: one in which immigrants and natives have the same preferences but different comparative advantages across sectors and the other in

Figure 1: The Effect of Immigration on Relative Native Wages Across Sectors



Note: Panels A and B display potential impacts of immigration on native wages in sector s relative to s' (denoted by $W_s^n/W_{s'}^n$), where RS is the relative supply curve of natives to s. In Panel A there is a representative consumer, RD is the initial relative demand curve for native labor (for each individual consumer and in the aggregate) in s and RD' is the relative demand curve for native labor in s after an inflow of immigrants. In Panel B the immigrant intensity of production is common across s and s', RD^{nat} and RD^{imm} are the relative demand curves for native labor in s to serve native and immigrant consumption, respectively, and RD and RD' are the aggregate relative demand curves for native labor in s when total immigrant expenditure is relatively lower and higher, respectively.

which they have different preferences but no comparative advantage.

If immigrants and natives have common, homothetic preferences, then they share a common relative demand for sectoral output and, therefore, a common relative demand for native labor (embodied in sectoral output) across sectors. This case is extensively studied in labor and international economics. *Immigrant intensities of production* (defined as the share of the wage bill paid to immigrants within each sector) shape the impact of immigration on each consumer's and, therefore, the aggregate relative demand curve for native labor across sectors, as shown in the shift from RD to RD' in Panel A of Figure 1.[1] Such a shift affects relative native wages across sectors if the relative native labor supply curve across sectors (RS in Panel A of Figure 1) is upward sloping. We refer to these differences across sectors in native exposure to immigration—which are shaped by immigrant intensities of production—as supply exposure.

Whereas we incorporate supply exposure, our focus is on differences in immigrant and native consumer demands for sectoral output and how this translates into differential demand shocks for native labor across sectors in response to immigration. To gain intuition, suppose that the immigrant intensity of production is common across two sectors, so that supply exposure is equalized. Suppose, additionally, that natives and immigrants have different preferences for the outputs of each sector—and, for simplicity, that preferences are Cobb Douglas—so that immigrants and natives have different expenditure shares across sector s and s', with the *immigrant intensity of consumption* (defined as the

[1] In general, the direction of this shift depends on values of elasticities, as we discuss in Section 2. If s is immigrant intensive in production, then the shift from RD to RD' in Panel A of Figure 1 occurs if and only if native and immigrant labor are sufficiently strong complements.

share of sectoral consumption purchased by immigrants) being higher in sector s. In this case, an inflow of immigrants leaves the relative demand for native labor across s and s' to satisfy immigrant consumers (RD^{imm} in Panel B of Figure 1) and to satisfy native consumers (RD^{nat} in Panel B of Figure 1) unchanged. However, aggregate relative demand for native labor is a weighted average of the relative demands of native and immigrant consumers. And if immigration increases the total expenditure of immigrants relative to natives, it generates a positive product demand shock for sector s. This sector-level demand shock increases the relative demand for native labor in sector s (the shift from RD to RD' in Panel B of Figure 1), which increases the relative wage of natives in s as long as the relative supply curve of native labor is upward sloping. We refer to these differences across sectors in native exposure to immigration—which are shaped by immigrant intensities of consumption—as demand exposure.

To formalize this intuition, combine both types of exposure, and provide a theoretically consistent approach to measuring exposures, we start with a non-parametric environment with two sectors. Changes in a sector's native (log) wage can be expressed as the sum of three terms: one that is common across sectors within the local labor market as well as both a demand exposure component and a supply exposure component that may vary across sectors within the market. 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 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 market. We show how underlying local elasticities shape the response of native wages to demand and supply exposures. Finally, we show that these non-parametric, two-sector results directly imply results in a many-sector, semi-parametric model (given typical functional forms). This theory helps guide our empirical investigation and interpret its results.

In Section 3, we describe our empirical context 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 analysis leverages the Norwegian immigration shock induced by these EU expansions.

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, separately for each year, on a sector fixed effect, a (local labor) market fixed effect, worker characteristics, and measures of supply and demand exposures, each constructed at the market-sector level. We instrument for both measures of exposure using a variant of what is often referred to as the Card instrument.

In Section 4, we introduce the data underlying our analysis and describe the details of measuring exposures. Our empirical contribution rests on the ability to combine individual worker employment histories and tax income data with a newly collected data set covering electronic payments for the universe of Norwegian residents between 2006 and 2018. 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 labor market-sector pair (defining markets as commuting zones) as well as the immigrant-relative-to-native expenditure shock at the market level, the two components of demand exposure. Using the employment history data, we are similarly able to construct supply exposure.

In Section 5 we present our empirical results. Our primary contribution is to present the first evidence on how demand exposure shapes the earnings trajectories of native Norwegian workers. Compared to similar individuals, a Norwegian employed in a market-sector with higher demand exposure to new accession immigration experiences a positive and statistically significant increase in wage income between 2004 and each year thereafter. The effect starts small, as the immigrant inflow begins slowly, peaks in 2014, but is relatively stable between 2009 and 2015. Our estimates imply that a worker's annual earnings in 2015 would be over 6,000 krone higher if employed in 2003 in a market-sector at the 75th percentile of demand exposure than at the 25th percentile, equivalent to 1.3% of annual average real earnings in 2003 of our estimation sample.

Moreover, we find no evidence of pre-existing differential trends. Workers in market-sector pairs that have higher demand exposure to new accession immigration in the shock period experience neither higher nor lower earnings growth over the pre-period. We then document that these effects are substantially larger in more tradable sectors (although estimates in the less tradable sectors are imprecise), as the theory predicts. We additionally show that our results are robust across alternative samples.

Finally, we turn our attention to the implications of supply exposure. The empirical literature on the impact of immigration via (what we refer to as) supply exposure omits demand exposure. This omission biases results if predicted supply and demand exposures are correlated, conditional on controls. In our particular setting, we show that this correlation is essentially zero, so omitting demand exposure does not bias estimates of supply exposure.[2] We show that supply exposure has small effects that are insignificantly different from zero on the evolution of Norwegian wage income in our baseline sample. However, this null effect averages across positive effects for college-educated natives and negative effects for less-educated natives. This is consistent with our theory if immigrants are better substitutes for less-educated than for more-educated natives.

Relation to the literature. There is a massive 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).

Much of the literature evolved to compare labor-market outcomes across jobs and across region-job pairs, answering the following question (in our terminology): Do native wages rise or fall in jobs that have relatively higher supply exposures? Canonical papers in this literature include Altonji and Card (1991), Card (2001), and Friedberg (2001), while papers using firm-level data include Foged and Peri (2016), Doran et al. (2022), and Brinatti and Morales (2025).[3] In this space, our paper is most closely related to Burstein et al. (2020) in its approach and to Bratsberg et al. (2023) in its focus on Norway's experience following EU expansion.

Borjas (2003) famously argued that immigration—as a labor supply shock—lowers native wages because the labor demand curve is downward sloping.[4] Here, we note that irrespective of the empirical approach, immigrants are both producers and consumers, and that it is the combination of these two channels that shapes the effects of immigrants on native labor-market outcomes. We show that whereas immigration may raise or lower

[2] Of course, this conclusion depends in part on our empirical context—the Norwegian economy in the 2000s—and, more so, on our empirical specification—we focus on exposures at the market-sector level, controlling for market effects and sector effects. At the local labor-market level, for instance, it is very likely that supply and demand exposure would be highly positively correlated.

[3] 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).

[4] See Ottaviano and Peri (2012) and Llull (2018) for extensions to more general labor demand curves and to native worker adaptation to immigration, respectively.

the relative wages of natives in jobs that have relatively higher supply exposure (as have others before us), immigration must raise relative native wages in jobs that have relatively higher demand exposure if the native labor supply curve across jobs is upward sloping.

Our contribution relative to these literatures is threefold. First, theoretically we generalize the foundations of supply exposure, dropping functional forms and restrictions on parameters; and we introduce demand exposure. Second, guided by our theory, we propose and implement an empirical research design that allows us to identify the impact of demand exposure on the evolution of native wages. Third we show that omitting demand exposure from our research design, as in the previous papers, does not bias the estimate of supply exposure, at least in our empirical context.[5]

Our contribution centers on variation in demand exposure across jobs, for which we find strong evidence in the data, defining sectors as jobs. There are a handful of papers that have identified immigrants' distinctive consumption patterns; see McCully et al. (2024). In this space, the papers most related to our work study regional migration shocks (whether international or not) that are associated either with larger local spending impacts than local labor supply impacts, e.g. using retirees as in Badilla Maroto et al. (2024), or the opposite, using remittances as in Olney (2015) and Albert and Monras (2022).[6] Relative to this literature, we provide a theory for measuring demand and supply exposures and we identify their impacts on native labor-market outcomes.

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), Costinot et al. (Forthcoming), and Acemoglu (2002).

2 Theory

We are interested in identifying how immigration into a local labor market differentially affects the income of workers initially employed in jobs (which we will refer to as sectors in what follows, given the nature of our empirical analysis) that are differentially exposed to the immigration shock. Our objective is to present a theoretical framework

[5] 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.

[6] 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).

that guides the subsequent empirical exercise and aids in interpreting its results. We first derive our main results in a non-parametric environment with only two sectors. We then show that results with many sectors and strong—but more general than imposed heretofore—parametric restrictions follow as a simple corollary. 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.[7] We refer to these groups as natives $g = n$ and immigrants $g = i$ throughout. The supply of each group g is exogenous and given by L^g. 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. Output of each sector s, Y_s, is a sector-specific constant returns to scale combination of employment of each group g in its production, denoted by L_s^g. 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 expenditures, denoted by $X^g \equiv \sum_s P_s C_s^g$ where P_s is the price of sector s, equal to total income, $\sum_s W_s^g L_s^g$.

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 across sectors, $w_s^n \equiv d \log W_s^n$.[8] We aim to achieve this characterization in terms of potentially observable variables and primitive elasticities.

Definitions. 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 (or revenues) 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

[7] We apply this model across many local labor markets indexed by m in our empirical analyses; we omit market subscripts here for notational simplicity. We additionally deviate from the closed economy assumption in the empirical analysis.

[8] We use lower-case variables to denote log changes in upper-case variables, $x = d \log X$ for all variables X.

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.

It is also useful to define two group-specific indices. Denote by

$$p^g \equiv \sum_s (P_s C_s^g / X^g) p_s$$

the change in the price index for group g. This is the average log change in sectoral prices, p_s, weighted by group g's initial expenditure shares across sectors, $P_s C_s^g / X^g$. Similarly denote by

$$\phi^g \equiv \sum_s (L_s^g / L^g) w_s^g$$

the change in the wage index for group g. This is the average log change in group g's wage in each sector, w_s^g, weighted by g's initial employment shares across sectors, L_s^g / L^g.

2.2 Non-parametric setting with two sectors

Here, we focus on a non-parametric setting in which there are exactly two sectors. 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.

We denote by ρ_s the local elasticity of labor demand within sector s,

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

where ρ_s shapes firm substitution—for firms in sector s—between immigrant and native labor in response to a change in their wages within s. 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 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 wages. We impose throughout that κ and η are common across groups, relaxing this in the Theoretical Appendix. Given these definitions, we now turn to results, starting from a simple case, where intuition is relatively transparent, before turning to the general case.

A simple case. To build intuition, suppose first that $\rho_s = \rho$ for both s and that $\eta = 1$. In this case, the log change in the native wage in sector s can be expressed as

$$w_s^n = \alpha_1 + \frac{1}{1+\kappa}\left\{ \underbrace{\Delta\left[x\right]\mu_s^i}_{\text{demand exposure}} + \frac{\kappa(1-\rho)}{\kappa+\rho} \underbrace{\Delta\left[\frac{1}{\kappa}\ell - \phi\right]\theta_s^i}_{\text{supply exposure}} \right\} \tag{6}$$

The first term on the right-hand-side of equation (6), α_1, is the component of the change in native wages that is common across sectors and, therefore, does not affect the difference in native wage changes across sectors.

The second and third terms in equation (6) can be understood in the context of Figure 1. The elasticity of the relative native wage across sectors with respect to a given shift in the relative demand curve for native labor equals the inverse of the sum of the elasticities of the relative demand curve for native labor ($\eta = 1$) and relative supply curve of native labor (κ). This explains the term $1/(1+\kappa)$ multiplying the second and third terms. The expression in the $\{\cdot\}$ brackets is the elasticity of the shift in the relative demand curve for native labor with respect to the aggregate immigration shock. This has two components. The term labeled "demand exposure" equals the elasticity of the aggregate relative demand curve for native labor in response to immigration via differences between immigrants and natives in sectoral demand (the shift from RD to RD' in Panel B of Figure 1). The term labeled "supply exposure" multiplied by $\kappa(1-\rho)/(\kappa+\rho)$ equals the elasticity of the shift in each agent's relative demand curve for native labor in response to immigration via differences between immigrants and natives in sectoral employment (the shift from RD to RD' in Panel A).

We refer to the second term in equation (6) as the differential effect of demand exposure. Here,

$$\Delta\left[x\right] \equiv x^i - x^n$$

is the aggregate change in immigrant-relative-to-native expenditure, which is common across sectors and interacts with the immigrant intensity of consumption, μ_s^i, which may vary across sectors. Intuitively, an increase in total immigrant-relative-to-native expenditure increases the share of expenditures 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. This shift in the relative demand for native labor is displayed in Figure 1—where s is the sector that is immigrant intensive in consumption—and weakly increases the relative wage of natives in that sector. The elasticity of labor supply, κ, plays a central role in determining the strength of this wage effect. If $\kappa = \infty$, so that the relative supply curve for native labor 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 sector s. 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, however, is closely tied to the first stage of our empirical specification.[9]

We refer to the third term in equation (6) as the differential effect of supply exposure. Here,

$$\Delta\left[\frac{1}{\kappa}\ell - \phi\right] \equiv \frac{1}{\kappa}\ell^i - \phi^i - \left(\frac{1}{\kappa}\ell^n - \phi^n\right)$$

combines the change in immigrant-relative-to-native populations, $(\ell^i - \ell^n)$, and immigrant-relative-to-native wage indices, $-(\phi^i - \phi^n)$. This is common across sectors and interacts with the immigrant intensity of production, θ_s^i, which may vary across sectors. An increase in the population of immigrants relative to natives generates a positive value of $\Delta[\ell/\kappa - \phi]$ both directly (via a positive value of $\ell^i - \ell^n$) and indirectly through wage changes (via a positive value of $-(\phi^i - \phi^n)$). Hence, an increase in the relative population of immigrants (weakly) raises native wages in the sector with the higher value of θ_s^i (the higher immigrant intensity of production) if and only if the elasticity of substitution in production, ρ, is lower than the elasticity of substitution in consumption, $\eta = 1$.[10] This result is not new. It is closely related to results in Altonji and Card (1991) and Burstein et al. (2020) in the immigration literature and is an application of the Hicks-Marshall laws of derived demand. Intuitively, the native wage in sector s equals the value marginal prod-

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

[10] Panel A of Figure 1 displays the result of immigration—via differences in supply exposure—on the relative demand for native labor across sectors s and s' either under the assumption that s is immigrant intensive in production and $\eta > \rho$ or under the assumption that s' is immigrant intensive in production and $\eta < \rho$.

uct of native labor there. An immigrant inflow disproportionately raises the marginal product of native labor in the high θ_s^i sector, and more so the more complementary are immigrant and native workers within sectors (i.e., the lower is ρ). And an immigrant inflow disproportionately lowers the value per unit of output (the price) in the high θ_s^i sector, and more so the less elastic is consumer demand (i.e., the lower is η). Hence, the value marginal product of labor rises more in the high θ_s^i sector if ρ is low or η is high. As in the case of demand exposure discussed above, the elasticity of the relative supply curve of native labor plays a central role in determining the strength of this wage effect.

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

$$w_s^n = \alpha + \frac{1}{\eta + \kappa} \left\{ \underbrace{\Delta\Big[x + (\eta - 1)p\Big]\mu_s^i}_{\text{demand exposure}} + \frac{\kappa\,(\eta - \rho_s)}{\kappa + \rho_s} \underbrace{\Delta\left[\frac{1}{\kappa}\ell - \phi\right]\theta_s^i}_{\text{supply exposure}} \right\} \tag{7}$$

Relative to equation (6), there are three changes. First,

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

in equation (7) replaces $\Delta\Big[x\Big] = x^i - x^n$ in equation (6). Importantly, this shock remains common across sectors (within the local labor market). Second, the role of η becomes explicit both 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) and in determining whether higher supply exposure induces an outward or inward shift in the relative demand curve for native labor (in the $\eta - \rho_s$ term multiplying supply exposure). Third, the impacts of immigration via supply exposure remain heterogeneous across sectors even after interacting the market-specific value of $\Delta[\ell/\kappa - \phi]$ with the market-and-sector-specific immigrant intensity of production θ_s^i. The reason, of course, is that the relevant elasticities that shape the strength of these exposures are now heterogeneous across sectors.

2.3 Semi-parametric setting with many sectors

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. This is the closed-economy version of the framework introduced by Burstein et al. (2020) and employed in Brinatti and Guo (2024), but instead of imposing CES production functions with common values of ρ_s across s, we continue to impose no restrictions on production functions beyond constant returns to scale; and instead of assuming common preferences across goods for immigrants and natives, we allow for differences across groups.

In this framework, equations (6) and (7) 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 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 the relationship between changes in labor allocation in a given sector, the wage change in that sector, and the group-specific wage index; see equations (15) and (16) in the Theoretical Appendix. The parametric assumptions of CES consumption aggregators and Fréchet distributed amenity draws directly imply these equations in the many-sector, semi-parametric setting.

3 Empirical context and specification

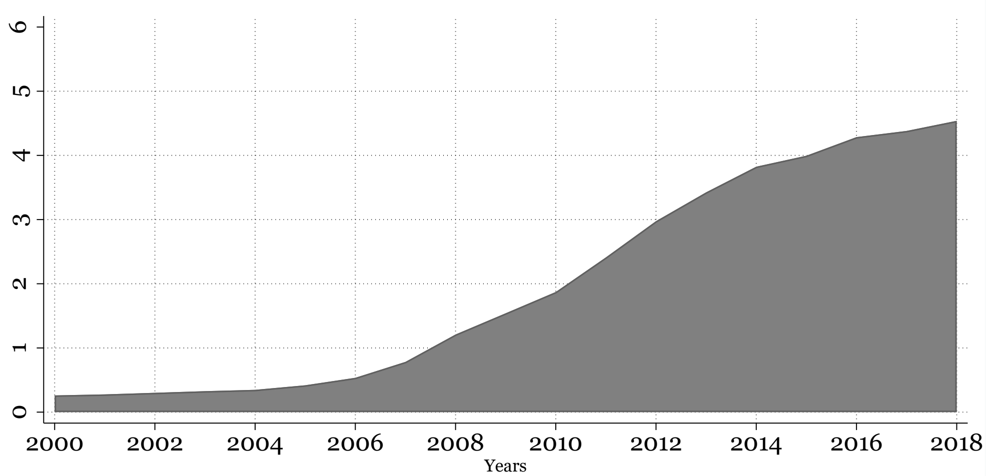
We aim to identify the differential impact of immigration on native worker incomes depending on workers' supply and, especially, demand exposures. In Section 3.1 we describe the empirical context and immigration shock. In Section 3.2 we describe the empirical specification and identification strategy.

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 4.

Second, Norway experienced an exceptionally 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. This immigration boom largely

Figure 2: New Accession Share (in %) of the Norwegian Workforce



Note: 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 (calculated for all employment relationships with at least 4 hours per week measured in November of each year)

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 few restrictions on migration from these new member states (Dølvik and Eldring, 2008).

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, as shown in Figure 2. Our empirical analysis leverages the Norwegian immigration shock induced by the EU expansions of 2004 and 2007.

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 markets 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 Empirical specification

The theory in Section 2 provides a useful guide for our empirical analysis. Our baseline empirical approach will follow equation (6) in most, but not all, respects.

Relative to our theory, our empirical analysis differs in a few respects. First, we simplify the measure of supply exposure. Instead of measuring $\Delta\left[\frac{1}{\kappa}\ell - \phi\right]$, we will instead focus exclusively on the differential change in employment of immigrants and natives, $\Delta\ell$, omitting the differential change in the wage index.

Second, whereas our theory focused on a single closed economy, our empirical analysis will consider many such geographic markets, indexed by m. These markets will differ both in their market-specific values of Δx_m and $\Delta\ell_m$ and in their market-and-sector-specific initial immigrant intensities of consumption and production, the μ^i_{ms} and θ^i_{ms} terms.[11]

Third, whereas the dependent variable in equation (6) is the change in the native wage within each market-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 market-sector pairs. In this, we follow a massive 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).

For each year t between 2000 and 2018, we separately estimate the individual-level regression

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

where j indexes native individuals, m geographic markets, s sectors, and t time. The dependent variable is the change in real income for individual j between 2004 and year t,

[11] This is not outside the scope of our theory; it simply introduces market-specific indices. Of course, one might worry about interactions between markets, which are not specifically modeled in Section 2. We address these concerns in Section 5.1.

$\Delta Income_{jt} \equiv Income_{jt} - Income_{j2004}$. We fix the market in which worker j resided, m_j, and the sector in which worker j was employed, s_j, in 2003 throughout the analysis. The time-varying market fixed effect, $\delta_{m_j t}$, then corresponds to the constant in equation (6). The time-varying sector fixed effect, $\delta_{s_j t}$, controls for national shocks to sectoral supply and demand. To understand 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 market-time and, separately, sector-time fixed effects in equation (8). Finally, the vector K_j contains a set of observable individual characteristics, defined in 2003, the returns to which may vary over time.

The coefficients of interest are β_t^D and β_t^S, which measure the time-varying effects of immigration on real income for natives who are initially employed in market-sector pairs with higher immigrant demand and supply exposures. The immigrant intensities μ_{ms}^i and θ_{ms}^i are the initial immigrant intensities of consumption and production in market m and sector s. And the shocks $\Delta x_{m_j} \equiv x_{m_j}^i - x_{m_j}^n$ and $\Delta \ell_{m_j} \equiv \ell_{m_j}^i - \ell_{m_j}^n$ are the changes over time within market m in new accession immigrant relative to native expenditure Δx_{m_j} and employment $\Delta \ell_{m_j}$.

We turn to how each of these variables is measured, the vector of controls included in K_j, and the estimation sample in Section 4. Throughout the paper, we present robust standard errors clustered by market-sector pair.

Instrumental variable approach. The residual in equation (8) contains demand and supply shocks at the market-sector level that would have occurred in the absence of immigration.[12] Even if the distribution of θ_{ms}^i is independent of the distribution of the residual, estimates of β_t^D and β_t^S could be inconsistent as the number of markets rises—for a given number of sectors—because migration responds to these demand and supply shock.

Consider, as an example, supply exposure. If large market-sector demand shocks induce local immigration especially when they occur in sectors that are immigrant intensive in production, as seems likely in practice, then supply exposure, $\theta_{ms}^i \Delta \ell_m$, will be correlated with the residual if there is not a very large number of sectors. Similarly, if large local supply shocks in sectors that are immigrant intensive in consumption generate large inflows of immigrants to the market, then demand exposure, $\mu_{ms}^i \Delta x_m$, will be correlated

[12] Given the inclusion of market-time effects and sector-time effects in equation (8), these demand and supply shocks are deviations from the average at the sector level across markets and from the average at the market level across sectors.

with the residual. We formalize this intuition in Section B.3 in the Empirical Appendix.

To address these concerns, we instrument for both demand and supply exposures, $\mu^i_{ms}\Delta x_m$ and $\theta^i_{ms}\Delta\ell_m$. Our approach is relatively standard. We instrument for demand and supply exposure using $\mu^i_{ms}\Delta\widetilde{\ell}^i_m$ and $\theta^i_{ms}\Delta\widetilde{\ell}^i_m$, where $\Delta\widetilde{\ell}^i_m$ is a measure of the predicted change between 2003 and 2018 in the new accession immigrant population within market m. This predicted change is constructed as in the traditional Card instrument. Index each of the new accession countries by o. For each market m we predict the percent change in the EU accession population over time as

$$\Delta\widetilde{\ell}^i_m \equiv \frac{\sum_o \frac{L^i_{mo}}{L^i_o}\Delta L^i_{-mo}}{\frac{1}{2}\left(L^i_m + \sum_o \frac{L^i_{mo}}{L^i_o}\Delta L^i_{-mo} + L^i_m\right)} \tag{9}$$

where L^i_{mo} and $L^i_o = \sum_m L^i_{mo}$ are the initial 2003 workforces of immigrants from EU accession origin o within market m and across all of Norway, $L^i_m = \sum_o L^i_{mo}$ is the initial 2003 workforce of immigrants within market m summed across all origins o, and ΔL^i_{-mo} is the change over time, between 2003 and 2018, in the national workforce of immigrants from origin o excluding market m. The numerator of the right-hand side of equation (9) is the predicted growth of employment of workers from the new EU accession countries within market m between 2003 and 2018. The denominator is the average of initial 2003 employment of the new EU accession countries and the predicted employment of workers from these countries within market m in 2018, which is itself the sum of the initial workforce and its predicted growth.

4 Data, measurement, and estimation sample

4.1 Employment, income, and worker characteristics data

The first key data set contains administrative records on the universe of employment relationships from 2000 to 2018.[13] This data provides us with a measure of contracted hours (reported in intervals) and five-digit industry code, from which we define each worker's sector of employment in equation (8) as the sector of his or her primary employment in 2003. We also use this information in measuring native and immigrant employment in constructing supply exposure and its instrument, as described in Section 4.3.

We link this information to tax income data to measure annual wage income, which in-

[13] 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.

cludes 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 use this measure of income (adjusted for inflation) to define the dependent variable in equation (8). The tax registers also provide information on the residential municipality of an individual. Using this data, we define each worker's market m in equation (8) as the commuting of his or her residence in 2003. 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 to population panel data, which allows us to measure background characteristics. Using this data, we define the vector of worker controls, K_j in equation (8), as fixed-over-time indicators for characteristics of each worker as defined in 2003: ten income deciles, four education levels, and each 2003 age. We additionally use country of origin both in defining the estimation sample—which includes only natives—and in measuring both demand and supply exposures.

4.2 Expenditure data

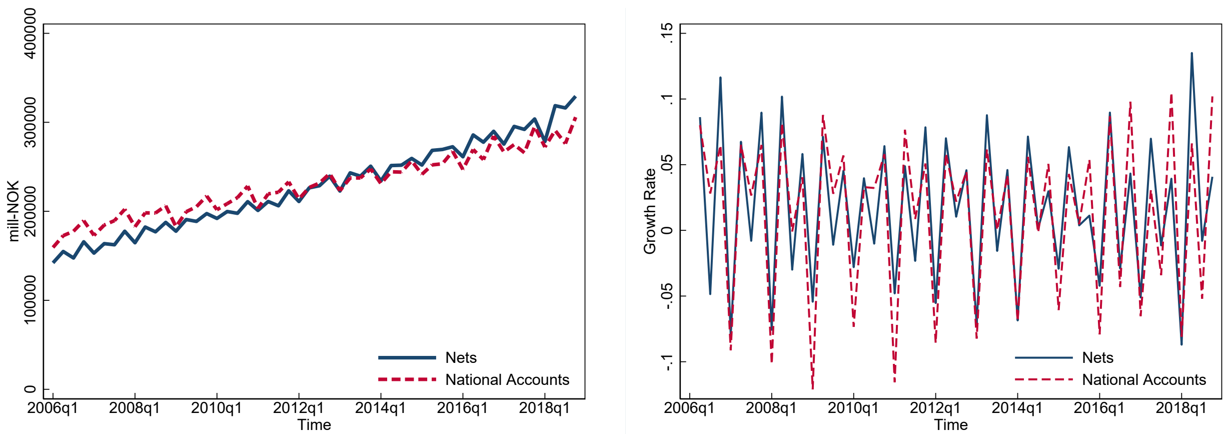
Our empirical contribution rests on the ability to combine employment histories with a newly collected data set covering electronic payments for the universe of Norwegian residents between 2006 and 2018. The electronic payments data are provided by the Norwegian retail clearing institution, Nets Branch Norway (henceforth referred to as Nets) and cover two data sources: (*i*) all debit card payments via BankAxept (*ii*) all online bank wire payments cleared via the Norwegian Interbank Clearing System (NICS).[14]

BankAxept is the national payment system in Norway and is owned by Norwegian banks. Typically, all debit card payments in domestic physical stores are BankAxept. Payments abroad, payments online, and mobile payments are typically paid with credit cards through VISA or Mastercard. NICS is the interbank clearing system for the Norwegian Krone (NOK). It is used by all banks operating in Norway, and that take part in the Norwegian banking community's infrastructure for payments.[15] The data is aggregated for each individual by zip code of expenditure and 27 broad consumption categories. We do not observe the consumption category of credit card expenditures; we allocate these credit card payments to expenditures on banking. However, credit card expenditure is low, comprising approximately 10% of consumer expenditures in 2006.

[14]The data also covers all incoming transfers cleared via NICS, which we do not make use of in this paper.

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

Figure 3: Nets Expenditure Data Compared with National Accounts Data.



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

The left panel of Figure 3 shows that our expenditure measure—aggregated across all commuting zones and 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 tracks the quarterly growth rate of consumption from the National Accounts very well.[16]

We link zip codes to commuting zones and use the location of expenditure to allocate expenditures across markets. We aggregate five-digit industry codes from the employment and worker income data to the more aggregated consumer categories in the expenditure data. These broad consumer categories are based on the United Nations' 1999 COICOP system, which classifies consumption expenditures according to their purpose.[17] Card payments are mapped to COICOP based on the Merchant Category Codes (MCC) of the card terminal. Online wire transfers are classified using creditors' five-digit industry codes (NACE). The crosswalks between MCC/NACE and COICOP are manually coded by Norges Bank and provided to Nets prior to aggregation.

Table A1 lists all categories in the raw data. Our categorization includes all 12 top-level COICOP codes, some of which are further divided into second-level COICOP groups. Starting from the 27 categories at the most disaggregated level, we combine a few that are either small or across which it is more difficult to allocate from the disaggregated

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

[17] The COICOP classification was revised in 2018.

employment data. We additionally drop three categories, two of which do not fit the context of the theoretical framework (Payments to public institutions and Cash withdrawals) and one of which (Alcoholic beverages, tobacco and narcotics) has an immigrant intensity of consumption measured at the national level that—unlike every other consumption category—is unstable across time. This leaves us with 20 sectors. See Section B.1 of the Empirical Appendix for details.

4.3 Measuring supply and demand exposures

We measure supply exposure, $\theta^i_{ms}\Delta\ell_m$, as follows. The immigrant intensity of production in market m and sector s, θ^i_{ms}, is measured using data on employment from 2003. The numerator is the employment of immigrants who live in market m in 2003 and whose primary employment in 2003 is in 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 four hours per week in 2003. Given the small number of immigrants from the new accession countries living in Norway in 2003, and given that we construct θ^i_{ms} across the product of 46 commuting zones and 20 sectors, we measure θ^i_{ms} using all immigrants, rather than only those from the new accession countries.

We measure the market-specific immigration shock $\Delta\ell_m$ using the log change in commuting zone m in the ratio of employment of immigrants from the new accession countries relative to employment of natives between 2003 and 2018. In the instrument, $\Delta\widetilde{\ell}^i_m$, is constructed using the employment of each of the EU accession origin countries o in each Norwegian commuting zone m in 2003 and the growth in this employment at the national level (omitting market m) between 2003 and 2018.

We measure demand exposure, $\mu^i_{ms}\Delta x_m$, similarly. There are two distinctions. First, we measure the location of consumption expenditure at the point of purchase rather than the consumer's residence. Second, since the expenditure data begins in 2006, we use 2006 data to measure the initial immigrant intensity of consumption, μ^i_{ms}, and we use 2006 as the base year in construction of Δx_m. Whereas the measure of demand exposure uses changes in expenditure between 2006 and 2018, the instrument—by using changes in predicted employment instead of expenditures—uses changes between 2003 and 2018, so that the start of the shock in the instrument predates EU accession.

Table 1 displays immigrant intensities of consumption and production across the 20 sectors, measured at the national level, where industries are ordered by national immigrant intensity of consumption. There is substantial variation in both measures, although

Table 1: National Immigrant Consumption and Production Intensities

	Immigrant intensity of	
	A. Consumption	**B. Production**
1. Education	0.088	0.071
2. Services	0.079	0.068
3. Electronics	0.066	0.067
4. Banks	0.064	0.060
5. Restaurants	0.063	0.215
6. Communication	0.063	0.081
7. Health	0.061	0.087
8. Finance	0.061	0.075
9. Clothing	0.059	0.072
10. Furnishing	0.058	0.059
11. Books, newspapers	0.056	0.065
12. Personal effects	0.054	0.057
13. Personal care	0.051	0.071
14. Insurance	0.050	0.037
15. Grocery stores	0.050	0.072
16. Recreation	0.049	0.085
17. Hotels	0.048	0.181
18. Other transport	0.047	0.059
19. Utilities	0.046	0.066
20. Motor vehicles	0.039	0.039

Notes: Immigrant intensity of consumption in Panel A uses spending of all residents in 2006. Immigrant intensity of production in Panel B uses employment in 2003, with shares taken across all employees who work in 5-digit industry codes that map into a spending sector in this table. These statistics are calculated at the national level.

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. The correlation between the two measures is very low; see Figure A2 in the Empirical Appendix. We return to the correlation of demand and supply exposures in Section 5.2 below. Finally, 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.

4.4 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 2003, to include individuals who actively participate in the workforce over the full 2000 – 2018 sample period, being at least 27 years old in 2000 and no greater than 65 years old in 2018. 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. Here, we define a worker as engaged in full-time employment if his or her contracted hours per week are greater than 30 (all employment outcomes are measured at the end of November in each year). 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 – 2018.

We additionally restrict our baseline sample to workers living outside of Oslo in 2003. 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 education sector in 2003 because wages in the education sector are not particularly responsive to local demand; hence, the model's mechanisms do not apply there.[18]

We revisit these choices in sensitivity and robustness exercises. Table A4 in the Empirical Appendix presents summary statistics for our estimation samples.

5 Empirical results

First-stage results. Table 2 displays results from estimating the first stage. 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 demand exposure on its instrument, market fixed effects, and sector fixed effects. The demand-exposure instrument strongly and positively predicts demand exposure.[19] In column 2 we additionally include the supply-exposure

[18]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, 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).

[19]In columns 1 and 4, the reported first-stage SW F statistic is equivalent to the KP F statistic, because we

Table 2: First-Stage Regression Results

	Demand Exposure			Supply Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Demand Exposure	1.147	1.148	1.148		-0.018	-0.018
	(0.017)	(0.017)	(0.017)		(0.017)	(0.017)
Predicted Supply Exposure		-0.008	-0.008	0.789	0.789	0.789
		(0.004)	(0.004)	(0.022)	(0.022)	(0.022)
SW F stat	4599.2	4767.7	4756.3	1230.9	1267.8	1267.9
Controls	No	No	Yes	No	No	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 $\mu^i_{ms}\Delta x_m$, supply exposure is $\theta^i_{ms}\Delta \ell_m$, and their instruments are $\mu^i_{ms}\Delta\widetilde{\ell}^i_m$ and $\theta^i_{ms}\Delta\widetilde{\ell}^i_m$. All specifications include controls for sector fixed effects and market fixed effects. Columns 3 and 6 additionally include worker-level controls. Columns 1 and 4 each include only the corresponding instrument. Columns 2, 3, 5, and 6 include both instruments and the SW F stats correspond to the joint first stage. There are 299,649 observations in all specifications.

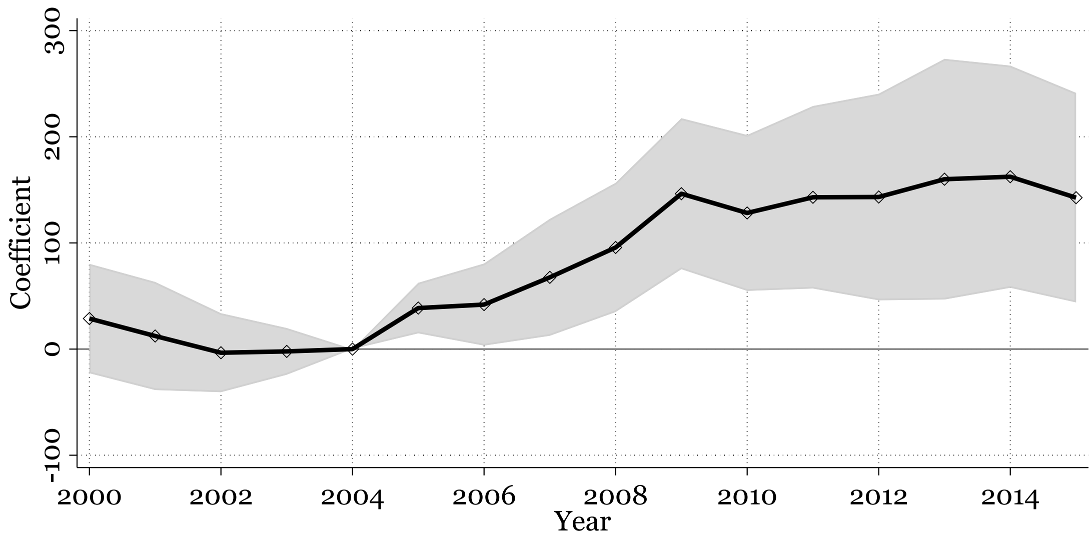
instrument and report the SW F statistic for demand exposure associated with instrumenting for both demand and supply exposures. The demand-exposure instrument continues to strongly and positively predict demand exposure whereas the supply-exposure instrument does not predict demand exposure. In column 3 we additionally include individual fixed effects, the K_j vector in equation (8). This leaves first-stage results unchanged. 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.

5.1 Demand exposure

Figure 4 presents our central empirical result. It shows how demand exposure, $\mu^i_{ms}\Delta x_m$, 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 market-sector with higher demand exposure to new accession immigration experiences a positive and statistically significant increase in wage income between 2004 and 2005. The 2005 effect is relatively small, growing by a factor of over four between 2005 and 2014. This is consistent with the flow of migrants from the new EU accession countries displayed in Figure 2: the effect peaks in 2014—when the inflow from the new accession countries slows—and is

predict a single endogenous variable in each.

Figure 4: The Impact of Demand Exposure on Native Income



Note: This figure reports the 2SLS estimate of β_t^D in equation (8)—in which supply and demand exposure are each instrumented—and the corresponding 95% confidence interval estimated in the baseline sample. Robust standard errors are clustered by market-sector pair.

relatively stable between 2009 and 2015.[20]

A natural concern is that markets and sectors with higher initial immigrant intensities of consumption differ from those with lower initial immigrant intensities of consumption in underlying trends. Figure 4 investigates this possibility and provides no evidence of pre-existing differential trends. Workers in market-sector pairs that have higher demand exposure to new accession immigration in the period 2003 – 2018 experience neither higher nor lower earnings growth over the period 2000 – 2004.

To quantify the implications of demand exposure, we consider the impact of moving a worker from the 25th percentile of demand exposure to the 75th percentile. This interquartile range is 0.044. We evaluate this effect at the 2015 estimate of β_t^D, which is 143. A worker's annual earnings would have grown by 6276 krone more between 2003 and 2015 if employed at the 75th percentile of demand exposure than at the 25th percentile (recall that the dependent variable is measured in thousands of krone). This equals about 1257.8% of the average 2003 earnings of workers in our sample. Since estimated effects are similar over the period 2009 – 2015, this entails a similar increase in earnings for all such years.

[20] We show results only through 2015 in all figures because there is a substantial spike in confidence intervals in 2016—which coincides with the highest national unemployment rate in Norway in the pre-Covid 2000s—which makes it harder to see the results in other years. In spite of this, results remain positive and statistically significant throughout the remaining years, and remain similar to those between 2009 and 2015 except for in 2016, where the point estimate is larger.

Table 3: The Impact of Demand Exposure and Tradability

Panel A: Effect of immigrant-induced demand exposure between 2004 and 2015

	All sectors	Less tradable sectors	More tradable sectors
	(1)	(2)	(3)
Demand Exposure	142.641	188.702	80.404
	(50.335)	(56.598)	(123.267)

Panel B: Placebo immigrant-induced demand exposure between 2000 and 2004

	All sectors	Less tradable sectors	More tradable sectors
	(1)	(2)	(3)
Demand Exposure	28.770	12.519	49.225
	(26.269)	(38.252)	(18.538)
Average in 2003	499.0	510.6	469.6
Observations	299649	215114	84535

Notes: This table reports the 2SLS estimate of β_t^D in equation (8) on alternative samples; all specifications include sector fixed effects, market fixed effects, worker controls, and supply exposure. Panel A reports estimation results with t equal to 2015 and Panel B reports estimation results with t equal to 2000. Column 1 replicates our baseline result, column 2 includes workers in less tradable sectors in 2003, and column 3 includes workers in more tradable sectors in 2003. "Average in 2003" refers to the sample average of real income (denominated in 1,000 krone) in the year 2003. Robust standard errors are clustered by market-sector pair.

Open economies. Our theoretical framework in Section 2 models each local labor market market as a fully closed economy. There are (at least) two important ways in which Norwegian (and other) markets interact.

First, native Norwegians may migrate across markets 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. We instrument for the change in immigrant-relative-to-native employment, $\Delta\ell_m$, and expenditure, Δx_m, using a plausibly exogenous component of immigration. Hence, we identify the causal effects of immigration and native migration on the evolution of native incomes.

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). They show that in more traded sectors, the relevant elasticity of substitution in consumption across sectors, our η, is 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, with a higher value reducing the impact of a shock to the relative native labor demand curve on relative native wages. 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. We test this. We allocate sectors into more and less tradable groups in Section B.4 in the Empirical Appendix.

Panel A of Table 3 displays results of this exercise, setting t to 2015 in equation (8). Column 1 replicates the baseline result, column 2 displays results estimated on the sample of workers employed in 2003 in the less tradable sectors, and column 3 displays results estimated on the sample of workers employed in 2003 in the more tradable sectors. Differences in point estimates are consistent with the theory. The estimated effect of demand exposure is greater within less tradable sectors than the baseline effect estimated on all sectors, which is in turn greater than the estimated effect within more tradable sectors. However, estimates are not sufficiently precise to reject equality of any of the estimates. Panel B of Table 3 presents placebo results, setting t to 2000 in equation (8).

Alternative samples and treatment heterogeneity. In our baseline specification we consider a sample of males with both college educations and without, we omit workers who initially reside in Oslo, and we omit workers who are initially employed in education. Panel A of Table 4 presents results, focusing on changes between 2003 and 2015, varying each of these choices.

Column 1 presents results estimating equation (8) on a sample with equivalent rules for sample inclusion, but restricted to females instead of males. The 2015 point estimate remains positive and statistically significant. Normalizing the income gains of moving a female at the 25th percentile of exposure to the 75th percentile by the average 2003 earnings of a female in the sample yields a 1.1% gain, similar to the corresponding result in the male sample. Column 2 replicates this analysis on a larger sample than in our baseline, including both males and females. The result is an average of the estimate for males and for females.

The remaining columns revert to the male sample. Column 3 expands the baseline sample to include workers employed in the education sector in 2003. As discussed above, incomes in the education sector are less responsive to local demand in the education sector; hence, the point estimate is smaller. Column 4 instead expands the sample to include residents of Oslo in 2003. The point estimate remains positive and significant. Finally, column 5 restricts the baseline sample by dropping workers employed in 5-digit industries within manufacturing in the more disaggregated employment data. Results in this subsample are similar to our baseline specification.

Panel B of Table 4 presents placebo results of the same analyses, setting t to 2000 in

Table 4: The Impact of Demand Exposure in Alternative Samples

Panel A: Effect of immigrant-induced demand exposure between 2004 and 2015

	Female	Female and male	Incl. Education	Incl. Oslo	No mfg.
	(1)	(2)	(3)	(4)	(5)
Demand Exposure	86.792	116.891	96.102	128.773	147.400
	(33.406)	(38.149)	(45.337)	(56.743)	(44.933)

Panel B: Placebo immigrant-induced demand exposure between 2000 and 2004

	Female	Female and male	Incl. Education	Incl. Oslo	No mfg.
	(1)	(2)	(3)	(4)	(5)
Demand Exposure	-5.218	10.909	29.780	82.285	47.528
	(14.462)	(18.960)	(20.798)	(30.938)	(25.223)
Average in 2003	349.7	433.5	497.9	519.7	482.0
Observations	234261	533910	318272	426647	232409

Notes: This table reports the 2SLS estimate of β_t^D in equation (8) on alternative samples; all specifications include sector fixed effects, market fixed effects, worker controls, and supply exposure. Panel A reports estimation results with t equal to 2015 and Panel B reports estimation results with t equal to 2000. Column 1 includes a female sample, column 2 combines the female and males samples, column 3 includes workers employed in the education sector in 2003, column 4 includes residents of Oslo in 2003, and column 5 excludes workers employed in disaggregated 5-digit industries within manufacturing. "Average in 2003" refers to the sample average of real income (denominated in 1,000 krone) in the year 2003. Robust standard errors are clustered by market-sector pair.

equation (8). Consistent with our baseline analysis, we find no evidence of pre-existing trends in all but one of the alternatives. In the case in which we include workers initially residing in Oslo, we find that incomes of workers employed in market-sectors that were more exposed to immigration were falling between 2000 and 2004 before rising following 2004, implying a larger positive break in the trend than is apparent from the positive coefficient in Panel A. Following Freyaldenhoven et al. (Forthcoming), in Figure A3 of the Empirical Appendix we present the full event study results including workers residing in Oslo in 2003 after de-trending changes in income.

Finally, Table 5 presents the impact of demand and supply exposure in the full sample and separately in the sample of workers without a college education in 2003 and with a college education in 2003. The 2015 point estimates (in Panel A) on demand exposure remain positive and statistically significant. Normalizing the income gains of moving a non-college worker and, separately, a college worker at the 25th percentile of exposure to the 75th percentile by the average 2003 earnings within each of these samples yields a 0.8% annual gain for the non-college-educated worker and a 1.7% annual gain for the

Table 5: The Impact of Demand and Supply Exposures by Education

Panel A: Effect of immigrant-induced demand and supply exposure between 2004 and 2015

	All		Non-College		College	
	(1)	(2)	(3)	(4)	(5)	(6)
Supply Exposure	2.030	1.619	-38.937	-39.154	87.574	87.520
	(29.784)	(28.398)	(24.600)	(24.104)	(72.980)	(70.006)
Demand Exposure		142.641		83.632		229.332
		(50.335)		(38.126)		(89.542)

Panel B: Placebo immigrant-induced demand and supply exposure between 2000 and 2004

	All		Non-College		College	
	(1)	(2)	(3)	(4)	(5)	(6)
Supply Exposure	4.675	4.592	15.383	15.194	-24.848	-24.837
	(16.674)	(16.792)	(14.071)	(14.117)	(31.312)	(31.016)
Demand Exposure		28.770		72.845		-44.959
		(26.269)		(28.174)		(44.747)
Average in 2003	499.0	499.0	464.6	464.6	604.4	604.4
Observations	299649	299649	225848	225848	73801	73801

Notes: This table reports the 2SLS estimate of β_t^D and β_t^S in equation (8) on alternative samples. All specifications include sector fixed effects, market fixed effects, and worker controls. Columns 1, 3, and 5 do not include demand exposure. Panel A reports estimation results with t equal to 2015 and Panel B reports estimation results with t equal to 2000. Columns 1 and 2 include the baseline sample, columns 3 and 4 include the sample of workers without college educations, and columns 5 and 6 include workers with college educations. "Average in 2003" refers to the sample average of real income (denominated in 1,000 krone) in the year 2003. Robust standard errors are clustered by market-sector pair.

college-educated worker.[21] We next turn to the implications of supply exposure.

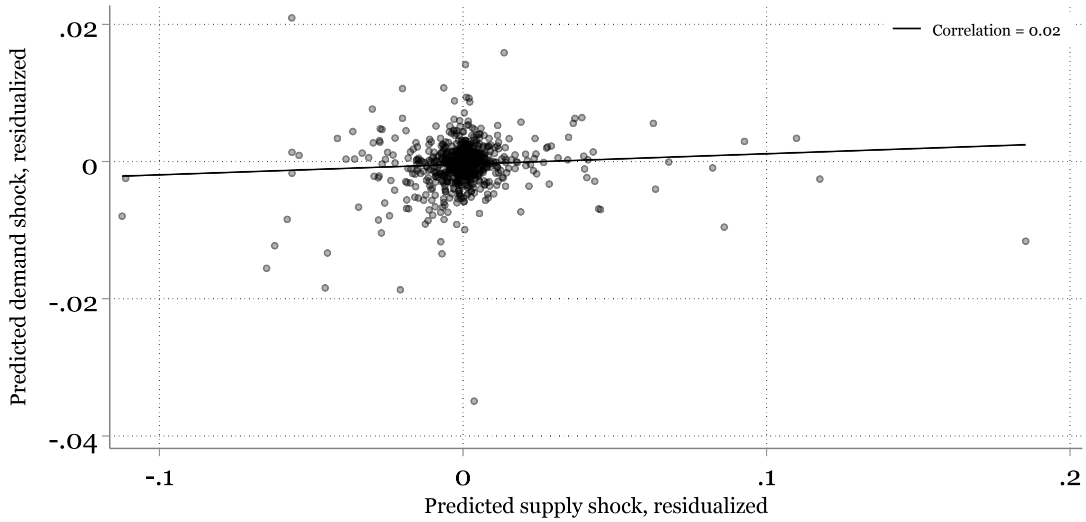
5.2 Supply exposure

Our primary contribution is to introduce and estimate the effects of demand exposure. In this section we revisit the massive literature on supply exposure. Our contribution here is to check whether or to what extent results on supply exposure are robust to controlling for demand exposure in our particular empirical context.

The correlation between demand and supply exposures. The empirical literature on the impact of immigration via (what we refer to as) supply exposure omits demand exposure. Omitting demand exposure when estimating equation (8) would result in a biased

[21] Panel B displays no evidence of pre-existing trends for the college-educated sample. For non-college-educated workers, we find that incomes of workers employed in market-sectors that were more exposed to immigration were falling between 2000 and 2004 before rising following 2004.

Figure 5: 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, market fixed effects, and the vector of individual controls.

estimate of the impact of supply exposure if, conditional on the other controls, predicted demand and supply exposures are correlated. We begin by investigating this correlation.

Figure 5 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, market fixed effects, and individual controls. This correlation is low (0.02). In our context, omitting demand exposure will not bias the estimate of supply exposure.

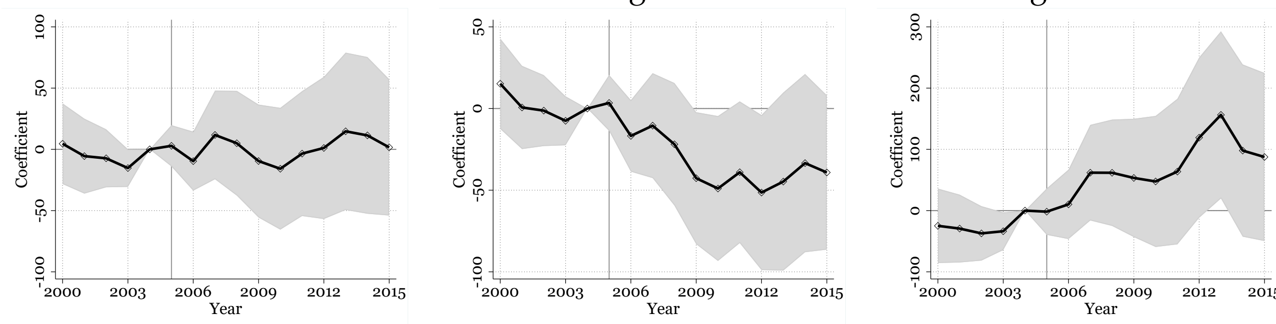
The impact of supply exposure. Given that omitting demand exposure will not bias the estimate of supply exposure in our empirical context, we have little to add to the vast literature studying the impact of supply exposure.

The first row of Panel A in Table 5 displays the estimated supply exposure coefficient, β_t^S, when setting t to 2015 in equation (8). Columns 1 and 2 display the coefficient estimates in our baseline sample, with column 1 omitting demand exposure and column 2 including it. From these results, we reach two conclusions. First, supply exposure has a negligible effect on native incomes. Second, this effect is almost identical whether or not we control for demand exposure, consistent with Figure 5. Panel A of Figure 6 confirms that the negligible effect of supply exposure in the baseline sample is robust to the estimation year t.

This zero effect, however, averages across an imprecise positive impact for college-educated natives and an imprecise negative impact for non-college-educated natives, as

Figure 6: The impact of supply exposure on native income

Panel A
All | Panel B
Non-College Educated | Panel C
College Educated



Note: Each figure replicates Figure 4, but reports the coefficient on supply exposure, β_t^S. The sample varies across panels. Panel A uses the baseline sample. Panel B uses the subsample of workers who are not college educated in 2003. Panel C uses the subsample of workers who are college educated in 2003.

documented in Panels B and C of Figure 6 and columns 3 – 6 of Table 5. This is consistent with our theory if immigrants are relatively better substitutes for less-educated than for more-educated natives (i.e., if ρ is higher between immigrants and low-education natives than between immigrants high-education natives).

6 Conclusions

What is the effect of immigration on native labor-market outcomes? A massive literature identifies the differential impact of immigration on natives employed in jobs with different supply exposures. But immigrants consume in addition to producing output. Despite this, no literature identifies the impact on natives employed in jobs with different demand exposures.

To make progress on this issue, we present a theoretical framework in which the immigrant intensity of production and the immigrant intensity of consumption may vary across jobs. We solve for the differential effects of immigration on native wages across jobs in a two-sector, non-parametric version of the model and in a many-sector, semi-parametric version of the model. Our 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 an exceptionally large and rapid inflow of immigrants induced by EU expansions in 2004 and 2007. 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 all native workers to immigration induced by the EU expansions in 2004 and 2007. We find large, positive, and persistent effects of demand exposure to EU expansion on native worker income: natives at the 75th percentile of demand exposure in 2003 experience an increase in annual income of 1.3% relative to natives at the 25th percentile between 2003 and 2015, with this effect being largely stable between 2009 and 2015. We also show that results on immigrant-induced supply shocks are robust to conditioning on demand exposure in our particular empirical context.

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APPENDIX

A Theoretical appendix

A.1 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.2 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.

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

$$c_s^g = -\eta p_s + (\eta - 1) p^g + x^g \tag{15}$$

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

$$\ell_s^g = \kappa w_s^g - \kappa \phi^g + \ell^g \tag{16}$$

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

For any sector s, equation (3) and equation (16) yield

$$w_s^n - w_s^i = \frac{\kappa}{\kappa + \rho_s} \Delta \left(\frac{\ell}{\kappa} - \phi \right) \tag{17}$$

where $\Delta\left(\ell/\kappa - \phi\right) \equiv \ell^i/\kappa + \phi^n - \left(\ell^n/\kappa - \phi^i\right)$. 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 (15) yield

$$\eta p_s = \sum_g \mu_s^g((\eta - 1)p^g + x^g) - [\ell_s^n - \theta_s^i(\ell_s^n - \ell_s^i)] \tag{18}$$

The previous expression, equation (3), and equation (17), yield

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

Equations (12) and (17) yield

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

The previous expression and equation (19) yield

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

which can be expressed as

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

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

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

This simplifies to equation (6), after imposing $\rho_s = \rho$ and $\eta = 1$. □

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 and derive a generalization of equation (7).

We denote by η^g group g's local elasticity of substitution in consumption across sectors,

$$c_s^g - c_{s'}^g = -\eta^g(p_s - p_{s'}) \tag{20}$$

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,

$$\ell_s^g - \ell_{s'}^g = \kappa^g(w_s^g - w_{s'}^g) \tag{21}$$

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 (15) and (16), we obtain

$$c_s^g = -\eta^g p_s + (\eta^g - 1)p^g + x^g \tag{22}$$

and

$$\ell_s^g = \kappa^g w_s^g - \kappa^g r^g \tag{23}$$

where we define

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

The system of equations is then (3), (10) - (13), (22), and (23).

From equation (23), of which there are four, we can solve for each w_s^g as a function of the corresponding ℓ_s^g,

$$w_s^g = \frac{1}{\kappa^g}\ell_s^g + r^g \tag{24}$$

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 (22), 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 (3) 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

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

where

$$\overline{\eta}_s \equiv \mu_s^n \eta^n + \mu_s^i \eta^i \tag{25}$$

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; and where

$$\nu_s \equiv \left(\frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i \right) \rho_s + \left[1 - \frac{\kappa^i - \kappa^n}{\kappa^i + \rho_s} \theta_s^i \right] \overline{\eta}_s \tag{26}$$

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. Substituting back in equation (24), we obtain

$$w_s^n = \alpha_s + \frac{1}{\nu_s + \kappa^n} \left\{ \Delta \Big[x + (\eta - 1) p \Big] \mu_s^i + \frac{\kappa^i \left(\overline{\eta}_s - \rho_s\right)}{\kappa^i + \rho_s} \Delta \left[\frac{1}{\kappa} \ell - \phi \right] \theta_s^i \right\} \tag{27}$$

where

$$\alpha_s \equiv \frac{1}{\kappa^n + \nu_s} \left[x_n + (\eta^n - 1) p^n + \left(\kappa^n + \nu_s - \overline{\eta}_s \right) r_n \right] \tag{28}$$

A.3 Proofs in the semi-parametric, many-sector setting

Deriving versions of equations (6) and (7) with many sectors. The two-sector assumption is used in deriving equations (6) and (7) only in the derivation of equations (15) and (16). The parametric assumptions of CES consumption aggregators and Fréchet distributed amenity draws directly imply these equations in the many-sector parametric setting.

B Empirical appendix

B.1 Adjustments to sector aggregation

Table A1 displays the raw COICOP sectoral aggregation of the Nets expenditure data. 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.

In addition, we combine consumption categories 072 (Operation of personal transport equipment) and 073 (Transport service) into one (Other transportation); 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 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 data set. See the bold line in Figure A1.

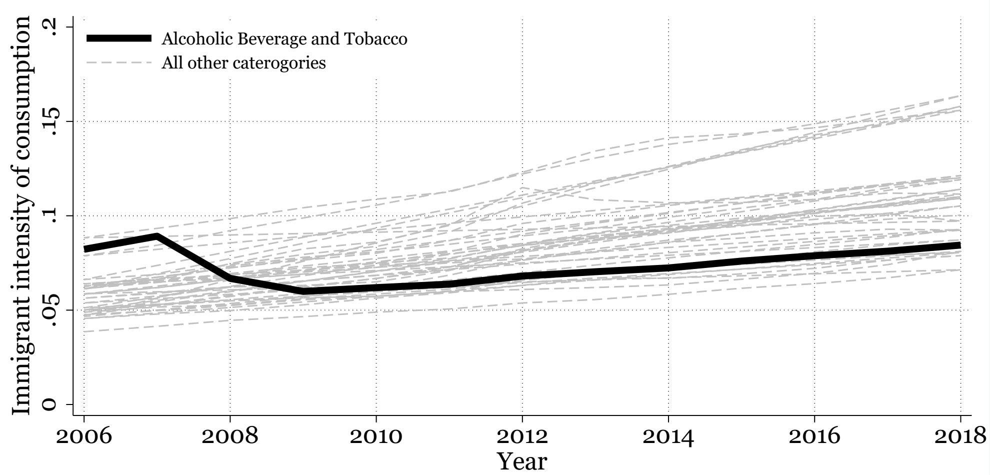
Table A2 provides examples of the concordance between 5-digit industry codes in the employment data and consumption categories. We highlight that the disaggregate employment industries that map into a given aggregate consumption sector include both production of products as well as wholesale and retail sale of these products.

Table A1: Consumption Categories

	Category	
01	Food and non-alcoholic beverages	
02	Alcoholic beverages, tobacco and narcotics	
03	Clothing and footwear	
04	Utilities, electricity, gasoline, housing rent	
05	Furnishings, household equip. and routine household maintenance	
06	Health	
07	Transport	
	071	Purchase of vehicles
	072	Operation of personal transport equipment
	073	Transport services
08	Communications	
09	Recreation and culture	
	091	Audio-visual, photographic and information processing equipment
	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 (credit)	
14	Payments to public institutions (public)	
cash	cash withdrawal	

Notes: Category 13 and 14 applies only to payments via NICS. Cash refers to withdrawals made when making a debit card payment.

Figure A1: 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.

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

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

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 m_j and is a member of group g_j—be denoted by x_j. Suppose that

$$\log x_{js} = \mu_{s_j}^{g_j} + \alpha_s \log Income_j + \varepsilon_{js} \tag{29}$$

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 (29) 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.

$$\log \widehat{x}_s^i - \log \widehat{x}_s^n = \underbrace{\widehat{\mu}_s^i - \widehat{\mu}_s^n}_{\text{taste differences}} + \underbrace{\widehat{\alpha}_s \left(\overline{Income}_i - \overline{Income}_n \right)}_{\text{income differences}} \tag{30}$$

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 A3: 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 (30) onto the left-hand side.

Table A3 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 Endogeneity

We conduct the following Monte Carlo simulation to document that even if the distribution of θ^i_{ms} is independent of the distribution of the residual, estimating equation (8) via OLS may lead to a biased estimator. And it may lead to an inconsistent estimator as the number of markets converges to infinity for a given number of sectors S. We focus on supply exposure, although demand exposure is similar.

We consider 100 markets m and S sectors s. For a given value of S, we iterate 500 times. In each iteration, we take the following approach.

We draw $\theta^i_{ms} \sim U[0,1]$ from a uniform distribution. We also construct the residual as the sum of a sector-specific random component and a market-sector-specific random component $\varepsilon_{ms} \equiv \widetilde{\varepsilon}_{ms} + \widetilde{\varepsilon}_s$, where $\widetilde{\varepsilon}_{ms} \sim U[0,1]$ and where $\widetilde{\varepsilon}_s \sim U[0,1]$. We then construct $\Delta\ell_m \equiv \varepsilon_m + \mathrm{Cov}_m(\theta_{ms}, \varepsilon_{ms})$, where $\varepsilon_m \sim U[0,1]$ and where $\mathrm{Cov}_m(\theta_{ms}, \varepsilon_{ms})$ is the realized covariance between the the immigrant intensity of production and the residual within market m.

These specific assumptions are consistent with the more general discussion in Section 3.2. First, the distributions of the residual and immigrant intensity of production are independent. Second, immigrant inflows in market m are particularly large when the realized value of the residual demand shock positively covaries with the realized value of the immigrant intensity of production within market m.

Given these variables, for each of the 500 iterations we measure the correlation between supply exposure and the immigrant intensity of production conditional on the other controls. Specifically, for each iteration we use OLS to estimate

$$\theta^i_{ms}\Delta\ell_m = \alpha_s + \alpha_m + \beta\varepsilon_{ms} + \iota_{ms}$$

and store the estimate $\widehat{\beta}_k$ associated with each of the 500 iterations k. Using these 500 values, we test whether the average estimate is significantly different from zero at the 5% level. We do this for a wide range of values of the number of sectors, $S \in \{10, 20, 50, 200, 500\}$. The average value of the estimate across iterations is always positive. Whereas this average falls towards zero as S grows, we reject at the 5% level that it equals zero for each of these values of S.

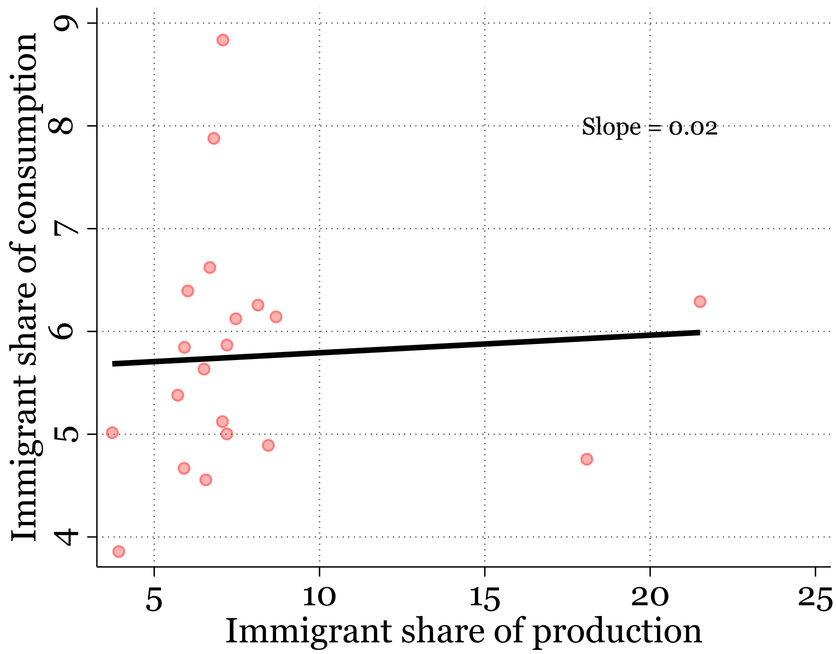
Finally, note that if we instrument for supply exposure using $\theta^i_{ms} \Delta \widetilde{\ell}^i_m$, where $\Delta \widetilde{\ell}^i_m = \varepsilon_m$, then the 2SLS estimate is consistent and unbiased for any value of S.

B.4 Sector tradability

We manually code each of the 19 sectors used in the empirical analysis as either more or less tradable. Given the sectoral allocation, we acknowledge that there is no way clear best way to do so. We allocate to tradables the following sectors: books + newspapers, clothing, communication, electronics, furnishing, grocery stores, motor vehicles, and transport. We allocate to non-tradables the following sectors: banks, finance, health, hotels, insurance, personal care, personal effects, recreation, restaurants, services, and utilities.

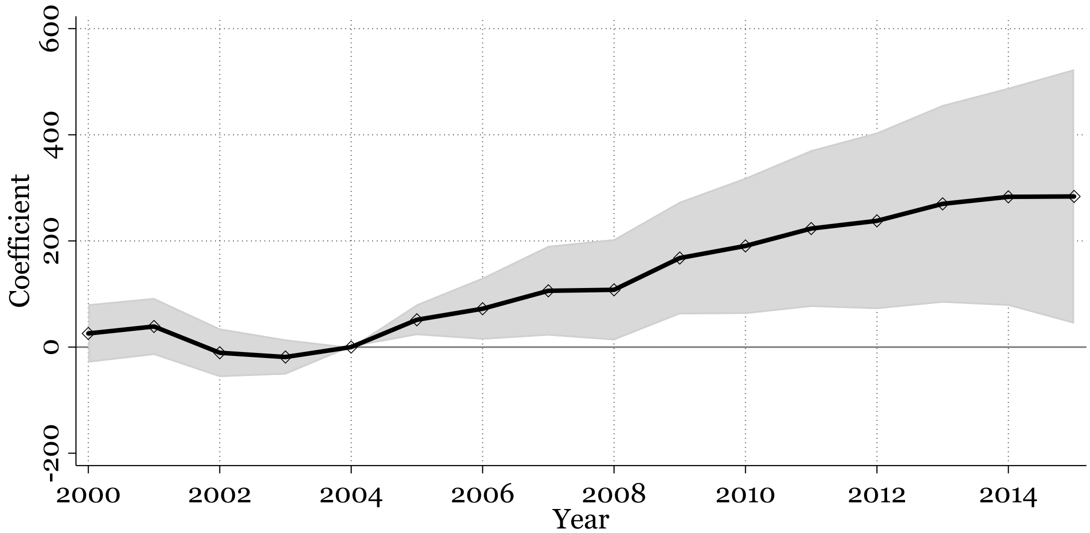
C Additional appendix tables and figures

Figure A2: Correlation between Immigrant Intensities of Consumption and Production



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

Figure A3: The Impact of Demand Exposure on Native Income Including Oslo



Note: This figure replicates Figure 4 on the expanded sample including workers who reside in Oslo in 2003 after de-trending worker real incomes using estimates of linear trends at the the market-sector level obtained on data from 2000 – 2004.

Table A4: Summary Statistics

	Male	Female	Include Educ.	Include Oslo	Exclude Manuf.
Income:					
Natives	499.08	349.70	497.97	519.79	482.08
Immigrants	473.68	356.65	472.73	478.20	454.85
New accession immigrants	500.73	370.12	491.69	511.28	496.37
Income, college graduates:					
Natives	604.58	402.94	586.03	631.16	574.88
Immigrants	566.05	412.77	553.97	572.03	537.55
New accession immigrants	595.56	420.60	559.17	595.11	583.60
Income, non-college graduates:					
Natives	464.60	322.31	463.61	474.26	448.91
Immigrants	418.85	310.93	417.68	420.25	401.49
New accession immigrants	420.62	317.90	419.71	420.97	418.67
Employment rate:					
Natives	0.97	0.96	0.97	0.97	0.97
Immigrants	0.94	0.95	0.94	0.94	0.94
New accession immigrants	0.96	0.96	0.96	0.96	0.94
Employment rate, college graduates:					
Natives	0.98	0.96	0.98	0.97	0.97
Immigrants	0.95	0.96	0.95	0.95	0.95
New accession immigrants	0.97	0.96	0.97	0.97	0.96
Employment rate, non-college graduates:					
Natives	0.97	0.97	0.97	0.97	0.96
Immigrants	0.93	0.95	0.93	0.93	0.92
New accession immigrants	0.94	0.95	0.95	0.95	0.92
Non-college graduate share:					
Natives	0.75	0.66	0.72	0.71	0.74
Immigrants	0.63	0.55	0.60	0.62	0.61
New accession immigrants	0.54	0.49	0.48	0.48	0.53

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 and before, rather than those who enter after accession.