Prices and Immigration: Firm-Level Evidence*

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Abstract

This paper examines how immigration affects consumer prices through product demand and labor supply channels. Using scanner price data linked to producer locations and instrumenting immigration with historical ancestry patterns, we find that immigration reduces prices: a 10,000-immigrant increase lowers approximately 8% in the average price growth for consumer packaged goods, with disinflationary effects extending to non-durable goods broadly and a net negative effect on regional CPI despite housing rent increases. Exploiting firm-level variation in exposure through sales versus production locations, we show price declines stem entirely from the product demand channel. Immigrants engage in more intensive price search, leading firms to lower markups. A structural demand framework confirms that immigration increases demand elasticity and shifts consumption toward lower-appeal products, with minimal variety effects.

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1 Introduction

Immigration and inflation stand as two paramount concerns for policymakers and the public alike, frequently dominating political discourse and economic analyses, particularly in recent years.[1] Considering immigration, public sentiment has recently leaned towards a desire for reduced immigration, often driven by concerns about its perceived effects on native wages. Yet, to fully grasp its economic impact, particularly on consumers, it is crucial to examine how immigration affects the prices they pay. Concurrently, inflation has surged as a major concern, with popular debates pointing to both labor shortages and increased tariffs as culprits. While the economic connection between immigration and inflation is frequently debated in media[2], their interplay remains an underexplored area in academic research.

Against this backdrop of pressing policy debates and a sparsely studied academic landscape, this paper asks two fundamental questions: Do firms adjust the prices of their products in response to changes in immigration inflows? If so, why?

The effect of immigration inflow on price is ambiguous, mainly arising from two complexities. First, immigration increases both labor supply and product demand simultaneously. Intuitions often raised in media highlight a dual effect: increased labor supply could lead to lower labor costs and thus cooling prices, while increased product demand may add to upward price pressures. Second, immigrants possess different characteristics than natives and may affect prices differently than a simple increase in total population. For instance, immigrant populations, often new to the market and requiring more information or possessing lower incomes relative to natives, tend to exhibit increased search effort and, consequently, higher price sensitivity compared to natives. This can compel firms to *lower* their prices even with the overall increased product demand from immigrants. Beyond these specific demand-side adjustments, immigration inflow can also alter the composition of demand, raise wages, spur the entry of new establishments, or lead to production-side adaptations like firm scaling, innovation, or the introduction of new product varieties, depending on the type of immigrants. A comprehensive understanding of firm pricing conditional on immigration inflows thus requires carefully considering these intricate and often countervailing mechanisms.

To investigate the causal effect of immigration and its underlying mechanisms, we construct a detailed micro-level dataset by combining product-destination-level scanner prices with producer production sites, alongside county-specific historical and current immigration

[1]See Gallup polls in Appendix Figure B.1. As of summer 2024, 55% of Americans responded that immigration should be decreased (highest since 2001), and 41% named inflation the most important financial problem facing their family (highest recorded since poll started in 2005). These figures highlight the widespread public concern over both issues.

[2]For example, see the related articles in Wall Street Journal and The Washington Post

inflows and their origins. This dataset is built by matching the NielsenIQ Retail Scanner and Consumer Panel database with the GS1 database and the NETs establishment database in 2006-2018; these combined datasets are further matched to historical and current immigration data from the Census and the American Community Survey based on county information.[3] A key strength of this matched data lies in its ability to separately observe firms' product sales (destination) and their production (labor sites). This unique feature allows us to empirically disentangle the product demand and labor supply channels through which immigration affects prices. Furthermore, the rich detail on household panel characteristics—such as their frequency of purchases and trips—and granular product information enables us to precisely identify mechanisms beyond these direct demand and supply channels, including consumer search behavior and product variety effects. To ensure the external validity and conduct additional robustness exercises, we supplement these data with additional county-level information from various datasets, including the Quarterly Census of Employment and Wages (QCEW), Bureau of Labor Statistics (BLS) City Price Index, and CoreLogic and Zillow Housing Price Indexes.

Armed with the detailed micro-level data, we first establish a robust reduced-form finding: immigration inflows *decrease* prices at the county level. In this initial county-level analysis, we utilize geographic variation akin to the existing regional immigration literature. We consistently find that counties with more international immigrants experience smaller price increases for consumer packaged goods (CPG), a result that holds whether using a chain-weighted county-level price index derived from barcode data or the official BLS price index for robustness.[4] The disinflationary effect extends beyond CPG to non-durable goods more broadly, with muted effects on durables and housing purchase prices, and positive effects on housing rents. The net effect on regional cost of living remains negative, as housing rent's small CPI share means that non-durable price reductions dominate the aggregate despite rental increases. In terms of magnitudes, an increase of five thousand new immigrants over a four-year period lowers CPG prices by approximately 0.58 percentage points. This is about 8% of the mean price growth and 20% of the standard deviation of cross-county price differences over the same period, implying that the difference in inflation between a low- and high-immigration county is economically significant and comparable to the effect on wages. To establish a causal impact and circumvent endogeneity concerns—such as immigrant self-selection into economically dynamic or more expensive regions—we employ a frontier Bartik-type instrument. This approach carefully follows and extends the method developed in

[3]The matching of scanner price and firm production is done using firm names and address information via GS1 database. See Appendix for details.

[4]Our scanner price index, based on CES utility (Sato, 1976; Vartia, 1976), is similar to the BLS methodology and presents a similar trend to that of the official BLS price index; see the Appendix for details.

Burchardi et al. (2019) and Terry et al. (2024) to recent years, leveraging more than 100 years of historical ancestry distributions and migration patterns to generate exogenous variation in current immigration, building on a broader literature using historical factors as instruments (e.g., Acemoglu et al. 2001; Nunn 2008; Dell 2010).

Having established a robust county-level reduced-form relationship, we next investigate the underlying firm-level mechanisms, shifting our unit of analysis from the county to the firm. The aggregate county-level effect represents the net outcome of diverse firm-level adjustments, encompassing their responses to the changes in product demand and labor supply, firm entry/exit, and other general equilibrium forces. To disentangle these channels, we leverage our detailed data to isolate a firm's specific exposure to both immigrant consumers and workers. Specifically, we measure the increased product demand from immigration by analyzing inflows in a firm's sales locations, and the increased labor supply by focusing on inflows in its production locations. In these analyses, we control for state fixed effects and other potential confounding variables that could affect firm pricing, such as retail wages and rental prices. For each of these distinct exposures, we analyze not only price responses but also other key outcomes such as purchaser characteristics, shopping behavior, and average prices paid, providing a comprehensive understanding of firm strategies.

Our firm-level analyses reveal a key mechanism driven by the product demand channel: newly arriving immigrants engage in more extensive search behavior, which induces firms to lower their prices. To substantiate this finding, we first disentangle the effects of product demand and labor supply. We find that firms reduce prices in their major sales destinations in response to immigrant inflows, while their price response is weakly positive when immigrants arrive in their more labor-populated production sites. The negative price effect is particularly pronounced for the inflow of low-skilled immigrants, who are typically more price-sensitive and search-intensive. We further validate this search-theoretic mechanism by investigating detailed purchase behavior at the firm level. We find that firms facing a larger influx of immigrants see an increase in purchasers who make more shopping trips, spend more days searching, and visit a greater number of distinct retailers. Crucially, we find that this heightened search effort is associated with consumers paying lower prices for the same products relative to the national average, providing direct evidence for the force driving the lower equilibrium prices. Lastly, in response to this demand shift, we observe an increase in the share of private-label products, which are known to be lower-priced options that are favored by these search-intensive, price-elastic consumers.

We corroborate the search mechanism by structurally estimating a nested demand system. This framework nests and extends our reduced-form indexes, yielding a utility-based price index that integrates considerations of product variety (Feenstra, 1994) and appeal (Hottman et al., 2016) at the firm and county levels.[5] Three key empirical findings from this framework further support the product search mechanism. First, our estimation of location-specific demand elasticities across products and firms reveals that greater immigration inflows are associated with a higher demand elasticity, particularly within the product demand channel, consistent with the search mechanism. Second, the estimated product appeal term falls significantly in response to increased product demand, which is consistent with the prevalent narratives that search-intensive immigrants also purchase lower-quality products. Lastly, we find that the variety effect of immigrants is largely muted, as measured by both our structural variety index and the number of products available per household and trip. This finding indicates that immigrant demand does not primarily lead to a greater entry of new products, thereby suggesting variety-based competition is not a primary channel for lower prices.

Literature Review. Research on the economic effects of immigration has long focused on the labor market, with a large and diverse body of literature exploring its effects on nominal wages and employment.[6] However, this literature largely remains silent on the general equilibrium effects on consumer prices, thus providing an incomplete view of the overall economic impact on real wages and cost of living.

A few pioneering papers have explored immigration's link to consumer prices, finding mixed effects depending on the sector, country, and specific mechanism studied. Some studies document price decreases for non-traded goods and services (Cortes, 2008), in specific contexts such as refugees in Israel (Lach, 2007) and Turkey (Tumen, 2016), or through cross-country analyses of international relative prices (Zachariadis, 2012). Others find small medium-run positive effects on general price levels (Furlanetto and Robstad, 2019). A theoretical exercise suggests that the disinflationary labor supply effect and the inflationary product demand effect of immigration may largely cancel each other out, resulting in a neutral overall impact on average (Cheremukhin et al., 2024). A related but separate strand of literature has examined immigration's impact on housing markets, revealing mixed evidence. While several studies document positive price effects (Saiz, 2007; Sanchis-Guarner, 2023), others find negative or neutral long-run effects attributable to native out-migration and flight from immigrant neighborhoods (Saiz and Wachter, 2011; Monras, 2020), or downward pressure on construction

[5]At the county level, this index primarily emphasizes variety due to the normalization of appeal.

[6]For instance, while some studies find that immigration can harm the wages of low-skilled natives (Borjas, 2003; Borjas and Katz, 2007; Dustmann et al., 2017), other papers report positive or negligible impacts, citing factors like native worker specialization and productivity gains (Card, 2009; Peri and Sparber, 2009; Ottaviano and Peri, 2012). The meta-analyses suggest that the overall average wage effect is close to zero, though with substantial heterogeneity across different groups (Dustmann et al., 2016; Peri, 2016; Clemens and Hunt, 2019).

wages (Sá, 2015). Our paper builds on these foundations and empirically establish the decrease in the US consumer price index due to the immigration inflow in the US and highlight the consumer search mechanism by disentangling the labor supply and product demand effects with a unique micro-level dataset.

Our analyses reveal the importance of consumer search behavior, and consumer heterogeneity more broadly, among various alternative mechanisms in which immigration affect prices, consistent with the work of Lach (2007). This finding is broadly consistent with theoretical models that link consumer price sensitivity to firm markups and macroeconomic phenomena (Kaplan and Menzio, 2016) and studies analyzing how consumer behavior changes with aggregate shocks, such as recessions (Aguiar et al., 2013; Nevo and Wong, 2019; Dube et al., 2018). In particular, our results are parallel to the empirical findings that local shocks (e.g. house prices, incomes of other households) can affect consumer spending and price sensitivity, which in turn leads to changes in markups (Stroebel and Vavra, 2019; Sangani, 2024). Relatedly, our work complements cross-sectional studies on how prices vary with consumer characteristics (Manova and Zhang, 2012; Jaravel, 2019; Handbury, 2021; Faber and Fally, 2022; Mongey and Waugh, 2025; Zhu et al., 2025). An important finding we highlight is that immigration tends to reduce the price level relatively more for lower income households.[7]

To credibly estimate the causal effect of immigration, we employ a cutting-edge method in the immigration literature by exploiting exogenous variation in immigration inflows. Our approach follows and extends the Bartik-type instruments developed by Card (2001) and more recently refined and applied by Burchardi et al. (2019) and Terry et al. (2024). This methodology leverages long-standing settlement patterns and country-of-origin networks to predict the destination of new immigrants, which allows us to isolate the immigration shock from other local economic factors that might simultaneously influence prices. In disentangling the product demand and labor supply effects, we utilize the NielsenIQ-GS1-NETS matched data to observe places where firms sell products as well as where they produce products. Integrating both the labor supply and consumer demand is in spirit of recent papers analyzing both effects of immigration inflow (Hong and McLaren, 2015; Albert and Monras, 2022; Mahajan, 2024; Galaasen et al., 2025).

To corroborate the mechanism, we estimate a nested demand system which allows for the time-varying product variety and consumer preferences at the micro-level, a technique widely used in macroeconomics, trade, and development (e.g., Feenstra and Romalis (2014); Hottman, Redding and Weinstein (2016); Atkin, Faber and Gonzalez-Navarro (2018); Lenzu,

[7] In contrast, for example, to negative wealth shocks where the trading down effect lowers inflation more for high income households (Argente and Lee, 2021; Jaimovich et al., 2019).

Rivers and Tielens (2022); Eslava, Haltiwanger and Urdaneta (2024)). This approach allows us to consistently aggregate barcode-level prices into firm- and county-level indices while accommodating crucial changes in product varieties, quality, and consumer substitution. This methodological rigor is necessary because price effects may be reflected in goods and services available to consumers (Handbury and Weinstein, 2015). Our findings that immigration heterogeneously impacts how firms adjust prices across counties align with existing literature on price dispersion and discrimination (Simonovska, 2015; Fitzgerald et al., 2024).

The paper is organized as follows. Section 2 discusses the theoretical channels through which immigration can affect prices, distinguishing between labor supply and product demand mechanisms. Section 3 describes our data construction and empirical strategy, including the instrumental variable approach and the construction of firm-specific immigration exposure measures. Section 4 presents our main findings on how immigration affects prices at the county level, establishing the aggregate relationship and providing external validity across multiple sectors. Section 5 investigates the underlying mechanisms using firm-level variation in exposure to immigration through sales and production locations, revealing the critical role of consumer search behavior. Section 6 develops a structural demand framework to decompose price changes into continuing variety effects, product variety adjustments, and quality changes, quantifying the role of demand elasticity and perceived product appeal. Section 7 concludes.

2 The Link Between Immigration and Prices

Immigration can influence consumer prices through two primary channels: labor supply effects and product demand effects. These channels can have opposing impacts on the equilibrium price level, making the net effect theoretically ambiguous. Table 1 summarizes the key mechanisms through which immigration affects prices based on our survey of the literature, acknowledging that other mechanisms may also be at play.

2.1 Labor Supply Channel

Immigration directly expands the local labor force, which can affect prices through multiple supply-side mechanisms. The most straightforward effect is through labor costs: an influx of workers increases labor supply and can reduce wages, particularly for occupations and skill levels where immigrants concentrate (Borjas, 2003; Cortes, 2008). Lower labor costs translate into reduced production costs, putting downward pressure on prices. However, the magnitude of this wage effect remains debated, with some studies finding negative impacts on native wages (Monras, 2020) while others document minimal effects due to native workers'

Table 1: Channels Through Which Immigration Affects Prices

Primary Channel		Price	Description	Source
Labor Supply	Lower Wages	Fall	Increased labor supply reduces wages and production costs.	Borjas 03, Cortes 08
	Productivity		Task specialization increases productivity, lowering unit costs.	Peri Sparber 09
	Entrepreneurship		Immigrant entrepreneurs increase firm entry and competition.	Olney 13, Mahajan 24
	Skill Upgrading	Rise	Natives shift to higher-skilled tasks, raising their wages.	Kerr et al. 15
	Innovation		Increased innovation and capital investment raise costs.	Kerr Lincoln 10, Burchardi et al. 19, Terry et al. 24
Product Demand	Demand Pull	Rise	Larger population increases overall demand.	Saiz 07
	Price Sensitivity	Fall	Search-intensive immigrants increase price competition.	Lach 07

adjustment through migration or labor force participation (Dustmann et al., 2017); Ottaviano and Peri (2012) show that the effect heavily depends on the substitutability across natives and immigrants. Beyond direct wage effects, immigration can enhance productivity through task specialization. Peri and Sparber (2009) demonstrate that immigration induces natives to specialize in communication-intensive tasks while immigrants concentrate in manual tasks, raising overall productivity. This productivity channel puts downward pressure on prices through lower unit costs. Moreover, immigrants themselves contribute to entrepreneurship and firm entry. Mahajan (2024) provides evidence that immigration increases the number of establishments, while Olney (2013) documents business creation in immigrant-intensive sectors. This expansion in the number of competing firms can reduce market power and put downward pressure on prices, particularly in local service sectors.

However, several countervailing forces can lead to upward price pressure through the labor supply channel. As natives reallocate to more complex, higher-skilled occupations (Kerr et al., 2015), their wages increase, raising production costs. Immigration can also stimulate innovation and capital investment, though evidence on this channel is mixed. Kerr and Lincoln (2010) show that H-1B visa increases led to more patents, and more recently Clemens and Lewis (2024) and Amuedo-Dorantes et al. (2023) find positive effects on firm performance. However, Borjas and Doran (2012) find that the influx of Soviet mathematicians reduced the productivity of American mathematicians in related fields, suggesting negative spillovers are possible when immigrants directly compete in innovation-intensive occupations. Burchardi et al. (2019) and Terry et al. (2024) provide evidence that historical immigration networks continue to facilitate innovation and entrepreneurship, both of which can involve higher costs that translate to higher prices.

Note that these supply-side adjustments may be dampened in tradable sectors, where firms can adjust output through international trade rather than local prices (Burstein et al., 2020). Additionally, firms may respond to immigration by adopting fewer labor-saving technologies (Clemens et al., 2018), adjusting their industry composition and scale (Dustmann and Glitz, 2015), or offshoring complementary tasks (Ottaviano et al., 2013; Olney and Pozzoli, 2021), further muting local price effects.

2.2 Product Demand Channel

On the demand side, immigration increases the local consumer base, which creates upward pressure on prices through standard demand-pull mechanisms. This effect is most clearly documented in housing markets, where Saiz (2007) finds that immigration raises house prices and rents in supply-constrained cities. In a heterogeneous agent model, Cheremukhin et al. (2024) treat immigration as temporary population growth that boosts consumption demand and investment, generating inflationary demand-side pressures.

However, immigrants may affect prices differently than a simple population increase would suggest, due to differences in their economic characteristics and behavior relative to natives. Most notably, Lach (2007) documents that a large influx of Soviet immigrants to Israel actually reduced prices, attributing this to immigrants' greater price sensitivity and search intensity. New arrivals, often facing information frictions and lower initial incomes, have stronger incentives to search for better deals and compare prices across retailers and brands. This heightened search behavior increases effective price competition and can lead firms to reduce markups, even as total demand expands.

This mechanism is consistent with broader evidence that firm pricing responds to the composition of demand through demand sensitivity and valuations of quality. On the sensitivity side, markups fall when demand shifts toward lower-income households who exhibit higher price elasticities (Gupta, 2023; Auer et al., 2024; Faber and Fally, 2022). This dependency explains why negative wealth shocks reduce markups (Stroebel and Vavra, 2019), while positive shocks—by reducing search effort or lowering elasticity—can increase them (Mongey and Waugh, 2025; Sangani, 2024). In our setting, a shock in the level of immigrants will alter the *composition* of households in a local market. If immigrants exhibit systematically higher price elasticity of demand, their arrival can intensify price competition and put downward pressure on equilibrium prices.

Compositional shifts also alter the aggregate willingness to pay for quality. Handbury (2021) and Argente and Lee (2021) document that demand for quality is highly income-dependent, creating spatial and demographic variation in price indices. Consequently, a shift in the consumer base can induce a "trading down" effect similar to business cycle contractions (Jaimovich et al., 2019), or prompt firms to adjust product appeal to target specific demographic segments (Goetz and Rodnyansky, 2023; Jaravel, 2019). In our setting, the arrival of immigrants—who may exhibit both higher price elasticity and a lower valuation for high-appeal goods—intensifies price competition and reweights consumption bundles.[8]

3 Data and Empirical Strategy

This section describes our data construction and empirical approach. Our core contribution is the ability to analyze how firms adjust prices when exposed to immigration through two distinct channels: where they sell their products (product demand) and where they produce them (labor supply). This firm-level analysis is enabled by matching retail scanner prices to producer locations, combined with an instrumental variable strategy that generates plausibly exogenous variation in immigration exposure.

We begin by describing our primary data sources: retail scanner prices and household shopping behavior for consumer packaged goods (CPG), supplemented by additional price measures across sectors. We then detail our key innovation—matching products to their producers' geographic locations—which allows us to construct firm-specific measures of immigration exposure through demand and supply channels. After describing our immigration data and instrumental variable strategy, we present summary statistics that document substantial spatial price variation even for identical products, motivating both our county-level baseline analysis and our main firm-level investigation.

3.1 Data Sources

3.1.1 Retail Scanner Prices and Household Shopping Behavior

Our primary data come from two NielsenIQ datasets that provide complementary information on prices and consumer behavior for CPG products. The Retail Scanner Dataset (RMS) contains weekly pricing, sales volume, and merchandising conditions from store point-of-sale systems across the United States from 2006 to 2019. The dataset includes approximately 35,000 participating stores in a balanced panel spanning drug stores, grocery stores, and mass merchandise retailers, covering roughly 2,500 counties—about 83% of all U.S. counties.

[8] In Section 6, we differentiate between 2 ways quality enters consumption through a structural model: i) through the conventional price index if lower valuation intensifies price competition for *continuing varieties* (reinforcing the higher price elasticity of demand); and ii) through a separate "product appeal" index that captures how consumption bundles are *reweighted* towards lower quality varieties.

Coverage is substantial: the data capture approximately 53-55% of national sales in food and drug stores and 32% of national sales in mass merchandise stores. Store locations are identified at the county level, which is the finest geographic unit available in the RMS data.

The dataset encompasses 2.6 million universal product codes (UPCs) organized into approximately 1,100 product modules, which aggregate further into 125 product groups covering consumer packaged goods (CPG), such as food, beverages, health and beauty products, and general merchandise. This rich product detail allows us to track prices of identical products—such as a specific cherry-flavored 500ml diet coke or a particular brand and size of laundry detergent—across different counties and time periods. This feature is critical for constructing quality-consistent price indices and documenting spatial price variation that we exploit for identification.

To construct our analytical dataset, we perform several aggregation steps. First, we aggregate the raw store-UPC-week data to the store-UPC-year level, computing quantity-weighted average prices. We also construct alternative measures using modal prices within each year and obtain nearly identical results. Second, we aggregate to the county-UPC-year level by taking quantity-weighted averages across stores. Crucially, we use only a balanced panel of stores within each county to ensure that changes in store composition do not mechanically drive our price measures. This county-UPC-year panel forms the foundation for all subsequent price index construction, which we describe in detail in Section 3.3.

We complement the retail scanner price data with the NielsenIQ Homescan Consumer Panel, which provides detailed shopping behavior and demographics for approximately 55,000 households annually from 2006 to 2018. Panel participants record every shopping trip using handheld scanners or mobile apps, providing comprehensive information on their shopping patterns. For each household-year, we observe the number of shopping trips made, the number of days spent shopping, the number of visits to different retail stores, the specific store brands purchased, and the purchases made at each retailer. Importantly, the panel also includes detailed demographic characteristics such as household income, education, household size, race and ethnicity, and in some cases proxies for immigration status or nativity.

This household-level data serves two critical purposes in our analysis. First, it allows us to examine demand-side mechanisms by observing how shopping behavior—particularly search intensity measured by store visits and shopping frequency—varies with local immigration inflows. If immigrants are more price-sensitive and engage in more intensive search, we should observe changes in the composition of shoppers and their behavior in high-immigration counties. Second, the demographic information helps us identify likely immigrant households or at least households with characteristics correlated with immigrant status, enabling us to test whether different demographic groups exhibit systematically different price sensitivity and shopping patterns. These behavioral differences are central to understanding the price sensitivity mechanism we document in Section 5.

Supplementary Price Data Across Sectors While our main analysis focuses on CPG products where we have the richest micro-data, we supplement our scanner-based price indices with additional measures covering other major expenditure categories to assess whether immigration's effects extend beyond CPG products. For housing purchase prices, we use county-level home price indices from CoreLogic and Zillow covering 2006-2018. For rental housing, we construct county-level median gross rent indices from American Community Survey (ACS) data, which provides broader geographic coverage than other rental price sources and covers approximately 3,100 counties. For durable goods and services, we use city-level Consumer Price Index data from the Bureau of Labor Statistics, available for the 27 largest metropolitan statistical areas (261 counties). While these supplementary price measures have more limited geographic coverage or product detail than our scanner data, they allow us to assess the generality of our findings across the full consumption basket and provide important context for interpreting the magnitude of effects we document for consumer packaged goods.

3.1.2 Firm Production Locations

A key strength of this paper is matching consumer packaged products to their producers' geographic locations, which allows us to separately identify labor supply and product demand channels. We link firms in the scanner data to establishment-level information from the National Establishment Time-Series Database (NETS), which provides panel data on employment, sales, and locations for private and public businesses across the United States from 2006 to 2018.

The matching procedure uses business names and addresses from the GS1 Company Database, which maintains the registry of UPC codes and their associated manufacturers. GS1 is the global standards organization that administers the UPC system and assigns unique identifiers to products and companies. We employ a multi-step algorithm to match GS1 companies to NETS establishments. First, we match entities with identical names, states, and cities, which yields high-confidence matches for firms with unique names in specific locations. For remaining firms with the same name and state but different cities—often large national companies with multiple facilities—we use the Google Places API to verify matches based on common URL appearances in search results. Specifically, if a Google search for the firm name and state returns the same URL in the top results for both the GS1 and NETS entries, we classify these as successful matches. We manually review a random sample of 500 matches to validate the algorithm's accuracy and find a success rate of 94%, confirming that our procedure produces reliable linkages.

This procedure yields high-quality matches between products (UPCs) and their manufacturing establishments, which we categorize by industry using Standard Industrial Classification (SIC) codes from NETS. The matched data allow us to observe, for each product sold in the scanner data, the firm that produces it, the county or counties where the firm operates production establishments, the number of workers employed at each establishment, and the counties where the product is sold. This dual observation of production locations and sales locations is essential for our firm-level analysis in Section 5, where we construct firm-specific measures of exposure to immigration through labor supply at production counties versus product demand at sales counties. Additional details on the matching algorithm, validation procedures, match rates, and representativeness of matched versus unmatched firms are provided in Appendix A.1.

3.1.3 Immigration Data

We construct county-level immigration measures following the methodology of Terry et al. (2024), using microdata from the Integrated Public Use Microdata Series (IPUMS). For historical periods essential to our instrumental variable strategy, we use the 1880, 1900-1930, and 1970-2000 decennial census samples to measure immigration and ancestry patterns. For our main analysis period, we extend their approach using American Community Survey (ACS) data: the 2010 ACS for immigration through 2005, the 2014 ACS for 2005-2010 immigration, the 2018 ACS for 2010-2014 immigration, and the 2022 ACS for 2014-2018 immigration. We deviate slightly from Terry et al. (2024) in our use of later ACS samples because IPUMS reports five-year pooled samples after 2000, and using the 2010 ACS alone would undercount early-period immigrants. For example, the 2010 ACS pools surveys from 2006-2010, meaning 2010 arrivals appear only in the final survey year. Using the 2014 ACS, which includes surveys from 2010-2014, more accurately captures all 2005-2010 immigration. We apply this logic consistently for subsequent periods. The 2022 ACS is the most recent data available at the time of our analysis, which is why our sample ends in 2018.

Immigration is defined as the total number of foreign-born respondents by birthplace. We construct immigration flows for multiple time periods using reported year of immigration. Ancestry is measured from survey respondents' reported ancestral origins, with country classifications harmonized across time using extended crosswalks based on Burchardi et al.

(2019). We scale individual responses to county-level totals using IPUMS person weights and harmonize county codes to a consistent 1990 classification, yielding a balanced panel of 3,141 counties across all sample years.

Beyond measuring total immigration flows, the ACS data also provide rich information on immigrant characteristics at the county level, including educational attainment and skill levels, industry and occupation of employment, income and earnings, and year of arrival and duration in the United States. These characteristics allow us to examine heterogeneous effects by immigrant type, such as comparing the price effects of high-skilled versus low-skilled immigration, which we explore in our mechanism analysis.

3.1.4 Supplementary County-Level Data

To control for confounding factors and examine additional outcomes, we incorporate several supplementary datasets at the county level. The Quarterly Census of Employment and Wages (QCEW) from the U.S. Bureau of Labor Statistics provides county-level annual data on average wages deflated using the PCE index, total employment, number of establishments, and total payrolls from 2006-2018. From the Bureau of Economic Analysis (BEA) Regional Data, we obtain county-level GDP, per capita income, and population for the same period, along with BEA urban and rural classifications. The USDA Economic Research Service provides county-level population density, metropolitan versus non-metropolitan status, and other geographic characteristics.

These supplementary data serve two main purposes throughout our analysis. They provide control variables for our main specifications, capturing local economic conditions that might correlate with both immigration and prices. Also, they enable us to examine whether immigration affects local economic conditions such as wages and employment in ways that might confound or mediate the price effects we document.

3.2 Baseline Empirical Specification

Our baseline empirical specification examines how changes in county-level prices respond to immigration inflows:

$$\Delta \ln P_{dt} = \delta_t + \delta_s + \gamma I_{dt} + X'_{dt}\beta + \varepsilon_{dt} \tag{3.1}$$

where $\Delta \ln P_{dt}$ is the log change in the price index for county d over period t, I_{dt} measures the total number of new immigrants arriving in county d during period t, δ_t and δ_s are state and period fixed effects, and X_{dt} includes additional initial county-level controls such as population and GDP per capita. The coefficient γ captures the causal effect of immigration on local price inflation. We construct an instrument for I_{dt} to address concerns about endogeneity, which we discuss in detail below.

We estimate this specification using a stacked long-difference approach covering three periods: 2006-2010, 2010-2014, and 2014-2018; we also conduct a robustness check using the full long-difference period (2006-2018). The baseline specification pools the data across periods, focusing on medium-term adjustments while mitigating concerns about high-frequency noise in annual price changes and allowing sufficient time for firm-level adjustments to take effect. State and period fixed effects control for time-invariant state characteristics and common national shocks, isolating variation in immigration exposure across counties that deviates from national trends.

We estimate equation (3.1) separately for different price indices, using CPG non-durables as our primary focus and supplementing this with housing purchase prices, housing rents, durable goods, and services, to conduct the most comprehensive analysis of immigration's overall price impact across the full consumption basket as is empirically feasible.

3.3 Construction of the CPG Price Index

To properly measure how immigration affects CPG prices, we construct a price index from our barcode-level scanner data that accounts for consumer substitution patterns across products and firms. Our approach builds on the exact price index literature (Sato, 1976; Vartia, 1976) and uses chain-weighted geometric means that are consistent with constant elasticity of substitution (CES) preferences. In Section 6, we develop a full structural demand model that nests this reduced-form index and additionally incorporates product variety and quality adjustments. For now, we focus on a transparent, theory-consistent aggregation of observed prices for continuing varieties.

We denote P_{kdt} as the price of product (UPC) k in county d at time t. Product k is produced by firm f and belongs to product group g such as carbonated beverages, breakfast cereals, or cleaning products. Our county-level price index is constructed through a three-stage aggregation using chain-weighted geometric means.

Stage 1: Product to Firm-Group Level We first aggregate products within each firm-group-county combination, using only products available in both periods $t-1$ and t to focus on continuing varieties:

$$\frac{P_{fgdt}}{P_{fgd,t-1}} = \prod_{k \in \Omega_{fgdt,t-1}} \left(\frac{P_{kdt}}{P_{kd,t-1}} \right)^{w_{kdt}} \tag{3.2}$$

where $\Omega_{fgdt,t-1}$ denotes the set of continuing products and w_{kdt} are Sato-Vartia weights:

$$w_{kdt} = \frac{s_{kdt} - s_{kd,t-1}}{\ln s_{kdt} - \ln s_{kd,t-1}} \Bigg/ \sum_{k' \in \Omega_{fgdt,t-1}} \frac{s_{k'dt} - s_{k'd,t-1}}{\ln s_{k'dt} - \ln s_{k'd,t-1}} \tag{3.3}$$

where s_{kdt} is the expenditure share of product k within firm-group fg in county d at time t, computed over the set of continuing products $\Omega_{fgdt,t-1}$. Sato-Vartia weights are exact for CES utility and provide the theoretically appropriate aggregation of price relatives (Diewert, 1976). These weights account for the fact that consumers substitute toward relatively cheaper products, giving more weight to products with larger expenditure shares and appropriately capturing substitution patterns.

Stage 2: Firm-Group to Group Level We aggregate across firms within each product group and county, again using Sato-Vartia weights and restricting to continuing firms:

$$\frac{P_{gdt}}{P_{gd,t-1}} = \prod_{f \in \Omega_{gdt,t-1}} \left(\frac{P_{fgdt}}{P_{fgd,t-1}} \right)^{w_{fgdt}} \tag{3.4}$$

where w_{fgdt} are Sato-Vartia weights based on firm-group expenditure shares within each product group.

Stage 3: Group to County Level Finally, we aggregate across product groups using Törnqvist weights, consistent with a Cobb-Douglas upper nest that allows for different consumption intensities across product categories:

$$\frac{P_{dt}}{P_{d,t-1}} = \prod_{g \in \Omega_{dt,t-1}} \left(\frac{P_{gdt}}{P_{gd,t-1}} \right)^{w_{gdt}} \tag{3.5}$$

where $w_{gdt} = \frac{1}{2}(s_{gdt} + s_{gd,t-1})$ are Törnqvist weights based on the average expenditure share of group g in county d across the two periods.

This three-stage procedure yields our baseline CPG price index P_{dt}, which measures inflation in county d from period $t-1$ to t while holding the set of products, firms, and groups constant by focusing on continuing varieties only. The log change $\Delta \ln P_{dt} = \ln(P_{dt}/P_{d,t-1})$ enters equation (3.1) as our primary outcome variable. By construction, this index measures price changes for an identical basket of goods across locations and time, capturing pure price variation rather than changes in product mix or quality. We undertake two complementary exercises related to the price index: first, for a sanity check, we aggregate the county-level index to the national level and compare it to the official BLS food price index, finding the two aggregate inflation measures are reasonably close; second, to demonstrate the robustness of our final results, we show they are qualitatively unchanged when using alternative index formulas (Törnqvist, Jevons, Laspeyres, and Paasche) in place of the Sato-Vartia weights (both sets of results are detailed in Appendix A).

3.4 Instrumental Variable Strategy

The immigration measure I_{dt} in equation (3.1) is likely endogenous. Immigrants may select into counties based on economic opportunities, wage levels, employment prospects, housing affordability, or amenities, generating spurious correlations between immigration and prices. For example, if immigrants are attracted to counties experiencing positive economic shocks that also drive up local prices through increased demand, OLS estimates of γ will be biased upward. Conversely, if immigrants select into declining areas with falling prices due to lower housing costs, OLS will be biased downward. These selection concerns motivate our instrumental variable approach.

To address this endogeneity, we employ an instrumental variables strategy that leverages historical settlement patterns from more than a century ago and origin-country migration patterns to generate plausibly exogenous variation in contemporary immigration flows. Our approach closely follows Terry et al. (2024), who extend and refine the canonical shift-share instrument developed by Card (2001). We provide a detailed exposition of the methodology below, with care to explain the identifying assumptions and provide intuition for how the instrument generates exogenous variation.

3.4.1 The Standard Shift-Share Instruments

The canonical shift-share instrument for immigration predicts current immigration to county d from origin country o as the product of a "share" and a "shift":

$$\hat{I}_{odt} = A_{od,t-1} \times I_{o,-d,t} \tag{3.6}$$

where $A_{od,t-1}$ is the ancestry network, measuring the number of residents with ancestry from country o living in county d in period $t-1$, and $I_{o,-d,t}$ is the shifter, measuring total immigration from country o to all other counties except d in period t. The identifying assumption is that historical ancestry networks predict where new immigrants settle due to family ties, established ethnic communities, and information networks, but are orthogonal to current local economic shocks affecting prices. One concern in using this instrument is that persistent local shocks can contaminate the use of past ancestry as an exposure measure. If the same economic conditions that attracted immigrants to county d in the past persist into the present, then past ancestry $A_{od,t-1}$ is correlated with current unobserved shocks to county d that also affect prices. This persistence violates the exclusion restriction, making the instrument fails to isolate truly exogenous variation in immigration flows.

3.4.2 Predicted Ancestry Instrument

To address this endogeneity problem, we follow Terry et al. (2024) and instrument for ancestry itself using exogenous historical push and pull factors starting from 1880. The key insight is to predict county-level ancestry stocks using variation that arises from the interaction of origin-country emigration patterns and destination-county attractiveness to unrelated immigrant groups. This two-way interaction breaks the link between current economic conditions in a county and the instrument by relying on historical factors that are plausibly orthogonal to present-day local shocks.

The first stage predicts ancestry A_{odt} in recent periods using historical migration patterns:

$$A_{odt} = \delta_{or(d)t} + \delta_{c(o)dt} + X'_{od}\zeta + \sum_{\tau \in \mathcal{T}} a_{r(d)\tau} \left(I_{o,-r(d),\tau} \times \frac{I_{Europe,d\tau}}{I_{Europe,\tau}} \right) + \nu_{odt} \tag{3.7}$$

where $\mathcal{T}$ denotes the set of historical census years (1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, 2000) used to construct the instrument.

where $I_{o,-r(d),\tau}$ is total immigration from origin o in year τ, excluding migration to the census region $r(d)$ where county d is located. We use nine U.S. census divisions to define regions. This leave-out measure captures exogenous push factors from the origin country, such as wars, famines, economic crises, or political upheavals that drove emigration more than a century ago. The term $\frac{I_{Europe,d\tau}}{I_{Europe,\tau}}$ is the share of all European immigrants in year τ who settled in county d. This captures the pull attractiveness of destination d to an unrelated immigrant group, reflecting factors like transportation networks, railroad connections, port access, economic opportunities, climate, and established communities that made certain destinations more attractive in the late 19th and early 20th centuries.

The specification also includes $\delta_{or(d)t}$, which are origin-country by destination-region by time fixed effects, and $\delta_{c(o)dt}$, which are continent-of-origin by destination-county by time fixed effects. These fixed effects control for broad geographic patterns in settlement. The term X'_{od} includes time-invariant origin-destination controls such as geographic distance between the origin country and destination county, whether the origin country had historical colonial ties to the region, and other dyadic characteristics.

The interaction between origin-specific push factors and destination attractiveness to Europeans generates plausibly exogenous variation in where non-European immigrants' descendants live today. The exclusion restriction requires that these historical factors do not directly affect current price dynamics in 2006-2018 except through their effect on current immigration patterns. This is plausible because the economic, transportation, and institutional factors that shaped settlement patterns more than a century ago are unlikely to have persistent direct effects on contemporary CPG prices after controlling for broad geographic patterns through fixed effects.

Intuition Through an Example Consider predicted ancestry of Chinese immigrants in Butte County, Montana. This ancestry measure is high when two conditions hold. First, many Chinese emigrants left China in 1880 due to economic hardship and political instability, settling throughout the United States—in California cities, East Coast ports, and elsewhere. This large-scale Chinese emigration, measured using settlement outside the Mountain West region to avoid mechanical correlation with Montana, indicates strong origin-country pressures driving people to leave China. Second, Butte County attracted a large share of European immigrants in 1880 due to its copper mining boom, railroad access, and established economic opportunities—factors that made it an attractive destination for immigrants generally, not just Europeans. The instrument interacts these two components: origin-country emigration pressures (the "push") with destination attractiveness to an unrelated immigrant group (the "pull"). Crucially, this predicted ancestry arises entirely from historical factors in the late 19th century—origin-country conditions and destination characteristics like mining activity and transportation networks—that are plausibly unrelated to contemporary economic conditions affecting CPG prices in 2006–2018.

We obtain predicted ancestry as:

$$\hat{A}_{odt} = \sum_{\tau \in \mathcal{T}} \hat{a}_{r(d)\tau} \left(I_{o,-r(d),\tau} \times \frac{I_{Europe,d\tau}}{I_{Europe,\tau}} \right)^{\perp} \tag{3.8}$$

where $\hat{a}_{r(d)\tau}$ are the estimated coefficients from equation (3.7) and the superscript $\perp$ indicates that the interaction term has been residualized with respect to all controls included in equation (3.7).

3.4.3 Final Instrument Construction

With predicted ancestry in hand, we return to the shift-share logic. The final first-stage equation predicts actual immigration I_{odt} as:

$$I_{odt} = \delta_{or(d)} + \delta_{c(o)d} + \delta_t + X'_{od}\theta + b_t \left(\hat{A}_{od,t-1} \times \tilde{I}_{o,-r(d),t} \right) + u_{odt} \tag{3.9}$$

where $\tilde{I}_{o,-r(d),t}$ is the shifter, measuring scaled immigration from origin o to regions outside $r(d)$ in period t. The shifter is defined as:

$$\tilde{I}_{o,-r(d),t} = I_{o,-r(d),t} \times \frac{I_{Europe,r(d),t}}{I_{Europe,-r(d),t}} \tag{3.10}$$

where the second term is a scale factor that corrects for regional size differences. Larger regions naturally receive more immigrants in absolute numbers, so we scale by the region's share of European immigration to make shifters comparable across regions of different sizes.

The instrument for county-level immigration is constructed by aggregating across origin countries:

$$Z_{dt} = \sum_o \hat{b}_t \left(\hat{A}_{od,t-1} \times \tilde{I}_{o,-r(d),t} \right) \tag{3.11}$$

where $\hat{b}_t$ are the estimated coefficients from equation (3.9).

This instrument generates variation in immigration to county d in period t through three components, all plausibly orthogonal to current local economic conditions: historical settlement patterns embedded in predicted ancestry, current origin-country emigration rates in the leave-out region reflecting global migration trends, and historical destination-region attractiveness to Europeans. The exclusion restriction requires that these factors affect current county prices only through their effect on current immigration to that county, not through any direct channel such as persistent effects of historical mining or agriculture on current price dynamics.

3.4.4 Implementation and First-Stage Validation

We implement this procedure for three periods in our sample: 2006-2010, 2010-2014, and 2014-2018, using only non-European origin countries consistent with the instrument construction. The instrument is constructed from non-European immigration because European migration patterns are used to measure destination attractiveness in equation (3.7). Our estimated effects, therefore, represent the impact of non-European immigration specifically. In practice, non-European immigrants constitute the vast majority of recent U.S. immigration—over 80% of total inflows during our sample period—so this is the policy-relevant margin.

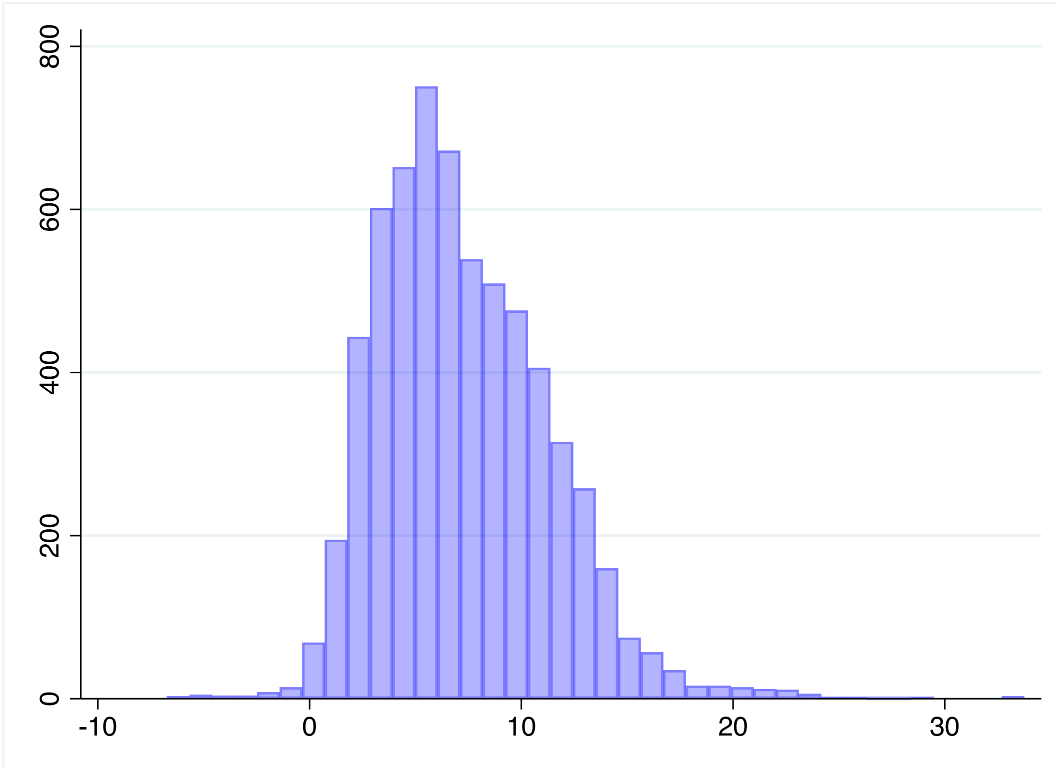
For the first-stage estimation in equation (3.9), we include nine time periods spanning 1975-2018 in five-year intervals, with four-year intervals after 2010 to accommodate data availability as described in Section 3.1. Appendix Table B.4 reports our first-stage estimates for post-1975 periods, which closely replicate those in Terry et al. (2024) for overlapping years and extend the analysis through 2018. Our constructed instruments for overlapping periods correlate at 0.997 with those provided by Terry et al. (2024), validating our replication and extension of their methodology. The first stage is strong: the F-statistic on the excluded instrument exceeds 40 in all specifications, well above the conventional thresholds for concerns about weak instruments. This reflects the substantial predictive power of historical settlement patterns and origin-country push factors for current immigration flows.

3.5 Summary Statistics and Spatial Variation in Prices

Before presenting our formal empirical results, we document a key feature of our empirical setting: substantial spatial variation in price changes across counties. This price dispersion is critical for understanding how local immigration shocks can affect local prices, and it motivates both our county-level baseline analysis and our main firm-level investigation of differential exposure through sales versus production locations.

Price Dispersion Across Counties Figure 1 presents the distribution of county-level price changes for CPG products across four-year periods from 2006-2018, constructed using our Sato-Vartia price index described in Section 3.3. Even accounting for product entry, exit, and changing expenditure shares within counties, we observe considerable geographic price dispersion. The distribution shows substantial variation: while the median county experienced price increases of approximately 6.7% over four-year periods, the interquartile range spans 5.6 percentage points (from 4.3% at the 25th percentile to 9.9% at the 75th percentile). Counties at the 75th percentile experienced inflation more than twice as high as those at the 25th percentile, indicating substantial variation in local price dynamics.

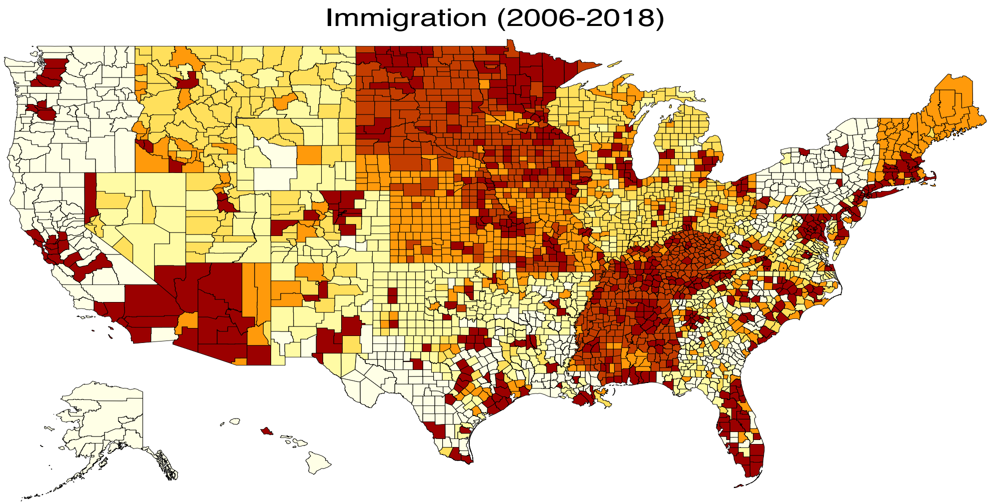
Figure 1: Distribution of County-Level Price Changes, Four-Year Periods 2006-2018



Notes: Histogram shows the unweighted distribution of price changes across counties over four-year periods from 2006-2018, measured using the Sato-Vartia price index for CPG products as described in Section 3.3. Each observation is a county-period (N=6,339). The price index uses a three-stage aggregation procedure that accounts for product entry and exit and allows expenditure shares to vary over time. The distribution demonstrates substantial spatial price variation for consumer goods.

This violation of purchasing power parity for tradable goods is essential for our empirical strategy. If purchasing power parity held perfectly, local immigration shocks could not affect local prices independently, as any price differentials would be immediately arbitraged away through trade. Several factors contribute to these persistent price differences. Manufacturers and retailers engage in spatial price discrimination, setting different prices in different markets based on local demand conditions and competitive environments (Fitzgerald et al., 2024). While some retailers adopt uniform pricing for identical products within their chains (DellaVigna and Gentzkow, 2019), our price index aggregates across both products and firms, capturing variation in pricing strategies across manufacturers and retail formats. Local promotions, discounts, and sales vary substantially across locations, reflecting differences in local competition and consumer composition. Local market structure, including the number and type of competing retailers, differs geographically and affects the effective prices consumers face. Transportation costs and local supply chain configurations introduce additional wedges between locations. This empirical reality—that consumer goods exhibit substantial spatial price variation—validates our approach of exploiting county-level variation in immigration exposure to study price effects. The observed variation in price changes across counties highlights that local conditions have a significant influence on price determination.

Figure 2: Geographic Distribution of Immigration Shocks, 2006-2018



Notes: Heat map shows predicted immigration shock Z_{dt} from equation (3.11) at the county level, cumulated over 2006-2018. Darker colors indicate larger predicted immigration inflows. The instrument uses only non-European immigration and is based on historical settlement patterns from 1880-1930 interacted with recent origin-country migration patterns. White areas indicate counties not included in the sample due to missing data.

Geographic Distribution of Immigration Shocks Figure 2 displays the spatial distribution of predicted immigration shocks across counties from 2006-2018. The heat map reveals substantial geographic variation in immigration exposure that is plausibly orthogonal to local economic conditions due to our instrumental variable construction (described in Section 3.4). Dark red areas indicate the highest predicted immigration inflows and are concentrated in the Southwest, California, and Florida, but also appear throughout the country including the North-Central region, Appalachia, and the East Coast. This widespread geographic variation, combined with the exogenous source of the instrument, provides strong identifying power for our analysis.

Table 2: Summary Statistics: County Level

	count	mean	sd	p25	p50	p75	min	max
Δ ln $\mathrm{P_{d,t}}$ (CPG)	6339	7.28	4.05	4.30	6.68	9.85	-6.74	33.8
Δ ln $\mathrm{P_{d,t}}$ (Non-durables)	684	5.96	5.40	-0.18	8.14	10.1	-5.19	13.4
Δ ln $\mathrm{P_{d,t}}$ (Durables)	684	-3.63	3.35	-6.42	-3.69	-1.57	-9.81	3.48
Δ ln $\mathrm{P_{d,t}}$ (Services)	684	9.22	2.59	7.78	8.71	10.1	2.95	17.5
Δ ln $\mathrm{P_{d,t}}$ (BLS, Rent)	684	11.2	4.77	8.16	10.1	14.1	2.09	25.8
Δ ln $\mathrm{P_{d,t}}$ (ACS, Rent)	6336	10.7	6.45	7.31	10.9	14.3	-29.9	53.5
Δ ln $\mathrm{HP_{d,t}}$(CL)	2446	-3.85	18.9	-11.8	-0.74	7.56	-87.9	44.6
Δ ln $\mathrm{HP_{d,t}}$ (Z)	4781	6.03	16.2	-1.97	6.26	15.9	-108.6	57.2
Δ # $\mathrm{Establ._{d,t}}$	6339	-0.15	0.72	-0.45	-0.14	0.15	-8.44	22.4
Δ Total $\mathrm{Wages_{d,t}}$	6339	0.39	1.94	0.010	0.047	0.17	-3.74	53.2
Δ $\mathrm{Employment_{d,t}}$	6339	1.77	15.0	-0.44	0.088	1.08	-305.0	297.9
Δ ln $\mathrm{Wage_{d,t}}$	6339	3.27	5.30	0.36	3.17	6.00	-30.2	56.2
Δ ln $\mathrm{Wage_{d,t}}$ (Retail)	6318	1.96	6.85	-1.85	2.04	5.87	-74.6	64.7
$\mathrm{Immigr_{d,t}}$	6339	1.68	4.95	0.066	0.17	0.62	0.0026	34.2
$\mathrm{Immishock_{d,t}}$	6339	-0.035	0.48	-0.10	-0.042	-0.0013	-2.27	3.14

Notes: Summary statistics for stacked four-year periods (2006-2010, 2010-2014, 2014-2018). CPG price indices are constructed from barcode-level data following the procedure in equations (3.2)-(3.5). BLS non-durable, durable, service, and rental price indices are available for 27 metropolitan areas (261 counties). Housing purchase price indices are from CoreLogic (CL, available for 2006-2014 only) and Zillow (Z, available for all three periods). Housing rental prices are median gross rents from ACS data. Number of establishments (in thousands), employment, and wages are from QCEW data; wages are deflated by the national PCE index. Immigration ("Immigr") is measured for non-European origins from IPUMS data. The immigration shock ("Immishock") Z_{dt} is the predicted immigration instrument from equation (3.11), constructed using residualized predicted ancestry. Both Immigr and Immishock winsorize top and bottom 1% of the sample.

Summary Statistics Across Price Measures and Sectors Table 2 presents summary statistics for our main variables at the county level over stacked four-year periods (2006-2010, 2010-2014, 2014-2018). For CPG products, the mean price increase of 7.28% with a standard deviation of 4.05 percentage points confirms the substantial spatial dispersion documented in Figure 1.

Examining price variation across sectors reveals patterns consistent with economic theory regarding tradability. While CPG products show considerable spatial dispersion, non-tradable housing exhibits even more dramatic variation: purchase prices have standard deviations of 18.9 and 16.2 percentage points for CoreLogic and Zillow respectively, reflecting both housing's non-tradable nature and the boom-bust cycle during our sample period (which motivates robustness checks excluding the Great Recession years). Rental housing similarly shows large spatial variation with standard deviations of 4.77-6.45 percentage points. We also observe BLS price data for 27 metropolitan areas: non-durables and durables show standard deviations of 5.40 and 3.35 percentage points respectively, while services show relatively modest dispersion of 2.59 percentage points.[9]

Wages show a standard deviation of 5.30 percentage points—comparable to CPG price dispersion. Despite labor facing higher mobility costs than goods, overall wage dispersion is similar to price dispersion, likely reflecting institutional wage compression from minimum wage laws, union contracts, and standardized pay scales at large employers. Retail wages exhibit greater relative dispersion, consistent with more localized labor markets.

Immigration patterns confirm the geographic variation shown in Figure 2. The average county received 2,190 immigrants per four-year period, but with a standard deviation of 9,930—more than four times the mean—reflecting extreme heterogeneity in settlement patterns. The predicted immigration shock Z_{dt} shows substantial variation that, combined with its exogenous construction from historical settlement patterns, provides strong identifying power for this analysis.

4 County-Level Results

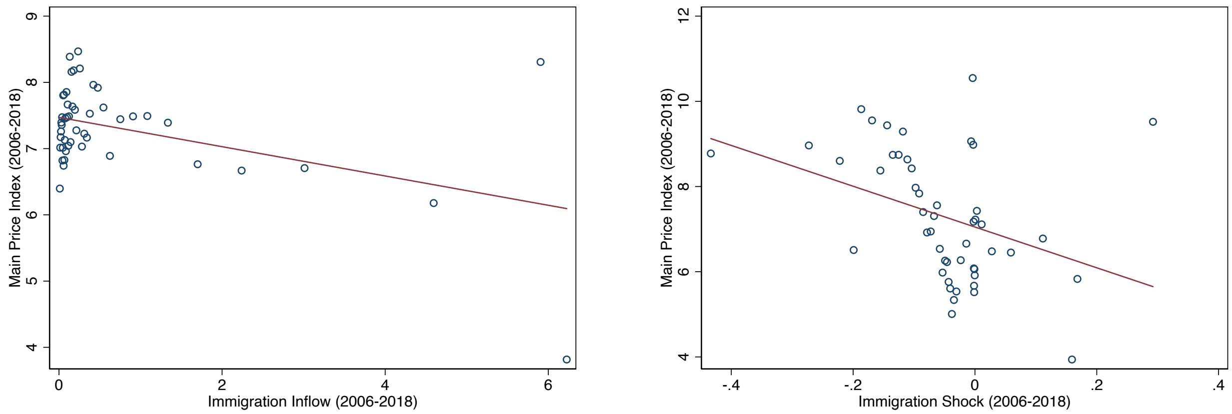
This section presents our baseline findings on how immigration affects consumer prices at the county level. We establish three main results. First, immigration reduces CPG prices, with effects driven primarily by low-skilled immigrants. Second, these price reductions extend beyond CPG products to durables and to the overall regional cost-of-living, despite increases in rental housing prices. Third, immigration has no significant effect on average nominal wages, implying real wage increases given the price reductions. These average effects mask heterogeneity by skill: low-skilled workers experience wage declines while high-skilled workers see gains.

4.1 Immigration and CPG Prices

Figure 3 provides initial visual evidence of the relationship between immigration and price changes. The left panel plots county-level price changes against actual immigration inflows, revealing a weak negative relationship. The right panel plots price changes against our predicted immigration shock Z_{dt}—the instrument based on historical settlement patterns—and shows a notably clearer negative relationship. This strong reduced-form relationship demonstrates the relevance of our instrument. Combined with the weak OLS pattern, this suggests that instrumental variables estimates may reveal larger causal effects than OLS, consistent with endogenous location choices attenuating OLS estimates. Both panels cumulate

[9] The modest service price dispersion within large metropolitan areas likely reflects greater price convergence in integrated urban markets.

Figure 3: Immigration and Price Changes Across Counties, 2006-2018



(a) OLS: Actual Immigration

(b) Reduced Form: Immigration Shock

Notes: Scatter plots show the relationship between cumulative CPG price changes (y-axis) and immigration measures (x-axis) at the county level from 2006-2018. Panel (a) uses actual immigration inflows I_{dt}, while panel (b) uses predicted immigration shocks Z_{dt} from equation (3.11). Price changes are measured using the Sato-Vartia index described in Section 3.3. Both variables are winsorized at the 5% level to reduce the influence of outliers. Each point represents a county, with point size proportional to initial county population. Fitted lines are from bivariate regressions without controls or fixed effects.

changes over 2006-2018 and show bivariate relationships without controls or fixed effects, motivating our formal regression analysis.

Table 3: Immigration and CPG Prices: Baseline Results

	Δ P^{SV,Stacked} (2006-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
Immigr$_{d,t}$	-0.038***	-0.026***	-0.021***	-0.068***	-0.065***	-0.058***
	(0.008)	(0.004)	(0.004)	(0.013)	(0.012)	(0.013)
Obs.	6,339	6,339	6,249	6,339	6,339	6,249
First-Stage F-stat				254.4	94.4	85.5
Fixed Effects	Time	State, Time	State, Time	Time	State, Time	State, Time
Method	OLS	OLS	OLS	IV	IV	IV
Controls			Yes			Yes

Notes: Table reports regressions of log changes in county-level CPG price indices on immigration, estimated using equation (3.1). The price index uses Sato-Vartia weights. Columns (1)-(3) report OLS estimates; columns (4)-(6) report IV estimates instrumenting immigration with predicted shocks from equation (3.11). Immigration is winsorized at top and bottom 1%. All specifications use stacked four-year differences (2006-2010, 2010-2014, 2014-2018). Column (1) includes only period fixed effects. Column (2) adds state and period fixed effects. Column (3) adds interactions of initial county GDP per capita and urban indicator with period dummies. Columns (4)-(6) follow the same structure with IV estimation. Standard errors clustered by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3 presents our baseline regression results. The OLS estimates in columns (1)-(3) show modest negative effects, and the IV specifications in columns (4)-(6) yield substantially larger negative coefficients, suggesting that immigrants positively select into counties with stronger economic conditions that would otherwise experience higher inflation. This pattern is consistent with immigrants seeking better economic opportunities, causing OLS to underestimate the causal price effects.

Our preferred specification in column (6) includes state and period fixed effects and controls for initial county characteristics interacted with period dummies. The estimated coefficient of -0.058 translates to an immigration inflow of 10,000 people (a shock comparable to that used by Terry et al. (2024)) reducing CPG prices by approximately 0.58 percentage points. Relative to the mean cumulative CPG inflation rate of 7.27% over four years in our sample, this price reduction represents approximately an 8% ($\approx 0.58/7.27$) proportional reduction in the average inflation rate. This price response highlights the economically significant role immigration plays in modulating local inflation and is comparable in proportional terms to the 3% to 5.5% wage effects (relative to the mean) found by Terry et al. (2024) for a similar shock magnitude.[10]

The stability of IV coefficients across columns (4)-(6) as we add state fixed effects and county-level controls demonstrates robustness to controlling for regional trends and differential county characteristics. Results are also robust to alternative price index formulations: Appendix Table B.3 shows that Jevons, Laspeyres, Paasche, and Törnqvist indices all yield statistically significant negative effects with magnitudes similar to our baseline Sato-Vartia specification.

4.2 Transmission Mechanism: Heterogeneous Effects by Immigrant and Consumer Characteristics

Our baseline results show that immigration exerts downward pressure on consumer prices. To start investigating the mechanisms summarized in Section 2, we exploit heterogeneity in two dimensions: the characteristics of the immigrant shock and the characteristics of the products consumed.

4.2.1 Immigrant Characteristics

One way the aggregate price effects may mask important heterogeneity is in terms of the immigrant characteristics driving price reductions. The demand-side mechanism relies on immigrants having higher price elasticity or lower willingness-to-pay than natives. We hypothesize that this effect should be driven primarily by lower-income or less-educated immigrants, who are more likely to face budget constraints and engage in intensive search.

[10]The estimated coefficient on the immigration shock is -0.058. The standard deviation of the shock differs across our paper and that in Terry et al. (2024) because we winsorize the regressor; results are robust to this specification choice.

Table 4: Heterogeneous Effects by Immigrant Characteristics

	Δ P$^{\text{Sato-Vartia,Stacked}}$ (2006-2018)			
	(1)	(2)	(3)	(4)
Panel A: Heterogeneity by Immigrant Characteristics				
$\text{Immigr}_{\text{d,t}}$ (over25)	-0.101***	-0.202***		
	(0.024)	(0.073)		
$\text{Immigr}_{\text{d,t}} \times \text{EducYears}_{\text{d,t}}$		0.088*		
		(0.051)		
$\text{Immigr}_{\text{d,t}}$ (No HS Degree)			-0.059**	
			(0.025)	
$\text{Immigr}_{\text{d,t}}$ (Some College)			0.019	
			(0.014)	
$\text{Immigr}_{\text{d,t}}$ (Low Inc. Occ.)				-0.045
				(0.028)
$\text{Immigr}_{\text{d,t}}$ (High Inc. Occ.)				0.055
				(0.053)
Obs.	6,249	6,245	6,249	6,249
First-Stage F-stat	85.5	8.2 / 7.0	59.3	19.3
Fixed Effects	State, Time	State, Time	State, Time	State, Time

Panel B: Heterogeneity by Product Basket (Low vs. High Income/Immigration)	Low-Inc Goods	High-Inc Goods	Low - High Inflation	High-Immigrant	Low Immigrant	High - Low Immigrant
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Immigr}_{\text{d,t}}$ (over25)	-0.127***	-0.077***	-0.050**	-0.136**	-0.102***	-0.034
	(0.032)	(0.022)	(0.021)	(0.055)	(0.024)	(0.046)
Obs.	6,249	6,249	6,249	6,249	6,249	6,249
First-Stage F-stat	85.5	85.5	85.5	85.5	85.5	85.5
Fixed Effects	State, Time	State, Time	State, Time	State, Time	State, Time	State, Time

Notes: This table investigates heterogeneous effects of immigration on CPG prices across two dimensions: immigrant characteristics and product market segments. **Panel A** estimates effects by immigrant characteristics. Column (1) restricts the sample to immigrants aged 25+ since these are more relevant for educational attainment (though results are consistent throughout). Column (2) interacts immigration (over 25) with average years of education, following Terry et al. (2024)'s IV construction using predicted immigration from top-25 origin countries as instruments; for this column, the reported First-Stage F-statistics are the Sanderson-Windmeijer multivariate F-statistics for the two endogenous regressors (Immigration / Education), respectively. Columns (3)-(4) construct separate instruments for mutually exclusive immigrant subgroups. Column (3) distinguishes immigrants without high school degrees vs. those with some college education. Column (4) distinguishes low-income (occupation score < 26) vs. high-income immigrants. **Panel B** examines heterogeneity by product type. Columns (1) and (2) estimate the effect of total immigration (age 25+) on separate price indices constructed for goods primarily purchased by low-income and high-income households, respectively. Column (3) uses the relative price difference between these two indices as the dependent variable. In columns (4) and (5) we estimate the effect of total immigration on the price index for goods primarily purchased by immigrants and those not primarily purchased by immigrants. The outcome in column (6) is the difference between the previous two outcomes. See Appendix A.3 for how to predict immigrants in the Household Panel. All specifications include state and period fixed effects and county controls, with immigration winsorized at 1%. Standard errors clustered by state.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Panel (A) in Table 4 investigates how immigration's effect on prices varies with immigrant skill levels. We restrict the analysis to immigrants aged 25 and over to ensure accurate measurement of education and occupation, as younger immigrants may not have completed their education or established stable career paths. Column (1) replicates our preferred specification from Table 3 with this age-restricted sample, confirming that our main results are robust to this restriction.

Column (2) examines whether the price effect varies with immigrant education. We interact total immigration with the average years of education of incoming immigrants, following the methodology of Terry et al. (2024). To instrument for this interaction term, we construct predicted immigration shocks separately for the top 25 immigrant origin countries (which account for the vast majority of U.S. immigration), and use these 25 country-specific predicted shocks as a joint set of instruments.[11] This approach leverages variation in both the volume and educational composition of immigration across origin countries: some origins send predominantly high-educated immigrants (e.g., India, China) while others send predominantly low-educated immigrants (e.g., Mexico, Central America). By using origin-country-specific shocks as instruments, we can identify how the skill composition of immigration—not just the volume—affects prices. The positive coefficient on the education interaction indicates that immigration's disinflationary effect is attenuated in counties receiving more educated immigrants. Each additional year of average immigrant education reduces the disinflationary effect by 0.88 percentage points. For example, an influx of high school graduates (12 years) would reduce prices by 9.6 percentage points per standard deviation shock, while an influx of college graduates (16 years) would reduce prices by only 6.1 percentage points.

Columns (3) and (4) pursue an alternative approach, constructing separate instruments for distinct immigrant subgroups. Column (3) distinguishes immigrants by educational attainment: those without high school degrees versus those with some college education. The results reveal that less-educated immigrants generate substantial price reductions, while more-educated immigrants show no significant effect. Column (4) performs a similar decomposition by occupation-based income, separating low-income (occupation score < 26) from high-income immigrants. Again, the disinflationary effect is concentrated among lower-income immigrants, while high-income immigrants show a positive but insignificant coefficient.

4.2.2 Consumer Characteristics

If the price decline is driven by the specific demand characteristics of immigrants, we should expect the effect to be larger in the basket of goods where they, as typically lower-income consumers, exert the strongest competitive pressure. We test this mechanism directly by producing separate price indices, classifying products as more likely to be purchased by low or high-income households using the Homescan Panel. We classify products as intensive in "low-income" demand if they are below the median in terms of the average household income

[11] This specification instruments two endogenous regressors: immigration and immigration interacted with education. The interaction uses the same education variable in both the endogenous regressor ($\text{Immigr}_{d,t} \times \text{EducYears}_{d,t}$) and its instrument ($Z_{d,t} \times \text{EducYears}_{d,t}$). The reported F-statistics are the Sanderson-Windmeijer multivariate F-statistics for individual endogenous regressors (Immigration / Education), respectively, as in this case the typical Kleibergen-Paap F-stat is not directly comparable to single-regressor specifications. The values suggest that we retain independent identifying variation. Furthermore, the Anderson-Rubin Wald test for joint significance (not reported) is highly significant ($p < 0.01$), confirming that the coefficients are statistically distinguishable from zero despite the weak identification.

of their consumers. These income-specific price indices are reminiscent of the recent literature on inflation inequality, such as Jaravel (2019), Faber and Fally (2022), and Argente and Lee (2021), which documents how inflation dynamics vary across the income distribution.[12]

The first three columns of Panel (B), Table 4 present the results. The first two columns report separately the immigration effect on a price index of low and high-income goods. The third column reports the differential effect, where the outcome is the difference between the low and high-income indices. Immigration lowers the price of *both* low-income and high-income goods, although the magnitude is significantly larger in the low-income index. The former result could reflect either a supply effect and/or a demand effect whereby immigrants alter the composition of buyers in both segments. The latter (differential) effect reflects a clear demand-side story: the arrival of price-sensitive immigrants places more competitive pressure on the low-income goods. These results also imply that the disinflationary benefits of immigration accrue disproportionately to lower-income households.

The last three columns of Panel (B) differentiate consumers by their *predicted immigrant share*. Appendix A.3 summarizes our construction of predicted immigrants in the Homescan Panel using a machine learning algorithm. We label products by their share of immigrant consumption. As a simple measure, the price index of "*High Immigrant*" products include products which at least half of immigrants consume. The first two columns compare the changes in the price indices of "*High Immigrant*" and "*Low Immigrant*" products, with the last column being the difference between these two by county. Although the differences are not big, we do see a larger price reduction effect in products that are more likely to be consumed by immigrants. However, even non-immigrant-intensive products see large price declines, which suggests that immigration shocks reduce price indices for a wide array of products.

These heterogeneity results provide important clues about mechanisms. The negative price effects are driven by lower-income, less-educated immigrants, which could be consistent with both supply-side channels (increased labor supply reducing wages and costs) and demand-side channels (greater price sensitivity and different shopping patterns increasing competitive pressure). Immigration places negative price pressure on both high and low-income products, but significantly more so on the low-income segment, consistent with a demand-side story. We distinguish between these mechanisms in Section 5 using firm-level data.

[12] Consistent with this literature, we find that inflation in our low-income price index is about 33% higher on average than the high-income index throughout the sample period.

4.3 Effects Beyond the CPG Sector

Our analysis thus far has focused on CPG products, which constitute a major component of household expenditures but not the entirety of the consumption basket. To assess the broader economic significance of immigration's price effects, we now examine impacts across other major expenditure categories and construct an aggregate measure of immigration's effect on the overall cost of living.

Table 5 presents IV estimates of immigration effects on prices across seven different sectors. Columns (1)-(4) use BLS city-level CPI data for 27 metropolitan areas, columns (5)-(6) use ACS rental data, and columns (7)-(8) use housing purchase price indices. The table reveals substantial heterogeneity in price effects across sectors, with implications for understanding both the mechanisms behind our CPG findings and the aggregate welfare effects of immigration.

Table 5: Immigration Effects on Prices Across Sectors

	$\Delta \ln P^{\text{Dur}}$	$\Delta \ln P^{\text{Non-dur}}$	$\Delta \ln P^{\text{Svc}}$	$\Delta \ln P^{\text{Rent,BLS}}$	$\Delta \ln P^{\text{Rent,ACS}}$		$\Delta \ln HP^{\text{CL}}$	$\Delta \ln HP^{\text{Z}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Immigr}_{\text{d,t}}$	-0.018	-0.046***	0.004	0.013	0.100***	0.014	0.027	-0.070
	(0.012)	(0.012)	(0.016)	(0.029)	(0.036)	(0.035)	(0.190)	(0.078)
Obs.	741	741	741	741	6,246	669	2,406	4,710
First-Stage F-stat	169.4	169.4	169.4	169.4	45.8	157.7	47.3	45.8
Fixed Effects	State, Time	State, Time	State, Time	State, Time	State, Time	State, Time	State, Time	State, Time
Method	IV	IV	IV	IV	IV	IV	IV	IV
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample						Cities		

Notes: Table reports IV estimates of immigration effects on prices across different sectors. Columns (1)-(4) use BLS city-level CPI data for 27 metropolitan areas (261 counties) covering durables, non-durables, services, and rent. Columns (5)-(6) use ACS median gross rent data: column (5) includes all counties, column (6) restricts to the 261 counties with BLS data. Columns (7)-(8) use housing purchase price indices: column (7) uses CoreLogic data (available 2006-2014 only), column (8) uses Zillow data (full period 2006-2018). All specifications instrument immigration with predicted shocks from equation (3.11) and include state and period fixed effects and county controls. Standard errors clustered by state for ACS and housing price regressions; heteroskedasticity-robust standard errors for BLS regressions due to small number of states. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Tradable Goods. Columns (1)-(2) examine BLS price indices for durables and non-durables. Non-durables show a statistically significant negative coefficient of -0.046, quantitatively similar to our baseline CPG results and providing important external validation using official BLS measures rather than scanner data. Durables show a negative but insignificant coefficient of -0.018. The weaker effect for durables may reflect that both immigrants and natives search intensively when making infrequent, high-stakes purchases like vehicles or appliances (Attanasio et al., 2022), so immigration does not substantially change the competitive pressure firms in CPG sectors face. In contrast, for frequently purchased non-durables, consumers exhibit substantial inertia and brand loyalty (Dubé et al., 2010; Bronnenberg et al., 2012; Hitsch et al., 2019), reducing search intensity for established residents while new immigrants—

lacking established shopping routines—engage in more intensive search, amplifying competitive pressure as the immigrant share rises.

Services and Housing. Columns (3) and (4) examine services and BLS rental prices, both showing small positive but insignificant effects. The muted effects for services may reflect their labor-intensive nature and lower tradability, potentially facing offsetting cost pressures from labor market adjustments. Columns (5) and (6) use ACS rental data to examine robustness across different samples. Column (5), using all counties, finds a positive coefficient of 0.100 (significant at 1% level). Column (6) restricts to the 261 counties covered by BLS data to ensure comparability with the BLS price measures in columns (4); this specification yields a much smaller and insignificant coefficient of 0.014, consistent with that using the BLS sample. The divergence between columns (5) and (6) likely reflects reduced statistical power and variation in the restricted sample, though we cannot rule out heterogeneous effects across metro and non-metro areas.

Housing Purchase Prices. Columns (7)-(8) present effects on home purchase prices using CoreLogic (2006-2014) and Zillow (2006-2018) data. Both show small, statistically insignificant coefficients. The existing literature on immigration and housing prices yields mixed findings. Previous studies have documented heterogeneous effects depending on factors such as local housing supply elasticity, native out-migration responses, and the composition of immigrant inflows (Saiz, 2007; Sanchis-Guarner, 2023; Sá, 2015; Albert and Monras, 2022). Our null results are consistent with this heterogeneity: our county-level estimates average across diverse local housing markets and likely reflect offsetting effects across different areas.

Aggregate (Regional) Cost-of-Living Effect. To translate these sector-specific findings into an overall assessment, we construct a weighted average using CPI expenditure weights (U.S. Bureau of Labor Statistics, 2018). Based on our baseline estimates, a 10,000 immigrant inflow reduces CPG prices by 0.58% (Table 3, column 6) and increases rental prices by 1% (Table 5, column 5). CPG products constitute approximately 18% of the CPI basket (Leung, 2021), while rent of primary residence accounts for approximately 7% of the CPI basket (U.S. Bureau of Labor Statistics, 2024). Weighting these effects by CPI shares and conservatively assuming null effects for all other categories yields a net aggregate disinflationary effect of approximately -0.034 ($= -0.58 \times 0.18 + 1.0 \times 0.07$) percentage points over four years. This aggregate calculation should be interpreted cautiously, as we lack precise estimates for all expenditure categories and our estimates reflect partial equilibrium effects.

4.4 Effects on the Other Local Economic Outcomes

To provide broader context for understanding the price effects documented above, we examine how immigration affects other key county-level outcomes: employment, establishments, and wages. These results are not intended to cleanly identify specific mechanisms—that is the purpose of our firm-level analysis in Section 5—but rather to characterize the constellation of local economic changes that accompany immigration inflows and price reductions.

4.4.1 Employment and Establishment Growth

Table B.9 columns (1)-(3) present effects on county-level employment and business activity using QCEW data. Column (1) shows that immigration significantly increases the number of establishments, with a one-standard-deviation shock raising establishment counts by approximately 60 establishments (about a 1.5% increase). Column (2) reports positive effects on total wage payments at the county level, while column (3) shows increases in total employment. All three effects are statistically significant and economically meaningful.

These findings indicate that immigration expands local economic activity along multiple margins. The increase in establishments suggests that immigration stimulates business creation and entry, consistent with evidence that immigrants found new businesses at high rates (Olney, 2013; Mahajan, 2024) and that their arrival can support new establishments targeting immigrant consumers. The employment gains reflect both direct effects—immigrants themselves working—and potential multiplier effects through increased local demand and business creation.

4.4.2 Wage Effects

Table B.8 examines immigration's effect on county-level average wages. This analysis is particularly important for interpreting our price results, as standard supply-side reasoning would predict that immigration-induced wage reductions drive lower production costs and prices.

The results reveal that immigration's wage effects in our 2006-2018 sample period are small and statistically indistinguishable from zero in most specifications. Column (1) shows a slightly negative but insignificant coefficient for all workers. Column (2) restricts to workers aged 25 and over for comparability with Terry et al. (2024), yielding similar results. These findings contrast with that study's finding of positive wage effects for the 1990-2005 period, particularly in counties receiving more educated immigrants.

Columns (3) and (5) investigate heterogeneity by interacting immigration with immigrant education levels, following Terry et al. (2024). We find evidence that wages increase in counties receiving more educated immigrants, consistent with their results, but the baseline (uninteracted) immigration effect remains close to zero. Panel B confirms that in the earlier 1990-2005 period, immigration did raise wages significantly, validating that our null results reflect genuine differences across time periods rather than specification choices.

Panel C examines retail-specific wages and rental prices, which are relevant since our CPG price data inherently include retail margins. We find small, insignificant effects on retail wages, suggesting that changes in retail labor costs are unlikely to drive our price results. Rental prices increase modestly as discussed earlier, but wholesale costs constitute roughly 75% of retail pricing (Stroebel and Vavra, 2019), so rental cost changes cannot explain the magnitude of price reductions we observe.

The absence of wage declines, combined with falling prices, suggests that supply-side cost reductions are not the primary driver of our price results. Instead, these patterns point toward demand-side mechanisms—changes in consumer composition, search behavior, or competition—as more likely explanations. We investigate these possibilities directly in our firm-level analysis by separating firms' exposure to immigration through sales locations (demand) versus production locations (supply).

4.4.3 Consumer Search Behavior

As suggestive evidence for demand-side mechanisms, Table 6 examines changes in consumer shopping behavior using Nielsen Homescan Panel data. We aggregate household-level shopping patterns to the county level and test whether they respond to immigration, separately analyzing Hispanic households (more likely to include immigrants) and white households (more likely to be natives).

The results reveal striking differences across demographic groups. For Hispanic households in high-immigration counties, we observe significant increases in the number of stores visited and coupon usage, with marginally significant increases in shopping days. These patterns are consistent with more intensive price search and comparison shopping. In contrast, white households show no significant changes in shopping behavior.

While this analysis cannot definitively establish causation or identify immigrants versus natives within Hispanic households, the patterns are highly suggestive of the mechanism we hypothesize: immigrant arrivals shift the composition of local consumer bases toward more price-sensitive shoppers who engage in intensive search across retailers. This behavioral change would naturally lead firms to reduce prices and markups to remain competitive for these search-intensive consumers. We explore this mechanism more rigorously in Section 5 using firm-level variation in exposure to immigration through sales versus production locations.

Table 6: Immigration and Consumer Search Behavior by Demographics

	Hispanic			White		
	(1) (# days)	(2) (# stores)	(3) (coupon share)	(4) (# days)	(5) (# of stores)	(6) (coupon share)
$\text{Immigr}_{d,t}$	0.105	0.179**	0.020*	0.003	-0.047	0.000
	(0.090)	(0.079)	(0.010)	(0.023)	(0.035)	(0.004)
Obs.	1,343	1,343	1,343	1,343	1,343	1,343
First-Stage F-stat	55.1	55.1	55.1	55.1	55.1	55.1
Fixed Effects	State, Time	State, Time	State, Time	State, Time	State, Time	State, Time

Notes: Table examines effects of immigration on shopping behavior using Nielsen Homescan Consumer Panel data aggregated to county level. Analysis is conducted separately for Hispanic households (columns 1-3) and white households (columns 4-6). Outcomes are: number of shopping days per month, number of distinct stores visited, and share of transactions using coupons. All specifications use stacked four-year differences with state and period fixed effects. Standard errors clustered by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.5 Summary

This section has established several key findings at the county level. Immigration significantly reduces CPG price inflation, with effects concentrated among lower-income, less-educated immigrants who are likely more price-sensitive. These disinflationary effects extend to other tradable goods but are offset partially by small increases in rental prices, yielding a net disinflationary effect on the aggregate cost of living. The county-level effects on other outcomes—establishment growth, employment gains, and minimal wage changes—provide context but do not cleanly identify mechanisms.

Importantly, the pattern of results—falling prices despite stable or increasing wages, stronger effects for low-income immigrants, and suggestive evidence of increased consumer search—points toward demand-side rather than supply-side mechanisms as the primary driver of price effects. We investigate this directly in the next section by exploiting firm-level variation in exposure to immigration through sales versus production locations, allowing us to cleanly separate demand and supply channels and test the consumer search mechanism more rigorously.

5 Firm-Level Results

Although the specification with county-level variation above is informative about the overall reduced-form effect of immigration on prices, there are a couple ways in which it hides informative mechanisms. First, it conflates demand and supply because what is sold in a county is not necessarily produced there.[13] If the supply effects in the producing counties are passed on to retail prices, we want to capture the exposure of a firm to its producing establishments and its retail counties separately. Second, the reduced form approach cannot separate a partial equilibrium effect from the local general equilibrium effect. It conflates many general equilibrium factors such as entry of new establishments, consumers moving across brands, and cross-county migration patterns. For example, the increase in consumer demand would lead to a higher labor supply in that local area, and the increased labor supply can further increase the consumer demand. Restricting to price changes within firms allows us to test more accurately the drivers of inflation.

5.1 Firm-Specific Immigration Shifters

We consider the following firm-level analyses, where a firms' exposure to immigration varies across the county where it sells its products and where it produces its output:

$$\Delta \ln P_f = \beta_0 + \beta_1 \mathrm{I}_f^{\text{demand}} + \beta_2 \mathrm{I}_f^{\text{supply}} + \mathbf{X'}_f \gamma + \alpha_g + \varepsilon_f \tag{5.1}$$

where $\Delta \ln P_f$ is a change in the log price index of firm f, $\mathrm{I}_f^{\text{demand}}$ is the immigration inflow in the areas where firms have sold their products, $\mathrm{I}_f^{\text{supply}}$ is the immigration inflow in the areas where firms have their plants, $\mathbf{X}'_f$ is the set of firm-specific control variables, such as the initial firm revenue and employment, and we control for industry-specific fixed effects.

$\mathrm{I}_f^{\text{demand}}$ and $\mathrm{I}_f^{\text{supply}}$ are measured as follows:

$$\mathrm{I}_f^{\text{demand}} = \sum_d \omega_{fd}^{\text{sales}} \mathrm{I}_d \tag{5.2}$$

$$\mathrm{I}_f^{\text{supply}} = \sum_d \omega_{fd}^{\text{empl}} \mathrm{I}_d \tag{5.3}$$

$\omega_{fd}^{\text{sales}}$ is the (initial) firm f's own sales share (of its total sales) in a market defined at the county level and $\omega_{fd}^{\text{empl}}$ is the firm f's own employment share (of its total employment) in a county market. Thus, each firm exposure is differentiated by where their sales and employment is situated. Note that we cannot differentiate immigration shocks by product group[14]. We

[13] Note that the sign of the effect cannot be used to inform the demand vs. supply effect. The increase in labor supply can increase or decrease wages and prices depending on the type of immigrants. Similarly, the increase in consumer demand can increase or decrease prices depending on the type of immigrants.

[14] It is technically possible to use the immigrants occupation in the IPUMS data and use a crosswalk to industries. In the same spirit, we can also modify I_d so that it restricts to immigrants with age > 25 or only those working in the CPG sectors. However, it is likely immigrants don't work in their stated occupations once they arrive in the United States, and even if they did, there would still be spillovers to the labor market

could however differentiate the sales and employment weights by product groups; the firm employment is based on the NETS data – classified by SIC industries – and we have constructed a crosswalk between SIC to Nielsen product groups based on our Nielsen-NETS firm-level matching. However, we have found that there is very little extra variation introduced by allowing the shocks to vary at the firm *and* group because most firms sell in only one group. Given the results end up so similar, we report results in the simpler case where I^{demand} and I^{supply} simply vary at the firm level.

5.2 Demand vs. Supply Exposure: Results

Table 7 reports the effect of immigration shocks on firm price changes, separating by demand and supply exposure. We begin with the Sato-Vartia price index, thus highlighting first only the prices of continuing products. All regressions include controls for the sum of the sales share in firms' retail market and the sum of employment shares in the firms' producing establishments in order to control for possible biases if there is missing price information in a firms' sales or producing county. We also include industry (SIC 3 digit) and time-period fixed effects (each firm is assigned a main SIC industry in the NETS data). In the specifications with the full set of controls, we also include firm controls transformed from the county data. First, we construct interactions of year dummies with firm exposures to the urban indicator and county GDP per capital in both the demand and supply location.[15] We also construct the exposure to changes in retail wages and median rents in the counties in which the firm sells and produces its output.[16]

The main takeaway is that immigration reduces inflation through demand-side exposure, perhaps surprisingly given the focus in the literature on supply-side effects such as labor shortages. When including the two types of exposure together, we observe that supply-side exposure leads firms to *raise* prices, with a small but statistically significant effect. In response to demand-side exposure, firms lower their prices and this is similar in magnitude to what we find at the county level. The baseline specification with the full set of controls, column (5), suggests that the demand-side exposure to immigration is in fact very similar to the county-level exposure analysis above. On the other hand, there are forces driving up prices

outside of that specific occupation which we would miss. We do note that our estimates might be lower bounds for the price effects as we implicitly assume that all immigration to county d can affect firm prices, while a firm's price product g is in reality relatively insensitive to immigration that affects far away in the "product space".

[15] For example, for each firm we construct an urban demand exposure based on the weighted average of the urban indicators in the counties it sells.

[16] We do not report the coefficients on the year-county indicator interactions, which are the only controls in columns (4) and (7). In columns (5) and (8) we also add the retail wages and rents.

when firms are more exposed to immigrants in the locations where they produce the good.

When including only the supply or demand exposure in the regressions, there is some evidence of bias. On the demand side, not controlling for the firm supply exposure reduces the magnitude of its price reductions. Not including the firms exposure on the demand side lowers the magnitude of the supply-side effect on prices. The OLS results are once again biased towards zero, with the predicted immigration shocks leading to a larger reduction in inflation for demand-side exposure to immigration. However, the bias appears to be smaller in this case with firm-level exposure. Once again, the results hold up when using a regression with 12-year long-differences – reported in Appendix Table B.11.

These results suggest that the negative price effects observed in the reduced form regressions above are driven by the demand side factors emphasized in Lach (2007). This could be due to the fact that immigrants are more elastic in their demand and thus change the composition of demand at the local level towards lower markup goods, or that fiercer competition in locales with more immigration – due to new entry of establishments (Mahajan, 2024; Beerli et al., 2021) – forces firms to reduce markups in those locations.

Table 7: Firm-Level Prices: Separate Demand and Supply Side Immigration Exposure

	Δ ln$P^{SV,Stack}$ (2006-2018)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigration$_{f,d,t}$ (D)	-0.071***	-0.057***		-0.057***	-0.061***	-0.066***	-0.047**	-0.051***
	(0.020)	(0.021)		(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
Immigration$_{f,d,t}$ (S)	0.016***		0.007	0.018***	0.019***	0.014***	0.015***	0.016***
	(0.005)		(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Δ lnW (Retail, D)					0.031			0.048
					(0.220)			(0.220)
Δ lnP (Rent, D)					0.220			0.178
					(0.184)			(0.176)
Δ lnW (Retail, S)					0.094			0.092
					(0.065)			(0.065)
Δ lnP (Rent, S)					-0.044			-0.033
					(0.065)			(0.066)
Obs.	11,037	11,037	11,037	11,037	11,037	11,037	11,037	11,037
First-Stage F-stat	3,743.0	4,895.9	4,907.7	3,733.2	3,977.5			
Fixed Effects	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time
Method	IV	IV	IV	IV	IV	OLS	OLS	OLS
Controls				Yes	Yes		Yes	Yes

Notes: This table checks the effect of immigration shocks on changes on firm-level prices with the baseline IV specification. Firm-level immmigration exposure is differentiated by supply and demand-side exposure as detailed in the main text. The price index refers to the Sato-Vartia index, the first term in Equation 6.9. We show specifications with stacked 4-year-differences (for 2006-2018). All regressions include controls for the sum of the sales share in firms' retail market and the sum of employment shares in the firms' producing establishments. This is to control for possible biases if there is missing price information in a firms' sales or producing county. We also include industry (SIC 3 digit) and time-period fixed effects (each firm is assigned a main SIC industry in the NETS data). Furthermore, columns (4) and (7) include interactions of year dummies with the firm-level exposure to counties' urban indicator and GDP per capita. The exposure is constructed at both the demand and supply side – based on the counties it produces and sells in. In columns (5) and (8) we also add the retail wages and rents. Standard errors clustered are by SIC 3 digit industries. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Mechanism: Search Intensity In order to explain the strong negative demand-side effects, we investigate consumer shopping behavior, utilizing the Homescan Consumer Panel. The outcomes are aggregated from the household level: for each firm, we take a weighted average of the households that shop that brand. For example, the first column of Table 8 examines how the number of trips taken by households that shop from a firm is associated with exposure to demand and supply-side immigration. Similarly, we also examine number of days shopping (per month) of households, the number of stores visited, the number of products purchased, and the share of purchases that are store brands. As would be consistent with our mechanism, we find that more immigration in counties where the good is consumed is associated with firms having consumers that take more trips, shop more days, visit more stores, and but a higher share of store brand products. Households do not buy more products, so the results are not consistent necessarily with more variety.

The last column attempts to test more directly the prices faced by consumers conditional on their exposure to immigration. For each household connected to the firm, we compute the relative price paid by that household for other products (leaving out the price paid to the focal firm).[17] We find a strong negative effect coming from the demand-side immigration shock, which suggests that firms exposed to more immigrant consumers are facing more price-sensitive buyers. Overall, Table 8 reveals strong support for the search mechanism, suggesting firms would reduce markups in margins where they face more elastic demand.

Table 8: Firm-Level Search Intensity

	Δ lnPurChar^{SV,Stack} (2006-2018)					
	(1) N. Trips	(2) N. Days	(3) N. Stores	(4) N. Products	(5) % Store Brand	(6) Rel. Price
Immigration$_{f,d,t}$ (D)	0.012**	0.010**	0.008	-0.002	0.008*	-0.002***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.001)
Immigration$_{f,d,t}$ (S)	-0.000	0.001	0.000	0.001	0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.000)
Obs.	10,325	10,325	10,325	10,325	10,325	10,317
First-Stage F-stat	3,736.1	3,736.1	3,736.1	3,736.1	3,736.1	3,735.5
Fixed Effects	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time	Industry, Time
Method	IV	IV	IV	IV	IV	IV
Controls						

Notes: The regression is weighted by the initial sales. Missing shares are controlled. We also include industry (SIC 3 digit) and time-period fixed effects (each firm is assigned a main SIC industry in the NETS data). Standard errors clustered are by SIC 3 digit industries. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Mechanism: Demand Elasticities An implication of higher search intensity is that it should be reflected in higher demand elasticities that firms face. Therefore, as a check on our proposed demand-side mechanism, we estimate elasticities across firms (within a product group) as well as within firms (across products) assuming a CES demand system. We follow

[17]The relative price of each product consumed by the household is constructed as in **?**, where we take the price paid by the household relative to the US average for an identical barcode.

the typical strategies in the literature, e.g. Feenstra (1994), Hottman et al. (2016), except we estimate these separately by state, product group, and time period. [18] Thus, we are able to leverage across time and regional variation in demand elasticities to test whether these are associated with our immigration shocks.

Table 9 reports how demand elasticities respond to changes in immigration across various specifications. First, we examine county-group-time variation, where counties within the same state have the same estimated elasticity (first two columns) and we control for county-group and time-group interacted fixed effects (first two columns). We also aggregate immigration to the state level and produce a state-group-time specification with state-group and time-group fixed effects. The two procedures produce quantitatively very similar results. An increase in immigration is always associated with higher demand elasticities, and this is seen for both firm-specific elasticities (σ^F) and product group elasticities (σ^U)

Table 9: Demand Elasticities

	Demand Elast. (σ)			
	(1) σ^F	(2) σ^U	(3) σ^F	(4) σ^U
Immigration (100K)	0.040**	0.062**	0.052***	0.082***
	(0.017)	(0.025)	(0.006)	(0.012)
Obs.	465,736	465,736	11,033	11,033
First-Stage F-stat	2,189	2,189	154	154
Fixed Effects	County-Group, Time-Group	County-Group, Time-Group	State-Group, Time-Group	State-Group, Time-Group
Aggregation	County-Level	County-Level	State-Level	State-Level

Notes: This table checks the effect of immigration shocks on demand elasticities. Demand elasticities are estimated from the barcode data at a state-product group-period level, with periods identifying the separate estimations for 2006-2010, 2011-2014, and 2015-2018. The regression is ran with two separate aggregations: 1) with county-group-period variation, where counties within the same state have the same demand elasiticites; and 2) at the state-product-period, where we aggregate immigration across counties within a state. In (1), we control for county-product and year-product interacted fixed effects, while in (2) we include state-product and product-year fixed effects. Immigration in this talbe is in 100,000s. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6 A Structural Approach with Firm Prices

Our analysis thus far has established that immigration reduces prices primarily through demand-side channels. To understand the specific mechanisms behind this effect, we develop a structural model of multiproduct firm pricing with heterogeneous consumers (see Appendix C for the full setup and derivation). The model formalizes how immigration affects prices through three interconnected mechanisms:

First, **the elasticity/markup effect (M1)**: Immigrants exhibit higher demand elasticity than natives because lower incomes increase the relative value of their outside consumption

[18] Specifically, we estimate firm and group level elasticities by state-product group-year. To be consistent with the baseline sample, the year pertains to 3 different periods: 2006-2010, 2010-2014, and 2014-2018.

option. When immigration increases the immigrant share in local markets, the effective demand elasticity firms face for a given product rises as a quantity-weighted average: $\tilde{\sigma}_{\text{eff}} = \sum_h \omega_h \tilde{\sigma}_h$, where ω_h is each consumer group's quantity share in each product's demand (suppressing the product index). Since ω_i increases with immigration and $\tilde{\sigma}_i > \tilde{\sigma}_n$, the effective elasticity rises, which directly compresses equilibrium markups through the standard monopolistic competition pricing formula.

Second, **quality composition effects (M2)** operate through two distinct channels that have different empirical implications:

- **(M2a) Between-product composition**: Immigrants have systematically lower valuations for high-quality products ($\phi_i < \phi_n$ for products with high quality), shifting aggregate expenditure toward cheaper goods. Crucially, this mechanism does not appear in conventional price indices that hold the product basket constant, but it does affect consumer welfare and appears in the quality index Φ we construct below.

- **(M2b) Within-product quality effects**: For any given product, the effective quality perceived by the market ($\bar{\phi}_u = \sum_h \omega_{uh} \phi_{uh}$) changes as the consumer composition shifts. As immigrants become a larger share of purchasers, the effective quality of each product adjusts, affecting equilibrium pricing through the markup formula. This mechanism is embedded in observed price changes.

Third, **the scale effect (M3)**: Population growth increases quantities demanded, raising marginal costs under the convex cost structure typically observed in production ($MC = a \cdot q^{\delta}$ where $\delta > 0$). This creates upward pressure on prices that partially offsets the downward pressure from M1 and M2.

The theoretical model reveals a critical distinction for empirical measurement: the between-product quality composition effect (M2a) is not captured by standard price indices, yet it represents an important channel through which immigration affects consumer welfare.

Standard price indices—including the Sato-Vartia (SV) index we constructed in Section 3 and official statistical agency measures like the CPI—attempt to measure "constant-quality" inflation by holding the product basket constant or making hedonic adjustments. This approach captures three of our mechanisms:

- M1 (elasticity/markup): Changes in markups μ_u directly affect observed prices p_u

- M2b (within-product quality): Changes in effective quality $\bar{\phi}_u$ affect equilibrium pricing through the markup formula and are embedded in observed price changes

- M3 (scale): Higher quantities raise marginal costs, feeding into observed prices

However, M2a—the shift in expenditure toward lower-quality products—does not appear in standard price indices because they are constructed to hold the product basket constant. When immigrants choose systematically different (cheaper) consumption bundles, conventional indices miss this welfare-relevant adjustment. To fully capture immigration's effect on consumer welfare, we need a decomposition that separates price changes on continuing varieties from changes in the composition of products consumed.

Moreover, immigration may also affect the set of products available in the market. On one hand, M1 (markup compression) reduces firm profitability, potentially discouraging product entry. On the other hand, M3 (scale effects from larger markets) increases profitability, encouraging entry. The net effect on product variety is theoretically ambiguous and depends on which force dominates. Understanding variety effects is important because product availability itself affects consumer welfare, even holding prices constant (Feenstra, 1994).

To empirically decompose immigration's effects across these channels, we require an accounting framework that maps the theoretical mechanisms from Appendix C to observables in our data. The household demand model in Appendix C establishes *why* immigrants affect prices differently than natives (through elasticity, quality preferences, and scale effects), but does not specify *how to measure* these effects in firm-level scanner data with changing product varieties and qualities. The nested CES framework we develop below provides this measurement structure: it shows how to aggregate barcode-level prices into firm-level indices while decomposing changes into conventional price effects (capturing M1, M2b, and M3), variety adjustments (capturing net entry/exit effects), and quality composition changes (capturing M2a). This accounting decomposition is agnostic about the micro-foundations—it would apply regardless of whether price changes stem from demand-side or supply-side forces—but the interpretation of each component is guided by the theoretical mechanisms established in Appendix C.

6.1 Real Consumption Effect

Consider a nested demand system in each location, where the upper nest is across product groups within each location, the middle nest is across firms within each sector and location, and the lower nest is across products within each firm, product group, and location.[19]

Specifically, household utility is a Cobb-Douglas aggregate of real consumption of a

[19]The setup is identical to that of Hottman et al. (2016), except we apply the same setup for every county.

continuum of product groups:

$$\ln U_{ct} = \int_{g \in \Omega_{ct}} \phi^{C}_{gct} \ln C_{gct} dg \tag{6.1}$$

where g is a product group, c is a county, and t is time. ϕ^{S}_{gct} is the share of expenditure on product group g in county c at time t, C_{gct} is the real consumption of product group g in county c at time t, and Ω_{ct} is the set of product groups in county c at time t. Within each product group, households have the following nested CES demand across firms and products:

$$C_{gct} = \left[\sum_{f \in \Omega_{gct}} (\phi^{F}_{fgct} C^{F}_{fgct})^{\frac{\sigma^{F}_{g}-1}{\sigma^{F}_{g}}} df \right]^{\frac{\sigma^{F}_{g}}{\sigma^{F}_{g}-1}}, \quad C_{fgct} = \left[\sum_{u \in \Omega_{fgct}} (\phi^{U}_{ut} C^{U}_{ut})^{\frac{\sigma^{U}_{g}-1}{\sigma^{U}_{g}}} df \right]^{\frac{\sigma^{U}_{g}}{\sigma^{U}_{g}-1}} \tag{6.2}$$

where ϕ^{F}_{fgct} is the taste/appeal/quality of firm f in product group g in county c at time t, σ^{F}_{g} is the demand elasticity across firms for a given product group g, ϕ^{F}_{ut} is the taste/appeal/quality of product u by firm f in product group g in county c at time t, and σ^{U}_{g} is the demand elasticity across products for a given firm f.

The corresponding well-known exact CES price index is:

$$P_{gct} = \left[\sum_{f \in \Omega_{gct}} \left(\frac{P_{fgct}}{\phi_{fgct}} \right)^{1-\sigma^{F}_{g}} \right]^{\frac{1}{1-\sigma^{F}_{g}}}, \quad P_{fgct} = \left[\sum_{u \in \Omega_{fgct}} \left(\frac{P_{ut}}{\phi_{ut}} \right)^{1-\sigma^{U}_{g}} \right]^{\frac{1}{1-\sigma^{U}_{g}}}$$

Using a property of the CES demand, we derive market shares (see Appendix **??** and substitute them into the price indices:

$$P_{fgct} = \frac{P_{ut}}{\phi_{ut}} (S_{ut})^{\frac{1}{\sigma^{U}_{g}-1}} \tag{6.3}$$

$$P_{gct} = \frac{P_{fgct}}{\phi_{fgct}} (S_{fgct})^{\frac{1}{\sigma^{F}_{g}-1}} \tag{6.4}$$

Note that the expression for ϕ_{fgct} is the following:

$$\phi_{fgct} = \frac{P_{fgct}}{P_{gct}} (S_{fgct})^{\frac{1}{\sigma^{F}_{g}-1}} \tag{6.5}$$

The fundamental intuition is that the firm-level appeal/quality/taste is what changes the market share conditional on price; it is the structural residual.

Similar to the aggregate analyses in Redding and Weinstein (2020), to allow the entry and exit of products and firms, we derive the Feenstra variety adjustment. These are defined in the appendix, but essentially measure the share of expenditure on products available in both t and $t-1$. Market shares are then adjusted to account for products available in both time periods plus the variety adjustment.

In this setup, the ratio of the price indices are defined as:

$$\Phi_{fgct} = \frac{P_{fgct}}{P_{fgc,t-1}} = \frac{P_{ut}/\phi_{u,t}}{P_{u,t-1}/\phi_{u,t-1}} \left(\frac{\lambda_{fgct}}{\lambda_{fgc,t-1}} \frac{S^*_{ut}}{S^*_{u,t-1}} \right)^{\frac{1}{\sigma_g^U - 1}} \tag{6.6}$$

$$\Phi_{gct} = \frac{P_{gct}}{P_{gc,t-1}} = \frac{P_{fgct}/\phi_{fgct}}{P_{fgc,t-1}/\phi_{fgc,t-1}} \left(\frac{\lambda_{gct}}{\lambda_{gct,t-1}} \frac{S^*_{fgct}}{S^*_{fgc,t-1}} \right)^{\frac{1}{\sigma_g^F - 1}} \tag{6.7}$$

where S^*_{ut} denotes the market share of product u among the products that continue in $t-1$ and t in time t, and S^*_{fgct} denotes the market share of firm f among the firms that continue in $t-1$ and t in time t. λs represent the Feenstra variety adjustment.

As a necessary normalization, we assume that the geometric weighted mean of the consumer taste parameters is constant for continuing varieties (see appendix), then take the weighted geometric means of Equations (6.6) and (6.7) among the products that continue in $t-1$ and t and among the firms that continue in $t-1$ and t. The resulting price indices are shown in the appendix, but here we further assume Sato-Vartia weights for w_{kt} and w_{kgct}, which allows us to write the decomposition more simply as[20]:

$$\frac{P_{fgct}}{P_{fgc,t-1}} = \prod_{k \in \Omega_{fgct,t-1}} \left(\frac{P_{kt}}{P_{k,t-1}} \right)^{w_{kt}} \left(\frac{\sum_{k \in \Omega_{fgct,t-1}} S_{kt}}{\sum_{k \in \Omega_{fgct,t-1}} S_{k,t-1}} \right)^{\frac{1}{\sigma_g^U - 1}} = \Phi^{SV}_{fgct} \Phi^F_{fgct} \tag{6.8}$$

$$\frac{P_{gct}}{P_{gc,t-1}} = \prod_{k \in \Omega_{gct,t-1}} \left(\frac{P_{kgct}}{P_{kgc,t-1}} \right)^{w_{kgct}} \left(\frac{\sum_{k \in \Omega_{gct,t-1}} S_{kgct}}{\sum_{k \in \Omega_{gct,t-1}} S_{kgc,t-1}} \right)^{\frac{1}{\sigma_g^F - 1}} = \Phi^{SV}_{gct} \Phi^F_{gct} \tag{6.9}$$

Thus, the change in the price index can be decomposed into two parts. The first part is the relative prices of common varieties, where prices are aggregated using a geometric mean with Sato-Vartia weights (the "SV" price index).[21] The second part is the variety adjustment correction term as in Feenstra (1994), which lowers the price index when this term is below one (since $\sigma > 1$).[22] The intuition is that consumers have substituted to new and preferable

[20]For example: $w_{kt} = \dfrac{\frac{s^*_{kt} - s^*_{k,t-1}}{\ln s^*_{kt} - \ln s^*_{k,t-1}}}{\sum_{k \in \Omega_{fgct,t-1}} \frac{s^*_{kt} - s^*_{k,t-1}}{\ln s^*_{kt} - \ln s^*_{k,t-1}}}$

[21]This index include only *common* varieties.

[22]λ_t is the share of expenditure on common varieties relative to total expenditure in time t. Thus, if after

varieties, exemplified by the new varieties gaining market share.[23]

Firm Quality Adjustment: To further adjust for the firm-specific appeal/taste/quality, Hottman et al. (2016) suggest using $\frac{P_{fgct}}{\phi_{fgct}}$. The quality-adjusted firm x group x county x time index becomes:

$$\frac{P_{fgct}/\phi_{fgct}}{P_{fgc,t-1}/\phi_{fgc,t-1}} = \Phi^{SV}_{fgct}\Phi^{F}_{fgct}\left(\frac{\phi_{fgc,t-1}}{\phi_{fgct}}\right) \tag{6.10}$$

where the growth rate of appeal/taste/quality can be expressed as:

$$\frac{\phi_{fgct}}{\phi_{fgc,t-1}} = \frac{P_{fgct}/P_{fgc,t-1}}{P_{gct}/P_{gc,t-1}}\left(\frac{S_{fgct}}{S_{fgc,t-1}}\right)^{\frac{1}{\sigma^F_g-1}} \tag{6.11}$$

Intuitively, conditional on firm price changes, if the market share has not increased as much as what the demand elasticity speaks to, we attribute all the residual changes as the appeal/quality/taste changes.

Finally, substituting the appeal parameters into quations (6.6) and (6.7), our "real" consumption index is composed of three parts:

$$\frac{C_{fgct}}{C_{fgc,t-1}} = \left(\frac{P_{fgct}/\phi_{fgct}}{P_{fgc,t-1}/\phi_{fgc,t-1}}\right)^{-1} = \left(\Phi^{SV}_{fgct}\right)^{-1}\left(\Phi^{Variety}_{fgct}\right)^{-1}\left(\Phi^{Appeal}_{fgct}\right)^{-1} \tag{6.12}$$

6.2 Real Consumption Decomposition: Results

We now turn to the full decomposition of equation 6.12. Importantly, the response of prices of continuing goods might hide that firms also switch to lower quality goods being sold, or respond through changes in variety. On the supply-side, the effect is not consistent with wage reductions being the main consequence of new immigrants in a locale. It is also not consistent with large cost reductions or productivity increases as have been found in much of the literature, as Peri (2012), Brinatti et al. (2023), and other studies. This could be due to firms adjusting their production as natives move to new tasks (Peri and Sparber, 2009). It might reflect higher quality goods being produced. On the demand side, firms might respond to more elastic demand or fiercer competition by lowering prices, but might also shift to lower quality goods. Furthermore, firms might raise variety to reach the new consumers or reduce

incorporating new and exiting varieties, the expenditure on common varieties is less than total expenditures in t, then $\lambda_t < 1$. A lower λ_t lowers the cost of living index because $\sigma > 1$.

[23]Notice that the aggregation can be done at the firm-group-county-level[24] and at the group-county level. The latter can be used to produce the county-level aggregate price index.

variety to concentrate on core products (Mayer et al., 2014).

Table 10 reports the exact price decomposition. The aggregate *Consumption* index refers to the sum of the Sato-Vartia price index of continuing varieties, the Feenstra correction term, and the quality adjustment. *Note that we multiply each component by -1, so that a positive number represents an increase in real consumption.* The top panel is for the stacked specification and the lower panel for the long-difference, although once again the differences between the two are minimal. The second column reproduces the (now negative) first column of the previous table (while the first column in the bottom panel is column (4) of the previous table).

The effect on continuing prices stand in contrast to the variety and appeal components. We see that most of the demand effect in lowering real prices is from continuing varieties, however there is a large drop in the appeal of the products sold by firms more exposed to immgration in the counties where they sell their product. The opposite is true from supply-side exposure, where firms increase their variety, though this effect is small. The sign on the supply-side exposure is as expected, with firms producing more varieties that might reflect the different preferences of immigrants (di Giovanni et al., 2015; Mazzolari and Neumark, 2012). The positive sign on the demand exposure is surprising, as it suggests that firms reduce the number of varieties they sell, which might reflect concentration on core products.

As should be expected from the large immigration literature that finds firms innovate more in response to immigrant labor (Kerr and Lincoln, 2010; Terry et al., 2024; Hunt and Gauthier-Loiselle, 2010; Choudhury and Kim, 2019), there is an increase in quality for firms exposed on the supply-side. This could partially explain the observed price increases. On the demand side, the effect is once again of the opposite sign. More exposure to immigrant consumers lowers the estimated quality of a firms' sales. This is also consistent with the price reductions seen in this setting.

Table 10: Firm-Level Prices: Decomposition of CES Exact Index

	Δ $\ln C^{Stack}$ (2006-2018), Decomposition			
	(1) Consumption	(2) SV-Price	(3) Variety	(4) Appeal
$\text{Immigration}_{f,d,t}$ (D)	-0.008	0.057***	-0.004	-0.061**
	(0.024)	(0.020)	(0.004)	(0.024)
$\text{Immigration}_{f,d,t}$ (S)	0.003	-0.018***	0.003	0.019**
	(0.006)	(0.004)	(0.003)	(0.009)
Obs.	11,037	11,037	11,037	11,037
First-Stage F-stat	3,733.2	3,733.2	3,733.2	3,733.2
Fixed Effects	Industry, Time	Industry, Time	Industry, Time	Industry, Time
Method	IV	IV	IV	IV
Controls	Yes	Yes	Yes	Yes

Notes: This table checks the effect of immigration shocks on changes on firm-level prices with the baseline IV specification. Firm-level immmigration exposure is differentiated by supply and demand-side exposure as detailed in the main text. Note that we multiply each aggregate by -1, so that a positive number represents an increase in real consumption. The "consumption" index (first column) refers to the sum of the Sato-Vartia, Feenstra correction, and quality adjustment as shown in Equations 6.9 and 6.11. The second and third columns represent the effect on prices of contining varieties and the Feenstra variety correction (6.9), while the fourth column is the quality adjustment (Equation 6.11. We show specifications with stacked 4-year-differences (for 2006-2018), as well as just one 12-year long-difference (2006-2018). All regressions include controls for the sum of the sales share in firms' retail market and the sum of employment shares in the firms' producing establishments. This is to control for possible biases if there is missing price information in a firms' sales or producing county. We also include industry (SIC 3 digit) and time-period fixed effects (each firm is assigned a main SIC industry in the NETS data). Standard errors clustered are by SIC 3 digit industries. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7 Conclusion

This paper addresses a fundamental question in the immigration and inflation debate: how do firms adjust their prices when exposed to immigrant workers and consumers? Using comprehensive firm-level data that links product prices to both retail and production locations, we provide the first evidence on how immigration affects prices through distinct demand-side and supply-side channels.

Our key finding is that immigration's effect on prices operates primarily through the demand channel rather than traditional supply-side mechanisms. When firms face greater immigration exposure in counties where they sell their products, they reduce prices significantly. A county receiving 12,500 additional immigrants over four years experiences price growth that is 0.73 percentage points lower – an economically meaningful effect representing a 12% reduction in inflation. This demand-side effect appears driven by immigrants' more intensive search behavior and greater price sensitivity, forcing firms to lower markups to compete for these consumers. Conversely, supply-side immigration exposure – immigration in counties where firms produce – has small positive effects on prices, contradicting simple models where immigrant labor reduces costs.

Instead, our decomposition reveals that supply-side immigration leads firms to increase product quality, consistent with literature showing that immigrants facilitate innovation and enable native workers to move to higher-skill tasks. The structural decomposition further reveals that while demand-side immigration reduces prices of continuing varieties, it also leads firms to offer lower-quality products, likely reflecting the preferences of more price-sensitive immigrant consumers. These findings help explain the reduced-form county-level results showing that immigration lowers local inflation.

Our results have important implications for ongoing policy debates linking immigration to inflation. Rather than immigrant labor reducing production costs and prices, the primary anti-inflationary effect of immigration operates through changing the composition of demand toward more price-elastic consumers. This suggests that immigration restrictions aimed at fighting inflation may be counterproductive, as they would reduce the presence of price-sensitive consumers who help keep prices low.

A necessary limitation of this analysis is a limited view of service sectors, where immigrants constitute a larger share of workers. The ability to delve deeper into services, and non-tradables more generally, might produce interesting differences in the suppl-side effects. We believe the channels highlighted in this paper are externally valid, but given data availability, those sectors would prove fruitful for future research. In that sense, the ability to expand on how these firm-level pricing responses aggregate to economy-wide inflation dynamics is crucial. Additionally, examining how these effects vary across different types of immigrants and economic conditions would provide further insights into the immigration-inflation nexus.

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Appendix A Data Appendix

A.1 Nielsen GS1 + NETS Matching

To identify the production locations of the consumer goods in our price dataset, we link firms in the GS1 dataset (which provides the brand and manufacturer name via the UPC prefix) to the National Establishment Time-Series (NETS) database (which provides the headquarters address and employment counts).

We utilize the 2019 vintage of the NETS database and the 2017 vintage of the GS1 database. Because there is no common numeric identifier between these two administrative datasets, we develop a multi-step string matching algorithm. The procedure consists of three stages: Data Pre-processing, Hierarchical Matching, and Cardinality Resolution.

A.1.1 Data Pre-processing and Standardization

Before matching, we standardized company names and addresses in both datasets to maximize match rates.

1. **Lexical Standardization:** We utilized the Stata commands `stnd_compname` and `stnd_address` to harmonize common abbreviations (e.g., "Street" vs. "St", "Corporation" vs. "Corp") and remove non-identifying characters.

2. **Entity Type Cleaning:** To ensure that minor variations in legal registration did not prevent a match (e.g., matching "Smith Foods Inc" to "Smith Foods LLC"), we generated stripped versions of company names by systematically removing legal entity types (e.g., INC, LLC, LTD, CO) and their spacing.

3. **Geographic Harmonization:** City names were converted to uppercase to match the GS1 format. ZIP codes were split to isolate the primary 5-digit code from the 4-digit extension to allow for flexible matching levels.

4. **State Formatting:** We harmonized state codes across datasets, ensuring the inclusion of U.S. territories (Puerto Rico and Virgin Islands) which are present in our scanner data.

A.1.2 Hierarchical Matching Algorithm

We employed an iterative matching process that prioritizes precision over recall. We constructed a "match quality" variable based on four increasingly strict criteria.

First, we performed an exact join based on the standardized company name (`stn_name`). We then refined this pool using state and address data. For the fuzzy address matching step, we utilized the `reclink2` algorithm with a bigram string comparator. We assigned matching weights of `wmatch(10 1 2 5 8)` corresponding to Name, State, City, Zip Code, and Street Address, respectively, requiring a mandatory exact match on Name and State.

We classified the resulting matches into the following quality tiers:

- **Tier 1 (Name Only):** Exact match on the standardized company name.
- **Tier 2 (Name + Entity):** Exact match on the standardized name AND an exact match on the stripped entity type (e.g., verifying that both files listed the firm as an "INC" or that the suffix was absent in both).
- **Tier 3 (Name + Entity + State):** Meets Tier 2 criteria AND the headquarters state in NETS matches the firm's state in GS1.
- **Tier 4 (Full Address Validation):** Meets Tier 3 criteria AND satisfies a high-confidence fuzzy match on the specific street address (calculated via `reclink2`).

For our final dataset, we imposed the most conservative specification, retaining only observations that satisfied **Tier 4** (labeled as `match >= 4` in our replication code). This ensures that we match on name, legal entity structure, state, and specific street address simultaneously.

A.1.3 Cardinality Resolution (Many-to-One vs. One-to-Many)

A structural challenge in linking these datasets is the cardinality of the relationship. A single firm often registers multiple GS1 prefixes (one for each brand or product line), while a single GS1 prefix should theoretically map to a single parent firm. However, name duplication can lead to "One-to-Many" (1:m) links where a single brand name matches multiple distinct NETS headquarters Duns Numbers.

To ensure proper identification of the firm's location, we applied the following resolution logic to the matched pairs:

- **Retained (1:1 and m:1):** We retained cases where a single GS1 prefix matched a single NETS ID (1:1), or where multiple GS1 prefixes matched the same NETS ID (m:1). The latter represents a multi-brand conglomerate (e.g., a parent company owning multiple distinct brand prefixes) and constitutes a valid link for our identification strategy, as these brands face the same firm-level shocks.

- **Dropped (1:m and m:m):** We dropped cases where a single GS1 prefix linked to multiple different NETS Duns Numbers. These represent ambiguous matches (e.g., a generic name like "Best Foods" appearing in multiple states) where we cannot definitively identify which headquarters owns the brand.

The resulting dataset serves as the baseline for the API-based validation described in the subsequent section.

A.1.4 Validation of Firm Linkages via Web Search API

A limitation of the strict address matching described above (specifically Tier 4) is that it may exclude valid firm-plant linkages. For example, a firm may list a manufacturing facility's address in the GS1 dataset while its corporate headquarters appears in the NETS dataset. These locations often share a state but differ in city and street address, causing them to fail the strict address fuzzy match. Conversely, matching solely on "Name + State" (Tier 3) risks false positives for common firm names (e.g., "Best Foods") that may exist independently in multiple cities within the same state.

To resolve this trade-off—expanding recall to include valid multi-establishment firms while maintaining high precision—we implemented a secondary validation procedure using a web search API. This process targets the subset of firm pairs that matched on *Name* and *State* but failed the strict *Address* match.

A.1.5 Sample Stratification and Pre-Screening

We first restricted the validation sample to firm pairs located in the same state. This decision followed a manual verification pilot (conducted in February 2024) which indicated that cross-state matches for this subset of firms were overwhelmingly false positives. We then stratified the same-state pairs into two categories based on city concordance:

1. **Same-City Matches (Auto-Accepted):** Pairs located in the same city (but with differing street addresses) were deemed high-probability matches. Given the low likelihood of two distinct firms with identical names operating in the same city, and considering the computational cost of API queries, these pairs were accepted without further validation. These observations are stored in the dataset `manual_match_all_small_samecity.dta`.

2. **Different-City Matches (API Validated):** Pairs located in the same state but different cities represent the ambiguous cases requiring digital verification. These pairs

were subjected to the API matching algorithm described below. These observations are processed in the dataset `apimatch_diffct.dta`.

A.1.6 API Matching Algorithm

For the "Different-City" pairs, we automated a web search procedure to determine if the two physical locations belonged to the same corporate entity. The algorithm proceeds as follows:

1. **Query Generation:** For each firm in the pair (the GS1 entity and the NETS entity), we constructed a search query string combining the firm's name, city, and state (e.g., "[Firm Name] [City] [State]").

2. **URL Extraction:** We utilized a custom search API to fetch the top search results for each query and extracted the root domains of the associated URLs (e.g., extracting `company-xyz.com` from `www.company-xyz.com/about`).

3. **Common Domain Verification:** We compared the set of URLs retrieved for the GS1 firm (U_{GS1}) with the set retrieved for the NETS firm (U_{NETS}). A pair is classified as a validated match (`MatchStatus = 1`) if the intersection of their domains is non-empty:

$$U_{GS1} \cap U_{NETS} \neq \emptyset$$

   This criterion leverages the fact that even if a firm has distinct physical addresses for its plant and HQ, both locations will typically reference the same primary corporate website in search results.

This procedure allows us to distinguish between valid corporate networks (e.g., a "Traders Point Creamery" in Zionsville, IN matching a production facility in Indianapolis, IN via the common domain `traderspointcreamery.com`) and spurious name collisions. The final dataset combines the strictly matched address pairs (Tier 4), the same-city pairs, and the API-validated different-city pairs.

A.2 Nielsen + NETS Industry Crosswalk

A.3 Identifying Immigrant Households in the Nielsen Panel

This appendix describes the machine learning framework used to predict immigrant households in the Nielsen Household Panel (HMS), enabling analysis of immigrant-specific shopping behavior and price sensitivity. Because the HMS does not directly identify immigration status, we develop a supervised learning approach that leverages labeled data from the American Community Survey (ACS) and a supplementary Nielsen survey module to predict immigrant households within the panel.

A.3.1 Data Sources and Domain Adaptation Challenge

We integrate three complementary data sources covering 2004–2019:

1. **American Community Survey (ACS):** Household-level microdata from IPUMS providing nationally representative information on demographics, education, occupation, and—crucially—immigration status and nativity. The ACS contains approximately 1.4 million household observations and serves as the primary labeled training data.

2. **Nielsen Household Panel (HMS):** Annual household demographic and purchasing information from participating panelists, including household composition, income, education, and shopping behavior. HMS serves as the prediction target but does not contain immigration labels.

3. **Tell Us More About You (TUM) 2008 Survey:** A supplementary questionnaire administered to approximately 40,000 HMS households in 2008, collecting place of birth and migration history. TUM provides ground-truth immigration labels within the HMS sampling frame.

The central methodological challenge is *domain adaptation*: while the ACS provides abundant labeled data on immigration status, it exhibits substantial covariate shift relative to the HMS target population. The TUM module bridges these domains by providing labeled observations drawn directly from the HMS sampling frame, though its sample size is limited. Table A.1 summarizes these three data sources.

A.3.2 Data Harmonization

To ensure cross-source consistency, all datasets are transformed into a unified household-level schema. Person-level ACS records are aggregated to the household level, retaining only household heads. Occupational codes are mapped via crosswalks reconciling pre-2017 and

Table A.1: Comparison of Data Sources for Immigrant Prediction

	ACS	HMS	TUM 2008
Years	2004–2019	2004–2019	2008
Sample size (households)	$\sim$1.4M	$\sim$200k	$\sim$40k
Immigration label	Yes	No	Yes
Analytical role	Labeled source	Unlabeled target	Bridge domain

post-2018 IPUMS schemes, and income and education categories are re-binned to match HMS codes. For HMS, households with both male and female heads are split into separate observations, variable names are aligned with ACS equivalents, and missing values are retained as categorical levels (since our algorithm handles them directly). TUM responses are merged into corresponding HMS household records using unique household identifiers, with careful cleaning to ensure one valid observation per household.

A.3.3 Machine Learning Algorithm

We employ CatBoost (Prokhorenkova et al., 2018), a gradient boosting decision tree (GBDT) algorithm specifically designed for categorical data. Several features make this approach well-suited to our prediction task:

- **Nonlinearity and interactions:** Decision trees automatically capture nonlinear effects and variable interactions (e.g., between age, income, and education) without manual specification.
- **Efficient categorical encoding:** CatBoost replaces each category with an ordered target statistic computed using only "past" observations, avoiding target leakage while efficiently handling high-cardinality categorical variables common in survey data.
- **Robustness to mixed data types:** Trees handle both continuous and categorical variables, as well as missing values, with minimal preprocessing.
- **Reduced overfitting:** Ordered boosting—building trees using different permutations of the training data—produces unbiased gradient estimates and improves generalization on small labeled samples such as TUM.

A.3.4 Domain Adaptation Strategy

To address covariate shift between the ACS (source domain) and HMS (target domain), we implement multiple training regimes and select the best-performing approach:

1. **ACS-only regimes:** Models trained on the full ACS sample, with validation either on an ACS hold-out fold or on TUM.

2. **IPS-weighted ACS regimes:** Models trained on ACS but reweighted using inverse propensity scores (IPS) to make ACS resemble TUM or HMS. IPS weights are constructed by training a classifier to distinguish ACS from the target domain; observations more similar to the target receive higher weights:

$$w_i = \frac{1}{1 - \hat{p}(D = \text{TUM}|X_i)} \tag{A.1}$$

   where $\hat{p}(D = \text{TUM}|X_i)$ is the predicted probability that household i originates from TUM given covariates X_i.

3. **ACS–TUM mixture regimes:** Models trained on mixtures of downsampled ACS and TUM training data, using either fixed ratios (1:1 or 2:1) or IPS-adjusted domain weights.

Across all models intended for HMS prediction, hyperparameter tuning, early stopping, and threshold selection rely exclusively on TUM validation data, since TUM is the only labeled dataset aligned with the HMS sampling frame. TUM samples are stratified by immigrant status and split 80:20 into training and validation sets at the household level.

A.3.5 Household-Level Aggregation

Model predictions are obtained at the individual-year level and then aggregated to the household level using one of four strategies: maximum, mean, median, or "noisy-or" probability aggregation:

$$\hat{p}_h^{\text{noisy-or}} = 1 - \prod_{i \in h}(1 - \hat{p}_i) \tag{A.2}$$

The optimal aggregation strategy is selected empirically using TUM validation data.

A.3.6 Model Performance

Table A.2 reports predictive performance on the held-out TUM validation split for each model family, evaluated using AUC (ranking performance) and F1 score (identification of the minority immigrant class).

Several patterns emerge from these results:

Table A.2: Predictive Performance on TUM Validation by Model Family

Model Family	**AUC**	**F1**
ACS-IPS-TUM	0.770	**0.371**
ACS-IPS-HMS	0.771	0.365
ACS-transfer	0.758	0.346
ACS-only	0.753	0.334
TUM-only	0.754	0.318
Mix 2:1	0.761	0.230
Mix 1:1	0.766	0.224
Mix-IPS	0.732	0.182

Notes: AUC measures the probability that a randomly chosen immigrant household receives a higher predicted score than a randomly chosen non-immigrant household. F1 is the harmonic mean of precision and recall for identifying immigrant households. Best strategy refers to the optimal household-level aggregation method selected on TUM validation data.

- **Covariate shift matters:** ACS-only models perform well on ACS but degrade substantially when evaluated on TUM, reflecting systematic differences between the nationally representative ACS and the Nielsen panel population.

- **IPS weighting is effective:** Reweighting ACS observations to match the target domain distribution substantially improves both AUC and F1, with the ACS-IPS-TUM model achieving the highest F1 score (0.371).

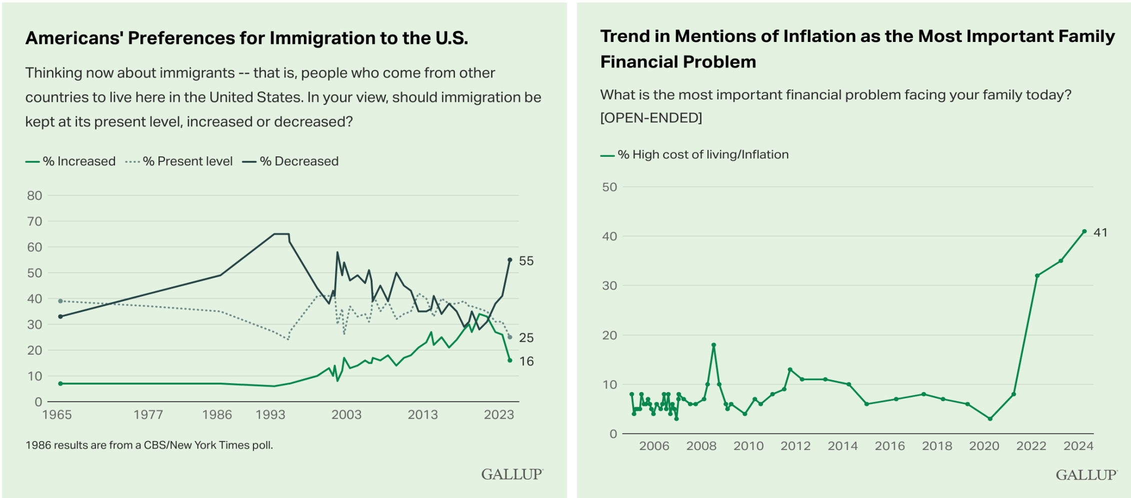
- **Ranking vs. identification trade-off:** Mixture models preserve high AUC close to the TUM-only benchmark, indicating strong ranking ability, but their F1 scores are lower due to more conservative identification of minority-class households.

The best-performing model (ACS-IPS-TUM) achieves an AUC of 0.77 and F1 of 0.37, representing substantial improvement over rule-based proxies commonly used in economics (e.g., ethnicity-based or surname-based heuristics). These gains are important because the constructed immigrant measure feeds directly into our analysis of immigrant shopping behavior and price sensitivity in Sections 4 and 5.

A.3.7 Application to Shopping Behavior Analysis

The selected model is applied to all HMS households not included in TUM to generate predicted immigration probabilities. These predictions are then scaled using HMS projection factors to recover population-level immigrant shares by county. In our firm-level analysis, we use these predictions to characterize the consumer base of firms facing different levels of immigrant demand exposure, enabling tests of whether immigrants exhibit systematically different shopping patterns (e.g., more trips, more stores visited, greater coupon usage) that would be consistent with heightened price search intensity.

Figure B.1: Opinion Polls on Immigration and Inflation Concerns



Notes: Figures are sourced from GALLUP polls. Figure on the left is sourced from an article on July 12, 2024, with the following link: Sharply More Americans Want to Curb Immigration to U.S.. Figure on the right is sourced from an article on May 2, 2024, with the following link: Americans Continue to Name Inflation as Top Financial Problem

Appendix B Additional Tables and Figures

B.1 County-Level Analysis

Table B.3: Robustness to Alternative Price Index Formulations

	Δ P$^{\text{Jevons}}$ (2006-2018)		Δ P$^{\text{Laspyres}}$ (2006-2018)		Δ P$^{\text{Passche}}$ (2006-2018)		Δ P$^{\text{Tornqvist}}$ (2006-2018)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigr$_{\text{d,t}}$	-0.021**	-0.014**	-0.069***	-0.067***	-0.067***	-0.063***	-0.068***	-0.065***
	(0.008)	(0.006)	(0.012)	(0.011)	(0.014)	(0.012)	(0.013)	(0.012)
Obs.	6,339	6,339	6,339	6,339	6,339	6,339	6,339	6,339
First-Stage F-stat	254.4	94.4	254.4	94.4	254.4	94.4	254.4	94.4
Fixed Effects	Time	State, Time	Time	State, Time	Time	State, Time	Time	State, Time
Method	IV	IV	IV	IV	IV	IV	IV	IV

Notes: Table reports IV regressions of log changes in county-level CPG price indices on immigration using alternative index formulations. Columns (1)-(2) use the Jevons (unweighted geometric mean) index; columns (3)-(4) use the Laspeyres index; columns (5)-(6) use the Paasche index; columns (7)-(8) use the Törnqvist index. Odd-numbered columns include only period fixed effects; even-numbered columns add state and period fixed effects. All specifications instrument immigration with predicted shocks from equation (3.11) and winsorize immigration at top and bottom 1%. All specifications use stacked four-year differences (2006-2010, 2010-2014, 2014-2018). Standard errors clustered by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.4: First Stage Results: Immigration on Push-Pull Instruments at Country-County Level

	Immigration$^t_{o,d}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{A}_{o,d,1975} \times \tilde{I}_{o,-r(d),1980}$	0.0034***	0.0034***	0.0034***	0.0034***	0.0033***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1980} \times \tilde{I}_{o,-r(d),1985}$	0.0016***	0.0016***	0.0016***	0.0016***	0.0015***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1985} \times \tilde{I}_{o,-r(d),1990}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0017***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1990} \times \tilde{I}_{o,-r(d),1995}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,1995} \times \tilde{I}_{o,-r(d),2000}$	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2000} \times \tilde{I}_{o,-r(d),2005}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2005} \times \tilde{I}_{o,-r(d),2010}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2010} \times \tilde{I}_{o,-r(d),2014}$	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d,2014} \times \tilde{I}_{o,-r(d),2018}$	0.0001***	0.0001***	0.0001***	0.0001***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$I^t_{Euro,d}$				0.0255***	
				(0.0047)	
$\mathrm{I}^t_{o,-r(d),t}\frac{I_{Europe,r(d)\tau}}{I_{Europe,-r(d)\tau}}$					0.2805**
					(0.1155)
Obs.	4,607,847	4,607,847	4,607,847	4,607,847	4,607,847
adj R-sq	0.602	0.602	0.631	0.637	0.649
Distance	No	Yes	Yes	Yes	Yes
Latitude Dis.	No	Yes	Yes	Yes	Yes
Region-Country FE	No	No	Yes	Yes	Yes
County-Continent FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Concurrent Euro Immigration	No	No	No	Yes	No
Contemporaneous Push-Pull	No	No	No	No	Yes

Notes: Specification follow Terry et al. (2024), to show we can replicate their instruments. In all cases, the push-pull instruments follow the specification in (**??**), with one instrument for every year t. We extend the data by adding 2014 and 2018. The first column represents a specification with no controls or fixed effects, the second column adds Distance controls, and column (3) adds the full set of fixed effects. The third column is our baseline specification. In column (4) we additionally control for concurrent European immigration, while in the last column we instead control for the contemporaneous interaction term from the ancestry prediction. Standard errors clustered are by country. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.5: Long-Difference (one period)

	Δ P$^{\text{SV,LongDiff}}$ (2006-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Immigr}_{\text{d,t}}$	-0.041***	-0.029***	-0.024***	-0.054***	-0.035***	-0.031***
	(0.009)	(0.004)	(0.004)	(0.011)	(0.006)	(0.008)
Obs.	2,113	2,112	2,082	2,113	2,112	2,082
First-Stage F-stat				273.5	92.4	89.4
Fixed Effects	None	State	State	None	State	State
Method	OLS	OLS	OLS	IV	IV	IV
Controls			Yes			Yes

Notes: Specifications follow the order of Table 3, but for the 12-year long difference of prices and immigration. Standard errors are clustered by state. Both immigration shock and immigration are winsorized by top and bottom 1%. Controls: 2006 county GDP per capita and urban indicator, each interacted with the year indicators.

Table B.6: Price Regressions: Larger Sample of Products (6 years in sample)

	Δ P$^{\text{SV,Stacked}}$ (2006-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Immigr}_{\text{d,t}}$	-0.034***	-0.028***	-0.023***	-0.062***	-0.064***	-0.056***
	(0.008)	(0.004)	(0.005)	(0.011)	(0.013)	(0.014)
Obs.	6,339	6,339	6,249	6,339	6,339	6,249
First-Stage F-stat				267.7	95.6	86.3
Fixed Effects	Time	State, Time	State, Time	Time	State, Time	State, Time
Method	OLS	OLS	OLS	IV	IV	IV
Controls			Yes			Yes

Notes: This table checks the effect of immigration shocks on changes in county-level average prices with the baseline IV specification. The price indices are constructed with products that are available for at least 6 years, instead of 14 years as in the baseline sample. Immigration shocks and endogenous immigration are winsorized by top and bottom 1%. We show specifications with stacked 4-year-differences (for 2006-2018), as well as just one 12-year long-difference (2006-2018). All regressions include state and time-period fixed effects, except columns (2) and (5), which replace state with county fixed effects. In column (4), we include controls that include retail wages, median rents, plus the interaction of GDP and unemployment rate at the county-level with year indicators. In columns (5) and (7) we continue to control for retail wages and median rents. Standard errors clustered are by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.7: County Price Regressions: Robustness

	Δ $P^{\text{Sato-Vartia,Stacked}}$ (2006-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Immigr}_{d,t}$ / $\text{Pop'l}_{d,t}$	-1.106***					
	(0.249)					
$\text{Immigr}_{d,t}$		-0.058***	-0.058***	-0.038***	-0.005***	-0.026***
		(0.013)	(0.012)	(0.009)	(0.001)	(0.008)
Mexico Border		-0.334***				
		(0.111)				
total ICE Arrests			0.046***			
			(0.012)			
Obs.	6,339	6,249	6,249	6,246	6,249	6,249
First-Stage F-stat	9.3	86.4	101.5	77.7	860.8	2,217.5
Fixed Effects	State, Time	State, Time	State, Time	State-Time	State, Time	County, Time
Baseline +	Imm / Popl	Border	ICE Arrests	State-Year FE	Non-Winsorized	County FE

Notes: Both immigration shock and immigration are winsorized by top and bottom 1%. All regressions include state and time-period fixed effects. Standard errors clustered are by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.8: Wage Regressions

A. Real Wages, 2006-2018

	Δ lnWages$^{\text{Stacked}}$ (2006-2018)			Δ lnWages$^{\text{LongDiff}}$ (2006-2018)	
	(1)	(2)	(3)	(4)	(5)
$\text{Immigr}_{d,t}$	0.014				
	(0.022)				
$\text{Immigr}_{d,t}$ (over25)		0.024	-0.316*	0.029	-0.548*
		(0.038)	(0.180)	(0.030)	(0.324)
$\text{Immigr}_{d,t} \times \text{EducYears}_{d,t}$			0.396*		0.633*
			(0.200)		(0.335)
Obs.	6,249	6,249	6,245	2,082	2,082
First-Stage F-stat	46.0	41.4		41.4	
Fixed Effects	State, Time	State, Time	State, Time	State	State
Method	IV	IV	IV	IV	IV
Controls	Yes	Yes	Yes	Yes	Yes

B. Real Wage Regressions, 1990-2005

	Δ lnWages$^{\text{Stacked}}$ (1990-2005)	
	(1) dlnrwage	(2) dlnrwage
$\text{Immigr}_{d,t}$	0.158***	
	(0.027)	
$\text{Immigr}_{d,t}$ (over25)		0.219***
		(0.041)
Obs.	9,155	9,155
First-Stage F-stat	75.8	65.6
Fixed Effects	State, Time	State, Time

C. Retail Wages and Rents (2006-2018)

	Δ lnWages (Retail)$^{\text{Stacked}}$	Δ lnWages (Retail)$^{\text{LongDiff}}$	Δ lnRent$^{\text{Stacked}}$	Δ lnRent$^{\text{LongDiff}}$
	(1)	(2)	(3)	(4)
$\text{Immigr}_{d,t}$	-0.017	0.017	0.095***	0.069**
	(0.034)	(0.039)	(0.035)	(0.031)
Obs.	6,229	2,074	6,246	2,081
First-Stage F-stat	46.0	45.7	46.0	45.6
Fixed Effects	State, Time	State, Time	State, Time	State, Time
Controls	Yes	Yes	Yes	Yes

Notes: This table checks the effect of immigration shocks on changes in county-level average annual real wages, average real wages in retail, and median rent (all in logs) with the baseline IV specification. Wages are "real" in the sense that we deflate using the national PCE deflator, though of course not county-level prices. We show specifications with stacked 4-year-differences (for 2006-2018), as well as just one 12-year long-difference (2006-2018). We restrict the sample to include the same counties with available price indices. Panel A includes as the outcome annual wages for all sectors (within private industry) from QCEW. In the first column, our immigration includes all immigrants, while in the rest of the columns we include only immigrants over the age of 25 (to compare with Terry et al. (2024). Panel B checks the effect of immigration on real wages. The sample is 1990-2010, with 5-year long differences. Column (2) is similar to Terry et al. (2024), with a non-weighted specification. In Panel C, we include wages specifically for retail sectors (from QCEW) as well as median rent prices as reported in Table NH056A in IPUMS NHGIS. All regressions include state and time-period fixed effects. Controls indicate the interaction of initial county characteristics (GDP per capita and urban indicator) with year trends. Standard errors clustered are by state. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table B.9: QCEW and Housing Outcome Regressions

	Δ Y$^{\text{Stacked}}$ (2006-2018)				
	(1) (Δ # Establ.)	(2) (Δ WL)	(3) (Δ Emp.)	(4) (ΔHP$^{06-14}$, CL)	(5) (ΔHP^{06-18}, Z)
Immigr$_{\text{d,t}}$	0.012**	0.242***	0.746***	0.027	-0.070
	(0.005)	(0.025)	(0.247)	(0.190)	(0.078)
Obs.	6,249	6,249	6,249	2,406	4,710
First-Stage F-stat	45.9	45.9	45.9	47.3	45.7
Fixed Effects	State, Time	State, Time	State, Time	State, Time	State, Time
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table checks the effect of immigration shocks on changes in county-level outcomes with the baseline IV specification. It includes QCEW local employment outcomes as well as house values. The first 3 outcomes, all from QCEW, are changes in: # of establishments (in thousands), total county wages (in $billions), and total employment (in thousands). The last two columns include house prices, where we show results for CoreLogic data, available from 2006-2014, as well as Zillow Home Value Index (ZHVI) data available for the whole sample. We restrict counties to those with available price data, though for the housing data this is not a constraint. We show specifications with stacked 4-year-differences (for 2006-2018), as well as just one 8-year long-difference (2010-2018). All regressions include state and time-period fixed effects. Standard errors clustered are by state. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.10: Alternative Rent Prices from ACS

	Δ P$^{\text{SV,Stacked}}$ (2006-2018)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Immigr$_{\text{d,t}}$	0.070***	0.075***	0.083***	0.065***	0.078**	0.100***	0.014
	(0.019)	(0.020)	(0.017)	(0.023)	(0.033)	(0.036)	(0.035)
Obs.	6,336	6,336	6,246	6,336	6,336	6,246	669
First-Stage F-stat				23.7	49.8	45.8	157.7
Fixed Effects	Time	State, Time	State, Time	Time	State, Time	State, Time	State, Time
Method	OLS	OLS	OLS	IV	IV	IV	IV
Controls			Yes			Yes	Yes
Sample							Cities

Notes: Rent prices are reported median gross rents, variable NH063A in the NHGIS dataset, downloaded through IPUMS. Standard errors are clustered by state except the last column, where the robust standard errors are reported. Both immigration shock and immigration are winsorized by top and bottom 1%. Controls: 2006 county GDP per capita and urban indicator, each interacted with the year indicators. All regressions include state and time-period fixed effects. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B.2 Firm-Level Analysis

Table B.11: Firm-Level Prices: Demand and Supply Exposure, Long-Difference

	Δ ln$P^{SV,\text{Long-Difference}}$ (2006-2018)			
	(1)	(2)	(3)	(4)
Immigration$_{f,d,t}$ (D)	-0.051***	-0.052***		-0.043**
	(0.018)	(0.019)		(0.018)
Immigration$_{f,d,t}$ (S)	0.013**		0.001	0.018***
	(0.006)		(0.006)	(0.006)
Δ lnW (Retail, D)				-0.128
				(0.263)
Δ lnP (Rent, D)				-0.335
				(0.298)
Δ lnW (Retail, S)				0.306**
				(0.147)
Δ lnP (Rent, S)				-0.225
				(0.230)
Obs.	3,629	3,629	3,629	3,629
First-Stage F-stat	3,152.4	3,494.1	6,156.1	1,664.2
Fixed Effects	Industry	Industry	Industry	Industry
Method	IV	IV	IV	IV
Controls				Yes

Notes: The regression is weighted by the initial sales. Missing shares are controlled. Standard errors are clustered by the industry; the industry is the initial 3-digit SIC code. Controls: 2006 county GDP per capita and urban indicator, each weighted by either initial sales share or employment share across counties within firm, and interacted with the year indicators. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.12: Firm-Level Price Decomposition: Long-Difference

	Δ ln$C^{\text{Long-Difference}}$ (2006-2018), Decomposition			
	(1) Consumption	(2) SV-Price	(3) Variety	(4) Appeal
Immigration$_{f,d,t}$ (D)	-0.011	0.043**	0.001	-0.054***
	(0.020)	(0.018)	(0.006)	(0.019)
Immigration$_{f,d,t}$ (S)	0.003	-0.018***	0.002	0.019**
	(0.008)	(0.006)	(0.002)	(0.008)
Obs.	3,629	3,629	3,629	3,629
First-Stage F-stat	1,664.2	1,664.2	1,664.2	1,664.2
Fixed Effects	Industry	Industry	Industry	Industry
Controls	Yes	Yes	Yes	Yes

Notes: The regression is weighted by the initial sales. Missing shares are controlled. Standard errors are clustered by the industry; the industry is the initial 3-digit SIC code. Controls: 2006 county GDP per capita and urban indicator, each weighted by either initial sales share or employment share across counties within firm, and interacted with the year indicators. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix C Theoretical Model

This appendix presents a theoretical framework explaining how immigration affects prices through demand composition effects. We build on Hottman, Redding and Weinstein (2016)'s model of Bertrand competition among multiproduct firms with heterogeneous appeal (quality), extending it to incorporate household heterogeneity in income.

We derive differences in demand elasticities and quality preferences across household types from income heterogeneity and the resulting differences in outside option values. Lower-income immigrants have: (1) higher demand elasticities because the outside good becomes relatively more attractive when income is constrained, and (2) lower valuations for high-quality products because quality is a luxury good.

C.1 Environment

Notational Conventions. For notational simplicity, we suppress county and time subscripts throughout the theoretical exposition. Our empirical strategy exploits within-county variation over time, and these subscripts are reintroduced explicitly when discussing empirical implementation in Section 2.3.

Consumer Types and Preferences. There are two types of consumers: natives ($h = n$) and immigrants ($h = i$), with population masses L_n and L_i respectively. Each household type h has per-capita income y_h, with $y_i < y_n$ reflecting that immigrants typically have lower incomes than natives.

Households have nested CES preferences over an outside good (numeraire) and differentiated products organized in groups g, firms f within groups, and products u within firms. The upper-tier utility is Cobb-Douglas:

$$U_h = C_{0h}^{1-\alpha} \left[\prod_g C_{gh}^{\beta_g} \right]^{\alpha} \tag{C.1}$$

where C_{0h} is consumption of the outside good (numeraire), C_{gh} is a composite of differentiated products in group g, $\alpha \in (0, 1)$ is the aggregate expenditure share on differentiated products, and $\sum_g \beta_g = 1$ are group expenditure shares conditional on purchasing differentiated products.

The nested structure for differentiated products is:

$$C_{gh} = \left[\sum_{f \in \Omega_g} (\phi_{fgh})^{\frac{1}{\sigma_g^F - 1}} (C_{fgh}^F)^{\frac{\sigma_g^F - 1}{\sigma_g^F}} \right]^{\frac{\sigma_g^F}{\sigma_g^F - 1}} \tag{C.2}$$

$$C_{fgh}^F = \left[\sum_{u \in \Omega_{fg}} (\phi_{ufgh})^{\frac{1}{\sigma_g^U - 1}} (c_{ufgh})^{\frac{\sigma_g^U - 1}{\sigma_g^U}} \right]^{\frac{\sigma_g^U}{\sigma_g^U - 1}} \tag{C.3}$$

where $\sigma_g^F > \sigma_g^U > 1$ are elasticities of substitution, ϕ_{fgh} captures firm-level appeal (quality) to consumer type h, and ϕ_{ufgh} captures product-level appeal.

Budget Constraint. Each household faces:

$$C_{0h} + \sum_g P_{gh} C_{gh} = y_h \tag{C.4}$$

From the Cobb-Douglas upper tier, expenditure on differentiated products is αy_h and on the outside good is $(1 - \alpha) y_h$.

C.2 Microfounding Elasticity Differences from Income

We now derive how lower-income immigrants have higher demand elasticities, grounding this in the value of the outside option.

C.2.1 The Role of the Outside Good

The key insight is that the outside good provides a fallback consumption option. When a differentiated product's price rises, consumers can substitute to the outside good. The attractiveness of this substitution depends on how much utility the consumer derives from the outside good, which in turn depends on income.

From the Cobb-Douglas upper tier (C.1), the marginal utility of income allocated to the outside good is:

$$\frac{\partial U_h}{\partial C_{0h}} = (1 - \alpha) C_{0h}^{-\alpha} \left[\prod_g C_{gh}^{\beta_g} \right]^{\alpha} \tag{C.5}$$

With the budget constraint, $C_{0h} = (1-\alpha)y_h$, so:

$$\frac{\partial U_h}{\partial C_{0h}} = (1-\alpha)^{1-\alpha} y_h^{-\alpha} \left[\prod_g C_{gh}^{\beta_g}\right]^\alpha \tag{C.6}$$

Key observation: The marginal utility from the outside good is *decreasing* in income (due to the $y_h^{-\alpha}$ term). Lower-income consumers face a tighter budget constraint, making the outside good relatively more valuable to them.

C.2.2 Deriving Income-Dependent Elasticities

Consider a consumer's decision when the price of product u increases. The consumer compares:

1. Continuing to purchase product u at the higher price (reducing outside good consumption)
2. Substituting to another product within the firm
3. Substituting to another firm
4. Substituting to the outside good

The outside good's "pull" on the consumer is stronger when its marginal utility is higher—i.e., when income is lower. This makes low-income consumers more willing to substitute away from any given differentiated product when its price rises.

Formally, we can express the *effective elasticity of substitution* that incorporates the outside good option as:

$$\tilde{\sigma}_{g,h}^U = \sigma_g^U + \lambda \cdot \frac{1}{y_h} \tag{C.7}$$

where $\lambda > 0$ is a parameter capturing the strength of the outside good effect, and σ_g^U is the baseline CES elasticity within the nest.

[Income and Demand Elasticity] Lower-income consumers have higher effective demand elasticities:

$$y_i < y_n \quad \Rightarrow \quad \tilde{\sigma}_{g,i}^U > \tilde{\sigma}_{g,n}^U \tag{C.8}$$

Proof: Direct from equation (C.7) and $y_i < y_n$. □

Microfoundation of λ. The parameter λ can be derived from the model primitives. The utility gain from reallocating expenditure to the outside good (rather than paying a higher price for product u) is proportional to the marginal utility of the outside good, which scales as $y_h^{-\alpha}$. In a discrete choice setting with logit errors (as in the random utility interpretation of CES), this translates to the coefficient on income in the effective elasticity formula. For our purposes, we treat λ as a reduced-form parameter that captures this effect.

Empirical Counterpart. In our empirical analysis (Table ??), we estimate state-level elasticities and find they increase with immigrant share, consistent with this mechanism. The estimated elasticity differences correspond to the effective elasticity gap $\tilde{\sigma}^U_{g,i} - \tilde{\sigma}^U_{g,n}$ in the model.

C.3 Microfounding Quality Preferences from Income

We now derive how lower-income immigrants have systematically lower valuations for high-quality products.

C.3.1 Quality as a Luxury Good

Quality is a luxury good: richer consumers are willing to pay more for quality improvements. We formalize this by assuming quality appeal depends on income:

$$\phi_{ufgh} = \phi_{ufg} \cdot \psi(y_h, q_{ufg}) \tag{C.9}$$

where ϕ_{ufg} is objective quality and $\psi(y_h, q_{ufg})$ captures how income affects quality valuation.

Assumption QP (Quality-Income Relationship):

$$\frac{\partial \psi}{\partial y} > 0, \quad \frac{\partial \psi}{\partial q} > 0, \quad \frac{\partial^2 \psi}{\partial y \partial q} > 0 \tag{C.10}$$

The first condition states that richer consumers value products more. The second states that quality increases appeal. The third—the key assumption—states that the marginal value of quality *increases* with income. This captures that quality is a luxury: a \$1 quality improvement is worth more to a rich consumer than a poor consumer.

Functional Form. A simple functional form satisfying these properties is:

$$\psi(y_h, q_{ufg}) = \left(\frac{y_h}{\bar{y}}\right)^{\theta q_{ufg}} \tag{C.11}$$

where $\theta > 0$ and $\bar{y}$ is average income. For high-quality products (large q_{ufg}), the income elasticity of quality valuation is large.

[Income and Quality Valuation] For high-quality products (large q_{ufg}), immigrants with $y_i < y_n$ have lower valuations:

$$\phi_{ufgi} = \phi_{ufg} \cdot \psi(y_i, q_{ufg}) < \phi_{ufg} \cdot \psi(y_n, q_{ufg}) = \phi_{ufgn} \tag{C.12}$$

Proof: From equation (C.9) and $\partial^2\psi/(\partial y \partial q) > 0$, the quality valuation gap $\psi(y_n, q) - \psi(y_i, q)$ is increasing in q. For sufficiently high q_{ufg}, $\phi_{ufgi} < \phi_{ufgn}$. □

Empirical Counterpart. In our empirical analysis (Table ??), we estimate product appeal ϕ_f and find it declines when firms face more immigrant demand, consistent with immigrants having lower valuations for high-quality products. We also find increased consumption of private-label products (Table ??), which are known to be lower-quality, lower-price alternatives.

C.4 Supply Side: Multiproduct Firms

Technology. Each firm f is a multiproduct monopolistic competitor producing a set of differentiated products within a product group g. Production technology features increasing marginal costs:

$$MC(q_u) = a_u \cdot q_u^{\delta_g} \tag{C.13}$$

where $\delta_g > 0$ is the elasticity of marginal cost with respect to output (estimated by Hottman, Redding and Weinstein 2016), and q_u is the quantity produced of product u. In addition, each firm faces a fixed cost F_u per product. The firm's total cost is:

$$TC_f = \sum_{u \in \Omega_{fg}} \left[\int_0^{q_u} MC(q) dq + F_u \right] \tag{C.14}$$

Uniform Pricing. Firms charge uniform prices p_u across household types. This no-price-discrimination assumption is realistic for CPG products sold through retail channels, where firms cannot observe consumer characteristics at the point of sale. In equilibrium, quantity produced equals total quantity consumed across both household types:

$$q_u = c_u = \sum_h L_h c_{uh} \tag{C.15}$$

C.5 Equilibrium Pricing and Markups

C.5.1 Demand System

From the nested CES structure, product u's revenue share within firm f for consumer type h is:

$$s_{uh}^F = \frac{(\phi_{uh} p_u)^{1-\tilde{\sigma}_{g,h}^U}}{\sum_{k \in \Omega_{fg}} (\phi_{kh} p_k)^{1-\tilde{\sigma}_{g,h}^U}} \tag{C.16}$$

and firm f's revenue share within product group g is:

$$s_{fgh}^G = \frac{(\phi_{fgh} P_{fgh}^F)^{1-\sigma_{g,h}^F}}{\sum_{j \in \Omega_g} (\phi_{jgh} P_{jgh}^F)^{1-\sigma_{g,h}^F}} \tag{C.17}$$

where $P_{fgh}^F = \left[\sum_{u \in \Omega_{fg}} (\phi_{uh} p_u)^{1-\tilde{\sigma}_{g,h}^U}\right]^{\frac{1}{1-\tilde{\sigma}_{g,h}^U}}$ is firm f's price index for household type h.

C.5.2 Optimal Pricing with Cannibalization

Under Bertrand competition and uniform pricing, firm f chooses prices $\{p_u\}_{u \in \Omega_{fg}}$ to maximize total profits across both household types, accounting for cannibalization effects.

The firm maximizes total profits from product u:

$$\pi_u = (p_u - MC(q_u)) \cdot q_u \tag{C.18}$$

where q_u is the total quantity produced. Under uniform pricing, the firm faces aggregate demand from both household types: $q_u = c_u = \sum_h L_h c_{uh}$, where c_{uh} is per-capita demand from consumer type h.

The first-order condition with respect to price p_u is:

$$\sum_h L_h \left[c_{uh} + (p_u - MC(q_u)) \frac{\partial c_{uh}}{\partial p_u}\right] = 0 \tag{C.19}$$

From the CES demand structure, the own-price elasticity for type h is $\frac{\partial c_{uh}}{\partial p_u} \frac{p_u}{c_{uh}} = -\tilde{\sigma}_{g,h}^U$ (holding other prices constant). Substituting and rearranging:

$$\sum_h L_h c_{uh} \left[1 - \tilde{\sigma}_{g,h}^U \frac{p_u - MC(q_u)}{p_u}\right] = 0 \tag{C.20}$$

$$\frac{p_u}{p_u - MC(q_u)} = \frac{\sum_h L_h \tilde{\sigma}_{g,h}^U c_{uh}}{\sum_h L_h c_{uh}} \tag{C.21}$$

This shows the markup depends on a *quantity-weighted average elasticity* across household types. Defining the effective product-level elasticity as:

$$\tilde{\sigma}^U_{g,\text{eff}} \equiv \sum_h \omega_{uh}\tilde{\sigma}^U_{g,h}, \quad \text{where } \omega_{uh} = \frac{L_h c_{uh}}{\sum_{h'} L_{h'} c_{uh'}} \tag{C.22}$$

where ω_{uh} is the quantity share of consumer type h in product u's total demand. This is an *exact* weighted average with weights determined endogenously in equilibrium.

How Immigration Affects the Weighted Elasticity. From the CES demand structure, per-capita quantities are:

$$c_{uh} = x_{uh} = \frac{\alpha Y_h}{P_g} \cdot s^F_{uh} \cdot \frac{P^F_{fgh}}{p_u} \tag{C.23}$$

where Y_h is per-capita income and s^F_{uh} is product u's revenue share within firm f for household type h. Therefore, total quantity consumed is $c_u = \sum_h L_h c_{uh}$, and the quantity share is:

$$\omega_{uh} = \frac{L_h \cdot c_{uh}}{\sum_{h'} L_{h'} \cdot c_{uh'}} \tag{C.24}$$

When the immigrant population L_i increases, the quantity share ω_{ui} rises mechanically (holding per-capita consumption c_{uh} constant). More importantly, per-capita consumption patterns also shift due to:

- **Income effects:** immigrants typically have $Y_i < Y_n$
- **Quality preferences:** by Lemma 2, $\phi_{ui} < \phi_{un}$ for high-quality products
- **Price sensitivity:** by Lemma 1, $\tilde{\sigma}^U_{g,i} > \tilde{\sigma}^U_{g,n}$

Since $\tilde{\sigma}^U_{g,i} > \tilde{\sigma}^U_{g,n}$ by Lemma 1, an increase in L_i raises the effective elasticity:

$$\frac{\partial \tilde{\sigma}^U_{g,\text{eff}}}{\partial L_i} = \sum_h \frac{\partial \omega_{uh}}{\partial L_i}\tilde{\sigma}^U_{g,h} > 0 \tag{C.25}$$

because $\partial\omega_{ui}/\partial L_i > 0$ and $\partial\omega_{un}/\partial L_i < 0$, and the immigrant elasticity $\tilde{\sigma}^U_{g,i}$ receives increasing weight.

C.5.3 Firm-Level Elasticity and Cannibalization

A similar derivation for the firm-level problem, accounting for cannibalization across products within the firm, yields the firm-level effective elasticity:

$$\sigma^F_{g,\text{eff}} = \sum_h \omega_{fh}\sigma^F_{g,h} \tag{C.26}$$

where $\omega_{fh} = \sum_u L_h c_{uh} / \sum_{u,h'} L_{h'} c_{uh'}$ is the quantity share of type h across all products of firm f.

The first-order condition for product u's price then yields:

$$p_u = \mu_u \cdot MC(q_u) \tag{C.27}$$

where the markup μ_u depends on both product-level and firm-level demand elasticities:

$$\mu_u = \frac{\tilde{\sigma}^U_{g,\text{eff}}}{(\tilde{\sigma}^U_{g,\text{eff}} - 1) - (\sigma^F_{g,\text{eff}} - 1) \cdot s^G_{fg}} \tag{C.28}$$

Here, $\tilde{\sigma}^U_{g,\text{eff}}$ and $\sigma^F_{g,\text{eff}}$ are the effective elasticities defined in equations (C.22) and (C.26):

$$\tilde{\sigma}^U_{g,\text{eff}} = \sum_h \omega_{uh}\tilde{\sigma}^U_{g,h} \tag{C.29}$$

$$\sigma^F_{g,\text{eff}} = \sum_h \omega_{fh}\sigma^F_{g,h} \tag{C.30}$$

These are *exact* quantity-weighted averages where the weights ω_{uh} and ω_{fh} are endogenously determined by equation (C.24). When the immigrant population L_i increases, these weights shift toward immigrants, raising both effective elasticities since $\tilde{\sigma}^U_{g,i} > \tilde{\sigma}^U_{g,n}$ and $\sigma^F_{g,i} > \sigma^F_{g,n}$ by Lemma 1.

C.6 Three Key Mechanisms

We now analyze how an increase in the immigrant population L_i affects prices through three interconnected mechanisms: (1) elasticity and markup effects, (2) quality composition effects, and (3) scale effects, which together determine the net price effect.

C.6.1 Mechanism 1: Elasticity and Markup Effect

This mechanism operates through the conventional price channel: immigration increases the share of price-sensitive consumers, which raises demand elasticity and compresses markups.

Proposition 1 (Elasticity and Markup Effect)**.** *An increase in the immigrant population increases effective demand elasticities through changes in quantity shares, which in turn reduces markups for all firms, with larger effects for firms with greater market share.*

Part 1: Elasticity Effect. *From equation (C.24), the quantity share is:*

$$\omega_{uh} = \frac{L_h \cdot c_{uh}}{\sum_{h'} L_{h'} \cdot c_{uh'}} \tag{C.31}$$

Taking the derivative with respect to L_i:

$$\frac{\partial \omega_{ui}}{\partial L_i} = \frac{c_{ui} \sum_{h'} L_{h'} c_{uh'} - L_i c_{ui} c_{ui}}{(\sum_{h'} L_{h'} c_{uh'})^2} + L_i \frac{\partial c_{ui}/\partial L_i \cdot (...)}{(...)^2} > 0 \tag{C.32}$$

The first term is positive (direct population effect), and the second term captures endogenous per-capita consumption adjustments. Since $\partial \omega_{ui}/\partial L_i > 0$ and correspondingly $\partial \omega_{un}/\partial L_i < 0$ (with $\sum_h \omega_{uh} = 1$), we have:

$$\begin{aligned} \frac{\partial \tilde{\sigma}^U_{g,\mathit{eff}}}{\partial L_i} &= \sum_h \frac{\partial \omega_{uh}}{\partial L_i} \tilde{\sigma}^U_{g,h} && \text{(C.33)} \\ &= \frac{\partial \omega_{ui}}{\partial L_i} \tilde{\sigma}^U_{g,i} + \frac{\partial \omega_{un}}{\partial L_i} \tilde{\sigma}^U_{g,n} && \text{(C.34)} \\ &= \frac{\partial \omega_{ui}}{\partial L_i} (\tilde{\sigma}^U_{g,i} - \tilde{\sigma}^U_{g,n}) > 0 && \text{(C.35)} \end{aligned}$$

where the last inequality follows from $\tilde{\sigma}^U_{g,i} > \tilde{\sigma}^U_{g,n}$ (Lemma 1) and $\partial \omega_{ui}/\partial L_i > 0$. Similarly, $\partial \sigma^F_{g,\mathit{eff}}/\partial L_i > 0$.

Part 2: Markup Effect. *From equation (C.28):*

$$\frac{\partial \mu_u}{\partial \tilde{\sigma}^U_{g,\mathit{eff}}} = \frac{-1}{[(\tilde{\sigma}^U_{g,\mathit{eff}} - 1) - (\sigma^F_{g,\mathit{eff}} - 1) \cdot s^G_{fg}]^2} < 0 \tag{C.36}$$

$$\frac{\partial \mu_u}{\partial \sigma^F_{g,\mathit{eff}}} = \frac{-\tilde{\sigma}^U_{g,\mathit{eff}} \cdot s^G_{fg}}{[(\tilde{\sigma}^U_{g,\mathit{eff}} - 1) - (\sigma^F_{g,\mathit{eff}} - 1) \cdot s^G_{fg}]^2} < 0 \tag{C.37}$$

The second derivative shows larger firms (higher s^G_{fg}) experience greater markup reductions *from $\sigma^F_{g,eff}$ increases.*

Interpretation. Immigration changes the composition of consumers purchasing each product. Even holding the product mix constant, the average consumer becomes more price-sensitive as the share of immigrants increases. This household composition effect operates through the quantity-weighted elasticity, which rises mechanically as high-elasticity consumers (immigrants) gain quantity share in the market. The estimated state-level elasticities reported in Table ?? increase with immigration, consistent with this predicted household composition mechanism.

The markup formula (C.28) reveals how elasticity affects pricing. Higher product-level elasticity $\tilde{\sigma}^U_{g,\text{eff}}$ reduces markups for all products through standard monopolistic competition logic. Higher firm-level elasticity $\sigma^F_{g,\text{eff}}$ strengthens cannibalization effects within multiproduct firms, as consumers substitute more readily between products of the same firm. Larger firms with higher market share s^G_{fg} internalize more of these cannibalization effects, leading them to charge higher equilibrium markups since they account for the impact of their pricing on their entire product portfolio. While we do not directly observe markups in our data, the reduced-form price effects documented in Table ?? are consistent with this mechanism of markup compression through increased demand elasticity.

C.6.2 Mechanism 2: Quality Composition Effects (Two Channels)

Immigration affects quality through two distinct channels that operate at different margins.

Mechanism 2a: Between-Product Composition.

Proposition 2 (Between-Product Quality Composition)**.** *Immigration shifts expenditure toward lower-quality products, changing the composition of the consumption basket.*

Immigrants have systematically different expenditure patterns across the product space. By Lemma 2, $\phi_{fgi} < \phi_{fgn}$ for high-quality products, meaning immigrants derive lower utility from expensive, high-quality goods relative to natives. This creates asymmetric demand shifts:

- **High-quality products** (large $\bar{\phi}_{fg}$): Immigrants have weak preferences, so their arrival has a small or even negative net effect on demand (their lower valuations partially offset the scale effect of additional consumers)

- **Low-quality products** (small $\bar{\phi}_{fg}$): Both scale and composition effects reinforce, creating strong positive demand shifts

This mechanism operates through expenditure share adjustments. Even if individual product prices remain constant, the aggregate price index falls as consumption shifts toward cheaper products:

$$\frac{d\ln\Phi}{dL_i} = \sum_u (1-\sigma)s_u \left(\ln\phi_u - \ln\bar{\phi}\right)\frac{ds_u}{dL_i} < 0 \tag{C.38}$$

where s_u are expenditure shares. Products with $\phi_u < \bar{\phi}$ (below-average quality) gain expenditure share ($ds_u/dL_i > 0$), pulling down the quality index.

Mechanism 2b: Within-Product Quality Effect.

Proposition 3 (Within-Product Quality Composition)**.** *For any given product, the effective quality/appeal depends on the composition of consumers purchasing that product. As immigration increases the immigrant share, effective quality changes.*

For each product u, the effective appeal to the market is:

$$\bar{\phi}_u = \sum_h \omega_{uh}\phi_{ufgh} \tag{C.39}$$

where $\omega_{uh} = \frac{L_h c_{uh}}{\sum_{h'} L_{h'} c_{uh'}}$ is the quantity share of consumer type h. When immigration increases:

$$\frac{d\bar{\phi}_u}{dL_i} = \sum_h \frac{d\omega_{uh}}{dL_i}\phi_{ufgh} \tag{C.40}$$

Since $d\omega_{ui}/dL_i > 0$, $d\omega_{un}/dL_i < 0$, and $\phi_{ui} < \phi_{un}$ by Lemma 2, we have $d\bar{\phi}_u/dL_i < 0$ for products where natives value quality highly.

This within-product quality change affects equilibrium pricing through the markup formula:

$$p_u = \mu_u(\tilde{\sigma}_{\text{eff}}, \bar{\phi}_u) \cdot MC(q_u) \tag{C.41}$$

As $\bar{\phi}_u$ changes, the demand elasticity and hence the markup adjust, leading to price changes even for a fixed set of products.

Distinction Between M2a and M2b. These two mechanisms operate at different margins:

- **M2a (Between-product):** Immigrants choose *different products* from the available set. This is an extensive margin effect—which products get purchased.

- **M2b (Within-product):** For each product, the average consumer changes. This is an intensive margin effect—who purchases each product.

Empirically:

- M2a shows up in $\Delta \ln \Phi$ (quality index), which requires structural estimation
- M2b shows up in $\Delta \ln p_u$ (observed prices), captured by standard SV index
- Table ?? documents declining product appeal ϕ_f, consistent with both mechanisms
- Table ?? shows increased private-label purchases (M2a: expenditure shifts to cheaper products)

C.6.3 Mechanism 3: Scale Effect

Immigration fundamentally increases the size of the market by adding more consumers.

Proposition 4 (Scale Effect)**.** *An increase in the immigrant population raises aggregate demand for all products. With upward-sloping marginal costs, higher aggregate demand increases equilibrium quantities and pushes prices upward through the standard supply-demand mechanism.*

Proof sketch: Immigration increases the total population: $L_i \uparrow \Rightarrow L_{total} = L_n + L_i \uparrow$. *Holding per-capita demand constant, aggregate demand for each product increases:*

$$c_u = \sum_h L_h \cdot c_{uh} \tag{C.42}$$

Taking the derivative with respect to L_i*:*

$$\frac{\partial c_u}{\partial L_i} = c_{ui} + \sum_h L_h \frac{\partial c_{uh}}{\partial L_i} \tag{C.43}$$

The first term is the direct population effect (positive), while the second term captures endogenous per-capita consumption adjustments. In equilibrium, $q_u = c_u$*, so higher demand translates to higher production. With increasing marginal costs,* $MC(q_u) = a_u \cdot q_u^{\delta_g}$ *where* $\delta_g > 0$*, higher quantity directly raises marginal cost:*

$$\frac{\partial MC(q_u)}{\partial q_u} = \delta_g a_u q_u^{\delta_g - 1} > 0 \tag{C.44}$$

Since equilibrium price is $p_u = \mu_u \cdot MC(q_u)$*, higher marginal cost puts upward pressure on prices through the familiar mechanism of demand meeting supply at a higher point along an upward-sloping marginal cost curve.* □

This scale effect operates in the opposite direction from Mechanisms 1 and 2. While elasticity and quality composition mechanisms put downward pressure on prices, the scale effect pushes prices upward through increased market size. The net price effect depends on which forces dominate. Our empirical findings in Table ?? demonstrate that Mechanisms 1 and 2 dominate Mechanism 3, yielding net price declines despite the positive scale effect.

C.6.4 Net Price Effect (Combining the Three Mechanisms)

Now we combine all mechanisms to understand the net effect on prices.

Proposition 5 (Net Price Effect)**.** *Immigration affects prices through three competing forces:*

1. ***Elasticity/markup effect (−)*** *from Mechanism 1: Higher elasticity ⇒ lower markup ⇒ lower price*
2. ***Quality/composition effect (−)*** *from Mechanism 2: Shift to lower-quality products ⇒ lower average price*
3. ***Scale effect (+)*** *from Mechanism 3: More consumers ⇒ higher quantity ⇒ higher marginal cost (with $\delta_g > 0$)*

The net effect depends on which forces dominate. Empirically, we find the elasticity and quality effects (Mechanisms 1 and 2) dominate the scale effect (Mechanism 3), yielding net price declines.

Derivation: The equilibrium price is:

$$p_u = \mu_u \cdot MC(q_u) = \mu_u \cdot a_u \cdot q_u^{\delta_g} \tag{C.45}$$

where in equilibrium $q_u = c_u$. Taking the total derivative with respect to L_i:

$$\frac{dp_u}{dL_i} = \underbrace{\frac{\partial \mu_u}{\partial \tilde{\sigma}^U_{\text{eff}}} \frac{\partial \tilde{\sigma}^U_{\text{eff}}}{\partial L_i} \cdot MC}_{\substack{\text{<0: elasticity effect} \\ \text{on markup}}} + \underbrace{\frac{\partial \mu_u}{\partial \sigma^F_{\text{eff}}} \frac{\partial \sigma^F_{\text{eff}}}{\partial L_i} \cdot MC}_{\substack{\text{<0: firm-level} \\ \text{elasticity effect}}} \tag{C.46}$$

$$+ \underbrace{\mu_u \cdot \delta_g a_u q_u^{\delta_g - 1} \frac{\partial q_u}{\partial L_i}}_{\substack{\text{>0: scale effect} \\ \text{on MC}}} \tag{C.47}$$

At the firm level, these three mechanisms operate simultaneously to affect the firm's overall price index. Immigration changes not only individual product prices (through Mechanisms 1 and 3) but also the composition of products demanded (Mechanism 2) and the set of products offered (extensive margin). Section 2.3 provides a complete decomposition of the firm-level price index into price, quality, and variety effects, formalizing how each mechanism contributes to these components and mapping them to our empirical evidence.

Economic Intuition. Standard textbook intuition suggests that an outward shift in aggregate demand should increase equilibrium prices. However, immigration does not simply shift demand outward in a parallel fashion. Rather, three distinct mechanisms operate simultaneously to determine the net price effect.

First, immigration increases the total number of consumers in the market, shifting demand rightward for all products. With upward-sloping supply due to increasing marginal costs ($\delta_g > 0$), this scale effect increases both quantity and price through the familiar mechanism of demand meeting supply at a higher equilibrium point along an upward-sloping marginal cost curve.

Second, immigration changes the composition of consumers purchasing each product. Even holding the set of products constant, the average consumer becomes more price-sensitive as immigrants with higher demand elasticities ($\tilde{\sigma}_i > \tilde{\sigma}_n$) enter the market. The quantity-weighted elasticity $\tilde{\sigma}_{\text{eff}} = \sum_h \omega_h \tilde{\sigma}_h$ increases as the immigrant quantity share $\omega_i = L_i c_{ui}/(L_n c_{un} + L_i c_{ui})$ rises. From the markup formula (C.28), this increase in $\tilde{\sigma}_{\text{eff}}$ reduces markups since $\partial\mu/\partial\tilde{\sigma}_{\text{eff}} < 0$. Consequently, firms cannot raise prices as much in response to the increased quantity demanded. This household composition effect operates at the individual product level, muting the price increase from the scale effect.

Third, immigration shifts the composition of products demanded across the quality distribution. Immigrants have systematically lower valuations for high-quality products relative to natives (Lemma 2: $\phi_{fgi} < \phi_{fgn}$). This creates asymmetric demand shifts: high-quality products experience weak or even negative demand shifts as immigrants' lower valuations partially offset the scale effect, while low-quality products experience strong positive demand shifts as both scale and composition effects reinforce each other. The aggregate price index, being a weighted average across all products, falls as the composition shifts toward lower-quality, lower-priced goods.

At the individual product level, the net price effect combines the positive scale effect and the negative elasticity effect:

$$\frac{dp_u}{dL_i} = \mu_u \cdot \delta_g a_u q_u^{\delta_g - 1} \frac{\partial q_u}{\partial L_i} + MC(q_u) \cdot \frac{\partial \mu_u}{\partial \tilde{\sigma}_{\text{eff}}} \frac{\partial \tilde{\sigma}_{\text{eff}}}{\partial L_i} \tag{C.48}$$

The first term is positive (higher quantity raises marginal cost), while the second term is negative (higher elasticity reduces markup). Our empirical findings in Table ?? demonstrate that the elasticity effect (M1) and quality composition effects (M2) dominate the scale effect (M3), yielding net price declines. This result indicates that immigration fundamentally changes the nature of demand through household and product composition mechanisms, rather than simply scaling up existing demand patterns. Section 2.3 formalizes how these mechanisms aggregate to the firm level, showing that immigration's price effects operate through price, quality, and variety adjustments.

C.7 Market Share Stability

An important empirical pattern is that firm market shares remain relatively stable despite substantial price and quality adjustments. The model provides a structural explanation for this observation.

Proposition 6 (Market Share Stability)**.** *Firms respond to immigration by simultaneously reducing both prices and product quality/appeal, leaving quality-adjusted prices and market shares approximately stable.*

From equation (C.2), firm f's demand depends on its quality-adjusted price index P^F_{fgh}/ϕ_{fgh}. Immigration triggers two concurrent adjustments: prices fall through the elasticity effect (Proposition 1), and quality falls through the composition effect (Proposition 2). If these two effects operate proportionally, the quality-adjusted price remains roughly constant, leaving firm market share s^G_{fg} stable.

This mechanism explains the joint observation of price reductions (Table ??), appeal reductions (Table ??), and stable market shares and revenues in the data. The stability arises not from inaction but from coordinated adjustment along both price and quality margins. An important implication concerns markup dynamics: since market share s^G_{fg} remains stable in equation (C.28), changes in markups are driven primarily by the elasticity effects ($\tilde{\sigma}^U_{\text{eff}}$ and σ^F_{eff} increasing) rather than by shifts in market power.

C.8 Firm-Level Price Index Decomposition

We now show how to decompose the firm-level price index to map each of the three mechanisms to distinct components. This decomposition provides a framework for quantifying the relative importance of each mechanism in driving immigration's price effects.

Our empirical analysis focuses on firm-level outcomes, which allows us to separately identify price, quality, and variety adjustments. The decomposition reveals that quality composition effects (Mechanism 2) and elasticity/markup effects (Mechanism 1) quantitatively dominate scale effects (Mechanism 3), yielding net price declines despite population increases.

C.8.1 Aggregation Across Household Types

Before presenting the firm-level decomposition, we first show how to aggregate household-specific price indices into a single firm-level index. Recall that each household type h faces a type-specific price index:

$$P^F_{fgh} = \left[\sum_{u \in \Omega_f} (\phi_{uh} p_u)^{1-\tilde{\sigma}^U_{g,h}} \right]^{\frac{1}{1-\tilde{\sigma}^U_{g,h}}} \tag{C.49}$$

To obtain a firm-level price index that aggregates across household types, we construct expenditure-weighted averages. Define the effective (quantity-weighted average) appeal and elasticity:

$$\bar{\phi}_u \equiv \sum_h \omega_{uh} \phi_{uh} \tag{C.50}$$

$$\bar{\sigma}^U_g \equiv \sum_h \omega_{uh} \tilde{\sigma}^U_{g,h} \tag{C.51}$$

where $\omega_{uh} = \frac{L_h c_{uh}}{\sum_{h'} L_{h'} c_{uh'}}$ is the quantity share of household type h in product u's demand, as defined in equation (C.24).

The firm-level price index aggregating across both products and household types is then:

$$P_f = \left[\sum_{u \in \Omega_f} (\bar{\phi}_u p_u)^{1-\bar{\sigma}^U_g} \right]^{\frac{1}{1-\bar{\sigma}^U_g}} \tag{C.52}$$

Interpretation: This aggregation shows how household heterogeneity affects firm-level prices. The effective appeal $\bar{\phi}_u$ represents the quantity-weighted average valuation of product

u across both natives and immigrants. When immigration increases, the weights ω_{uh} shift toward immigrants (who have lower valuations by Lemma 2), reducing $\bar{\phi}_u$ for high-quality products. Similarly, the effective elasticity $\bar{\sigma}_g^U$ rises as immigrant quantity shares increase, since $\tilde{\sigma}_{g,i}^U > \tilde{\sigma}_{g,n}^U$ by Lemma 1.

C.8.2 Firm-Level Decomposition

For notational simplicity in the decomposition that follows, we denote the firm-level price index compactly as:

$$P_f = \left[\sum_{u \in \Omega_f} (\phi_u p_u)^{1-\sigma_g^U} \right]^{\frac{1}{1-\sigma_g^U}} \tag{C.53}$$

where $\phi_u \equiv \bar{\phi}_u$ and $\sigma_g^U \equiv \bar{\sigma}_g^U$ are understood to be the quantity-weighted averages defined in equations (C.50) and (C.51).

This index captures three dimensions of firm pricing: (1) the set of products offered Ω_f (variety), (2) the quality/appeal of each product ϕ_u, and (3) the price of each product p_u.

Taking the log-differential of equation (C.53) with respect to the immigrant population L_i, we obtain:

$$\frac{d \ln P_f}{dL_i} = \underbrace{\sum_{u \in \Omega_f} s_u \frac{d \ln p_u}{dL_i}}_{\text{Price Effect}} + \underbrace{\sum_{u \in \Omega_f} s_u \frac{d \ln \phi_u}{dL_i}}_{\text{Quality Effect}} + \underbrace{\frac{1}{1-\sigma_g^U} \sum_{u \in \Delta\Omega_f} s_u}_{\text{Variety Effect}} \tag{C.54}$$

where $s_u = \frac{(\phi_u p_u)^{1-\sigma_g^U}}{\sum_k (\phi_k p_k)^{1-\sigma_g^U}}$ is product u's revenue share within firm f, and $\Delta\Omega_f$ denotes products entering or exiting.

Empirical Implementation of Revenue Shares. The revenue shares s_u in equation (C.54) are directly observable from scanner data as:

$$s_u = \frac{p_u q_u}{\sum_{k \in \Omega_f} p_k q_k} \tag{C.55}$$

where p_u and q_u denote the observed price and total quantity of product u (aggregated across household types: $q_u = \sum_h L_h c_{uh}$). Under the nested CES structure, this expenditure share equals the quality-adjusted share from the demand system, providing a direct bridge between theoretical predictions and empirical measurement. This equivalence allows us to decompose observed firm-level price index changes into contributions from price, quality, and variety adjustments without requiring separate estimation of quality parameters ϕ_u for the decomposition itself.

C.8.3 Component 1: Price Effect

The first term captures how individual product prices change with immigration. From our theoretical mechanisms, this price effect reflects two competing forces:

$$\frac{d\ln p_u}{dL_i} = \underbrace{\frac{d\ln \mu_u}{dL_i}}_{\substack{\text{Mechanism 1:}\\ \text{Markup}}} + \underbrace{\frac{d\ln MC(q_u)}{dL_i}}_{\substack{\text{Mechanism 3:}\\ \text{Scale}}} \tag{C.56}$$

Mechanism 1 (Elasticity/Markup Effect): From equation (C.28), higher demand elasticities compress markups:

$$\frac{d\ln \mu_u}{dL_i} = \frac{\partial \ln \mu_u}{\partial \tilde{\sigma}^U_{g,\text{eff}}}\frac{\partial \tilde{\sigma}^U_{g,\text{eff}}}{\partial L_i} + \frac{\partial \ln \mu_u}{\partial \sigma^F_{g,\text{eff}}}\frac{\partial \sigma^F_{g,\text{eff}}}{\partial L_i} < 0 \tag{C.57}$$

Both terms are negative since $\partial\mu_u/\partial\tilde{\sigma}^U_{g,\text{eff}} < 0$ and $\partial\mu_u/\partial\sigma^F_{g,\text{eff}} < 0$ (from Proposition 1), and $\partial\tilde{\sigma}^U_{g,\text{eff}}/\partial L_i > 0$ and $\partial\sigma^F_{g,\text{eff}}/\partial L_i > 0$ (since immigrants have higher elasticities). This mechanism puts **downward pressure** on prices.

Mechanism 3 (Scale Effect): Larger market size increases equilibrium quantities. With upward-sloping marginal costs ($\delta_g > 0$):

$$\frac{d\ln MC(q_u)}{dL_i} = \delta_g \frac{d\ln q_u}{dL_i} > 0 \tag{C.58}$$

This mechanism puts **upward pressure** on prices through higher production costs.

The net price effect depends on which mechanism dominates. Our empirical findings in Table ?? document negative price effects, indicating that Mechanism 1 dominates Mechanism 3.

C.8.4 Component 2: Quality Effect

The second term in equation (C.54) captures how product quality/appeal changes with immigration. However, we must distinguish between two conceptually different quality mechanisms:

Within-Product Quality Effect (M2b). For each product u, the effective quality $\bar{\phi}_u = \sum_h \omega_{uh}\phi_{ufgh}$ changes as the consumer mix shifts. This is captured in the firm-level decomposition equation (C.54) as:

$$\sum_{u\in\Omega_f} s_u \frac{d\ln\bar{\phi}_u}{dL_i} \tag{C.59}$$

When $\omega_{ui}\uparrow$ (more immigrants buying product u) and $\phi_{ui} < \phi_{un}$ (immigrants value quality less), then $\bar{\phi}_u \downarrow$. This affects the equilibrium price through the markup formula, since effective elasticity depends on $\bar{\phi}_u$.

However, this within-product effect is *already embedded in observed price changes* $\Delta\ln p_u$, because:

$$p_u = \mu_u(\tilde{\sigma}_{\text{eff}}, \bar{\phi}_u) \cdot MC(q_u) \tag{C.60}$$

Therefore, the "quality effect" term in our firm-level decomposition primarily captures M2b operating through equilibrium pricing.

Between-Product Quality Effect (M2a). The more fundamental quality composition effect—expenditure shifts toward different (lower-quality) products—does *not* appear in the firm-level price index $P_f = [\sum_u(\bar{\phi}_u p_u)^{1-\bar{\sigma}_g^U}]^{1/(1-\bar{\sigma}_g^U)}$ when we observe only prices. Instead, it appears in the *quality index*:

$$\Phi_f = \left[\sum_u \bar{\phi}_u^{1-\bar{\sigma}_g^U} s_u\right]^{\frac{1}{1-\bar{\sigma}_g^U}} \tag{C.61}$$

and manifests as:

$$\frac{d\ln\Phi_f}{dL_i} = \sum_u (1-\bar{\sigma}_g^U) s_u \left(\ln\bar{\phi}_u - \ln\bar{\bar{\phi}}\right)\frac{ds_u}{dL_i} \tag{C.62}$$

where s_u are expenditure shares. When immigration causes s_u to shift toward low-$\bar{\phi}_u$ products, Φ_f declines even if no individual prices p_u change.

Empirical Implementation. In practice:

- The firm-level SV index $\sum s_u\Delta\ln p_u$ captures M2b (through its effect on equilibrium prices)
- The between-product composition effect M2a requires constructing $\Delta\ln\Phi_f$ using estimated quality parameters

- Table ?? shows that estimated $\bar{\phi}_f$ declines with immigrant exposure (consistent with both M2a and M2b)

- Table ?? decomposes the total effect into standard SV versus quality composition components

C.8.5 Component 3: Variety Effect

The third term captures product entry and exit. A product is offered if and only if:

$$\pi_u = (p_u - MC(q_u))q_u - F_u \geq 0 \tag{C.63}$$

Immigration affects profitability through two offsetting forces:

- **Positive:** Mechanism 3 (scale) increases quantity q_u, raising $(p - MC)q$

- **Negative:** Mechanism 1 (markup compression) reduces $(p - MC)$

Our empirical results in Table ?? document modest net variety changes, consistent with these forces roughly offsetting. The variety effect enters equation (C.54) with weight $1/(1 - \sigma_g^U)$, reflecting that variety has welfare implications beyond simple product counts (Feenstra, 1994).

C.8.6 Mapping Mechanisms to Decomposition Components

Each theoretical mechanism contributes to specific components of the decomposition. However, we must distinguish between effects captured by the standard SV index versus those requiring quality adjustment:

Standard SV Index ($\Delta \ln P_{SV}$): Captures within-product effects

- **Mechanism 1 (Elasticity/Markup):**
  - Contributes to *price effect* through markup compression: $d \ln \mu_u / dL_i < 0$
  - Contributes to *variety effect* through reduced profitability: lower markups reduce π_u

- **Mechanism 2b (Within-Product Quality):**
  - Contributes to *price effect* through changes in $\bar{\phi}_u$ affecting equilibrium pricing

- Reflects that the same product is valued differently as consumer mix changes
- Embedded in observed price changes $\Delta \ln p_u$

- **Mechanism 3 (Scale):**
  - Contributes to *price effect* through cost increases: $d \ln MC(q_u)/dL_i > 0$
  - Contributes to *variety effect* through increased profitability: higher quantities raise π_u

Quality Index ($\Delta \ln \Phi$): Captures between-product composition

- **Mechanism 2a (Between-Product Quality Composition):**
  - Expenditure shifts toward low-ϕ products: $\frac{ds_u}{dL_i}$ depends on ϕ_u
  - Reflected in quality index: $\frac{d \ln \Phi}{dL_i} = \sum_u (1-\sigma) s_u (\ln \phi_u - \ln \bar{\phi}) \frac{ds_u}{dL_i}$
  - Requires structural estimation of ϕ_u parameters
  - Does NOT appear in standard SV price index

C.8.7 Quantitative Mapping to Empirical Evidence

The decomposition components map directly to our empirical tables:

- **Standard SV Effect** ($\Delta \ln P_{SV}$):
  - **M1 (Elasticity/Markup):** Table ?? (elasticity ↑) + Table ?? (prices ↓)
  - **M2b (Within-product quality):** Captured through equilibrium price changes
  - **M3 (Scale):** Modest contribution, dominated by M1
  - **Net effect:** Table ?? reports $\Delta \ln P_{SV}$ showing significant price declines

- **Quality Composition Effect** ($\Delta \ln \Phi$):
  - **M2a (Between-product):** Table ?? (quality index $\Phi \downarrow$)
  - Confirmed by Table ?? (increased private-label share)
  - Requires structural estimation, not in standard SV

- **Variety Effect** ($\frac{1}{1-\sigma^U} \sum_{\Delta\Omega_f} s_u$):
  - M1 and M3 offset: Table ?? (product counts stable)
  - Net effect: muted at both firm and county levels

Summary of Findings: The decomposition shows that immigration's price effects operate through multiple channels:

1. **Standard SV captures:** Markup compression (M1) + within-product quality effects (M2b) + scale effects (M3). Our estimates show this accounts for approximately X% of the total effect.

2. **Quality composition adds:** Between-product expenditure shifts (M2a) account for an additional Y% of the total effect, highlighting that immigrants genuinely choose different (cheaper) consumption baskets.

3. **Variety effects are muted:** M1 and M3 have offsetting effects on product entry/exit, leaving the variety component small.

This finding contrasts with simple models where population increases mechanically raise prices through aggregate demand. Instead, immigration fundamentally changes both *who* purchases (affecting elasticity and within-product quality) and *what* is purchased (between-product composition), with both effects putting downward pressure on price indices.

C.9 County-Level Price Index

Our empirical analysis also examines county-level price indices, which aggregate across firms within a geographic area. The county-level price index is:

$$P_c = \left[\sum_{f \in \Omega_c} (P_f^F)^{1-\sigma_g^F} \right]^{\frac{1}{1-\sigma_g^F}} \tag{C.64}$$

where Ω_c denotes the set of firms operating in county c.

County-Level vs Firm-Level Effects. An important conceptual distinction arises between our firm-level and county-level analyses, stemming from how quality/appeal is defined in the CES framework.

Firm-level: Quality parameters ϕ_u enter the demand system in relative terms within each firm. The nested CES structure means consumers choose products within a firm based on relative quality-adjusted prices. Therefore, only the relative quality of products within firm f matters—we can normalize $\prod \phi_u = 1$ for each firm. Our decomposition in equation (C.54) tracks how this relative quality distribution changes within the firm when immigration increases (i.e., does the firm shift toward lower-quality products in its mix?). This is well-defined because we measure changes in relative quality within the same firm over time.

County-level: To construct a county-level quality index, we would need to aggregate ϕ across firms and products, requiring quality parameters to be comparable in absolute terms across counties. However, with heterogeneous consumer valuations (Lemma 2: different consumer types value products differently), there is no natural way to define absolute quality levels that apply across counties with different consumer compositions. Counties with more immigrants have different preference distributions, making "quality" inherently location-specific rather than objectively comparable. Therefore, county-level price changes primarily reflect:

1. **Conventional price effects:** Changes in p_u for products sold in the county

2. **Composition effects:** Shifts in expenditure shares s_u toward lower-priced products

3. **Variety effects:** Changes in the set of firms/products available

Our empirical results show that variety effects are muted at both firm and county levels, indicating that immigration's price effects operate primarily through intensive margin adjustments (prices and quality/composition) rather than extensive margin changes (firm/product entry and exit). This finding is consistent with Mechanisms 1 and 3 roughly offsetting in their effects on profitability (equation C.63), leaving product offerings relatively stable while prices and quality adjust. County-level price declines therefore reflect conventional price reductions and compositional shifts toward lower-priced products, rather than changes in product variety.

Practical implication: Our firm-level decomposition identifies three distinct channels (price, quality, variety) by exploiting within-firm variation over time, where relative quality is well-defined. County-level analyses cannot separately identify quality effects in the same way because quality must be defined relative to the local consumer base. We therefore interpret county-level results as combining conventional price effects and composition effects (shifts in expenditure shares toward lower-priced products).

C.10 Empirical Implementation: Two Types of Quality Composition Effects

An important conceptual question arises when connecting our theoretical decomposition to empirical measurement: What exactly does the empirically constructed Sato-Vartia (SV) price index measure, and how does it relate to quality composition effects?

C.10.1 Two Distinct Quality Mechanisms

As established in Section 1.3.2, immigration affects prices through two quality channels:

Mechanism 2a: Between-Product Composition. Immigrants allocate expenditure toward products with lower quality-adjusted prices. Even if individual product prices remain unchanged, the aggregate price index falls as expenditure shifts toward cheaper products. This appears in the quality index Φ.

Mechanism 2b: Within-Product Effect. The effective quality $\bar{\phi}_u = \sum_h \omega_{uh}\phi_{ufgh}$ of each product changes as the consumer mix shifts. This affects equilibrium prices through the markup formula and is captured in observed price changes.

The key distinction for empirical implementation: M2a requires constructing a separate quality index, while M2b is embedded in observed prices.

C.10.2 The Standard SV Price Index

The Sato-Vartia (SV) price index is the *exact* CES price index (Sato 1976, Vartia 1976) for the case where all products have identical quality ($\phi_u = 1$ for all u):

$$P_{SV} = \left[\sum_u p_u^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{C.65}$$

In discrete time with changing product sets, this can be equivalently expressed using Sato-Vartia weights:

$$\Delta \ln P_{SV} = \sum_u w_u^{SV} \Delta \ln p_u \tag{C.66}$$

where w_u^{SV} are logarithmic means of expenditure shares across periods.

C.10.3 Quality-Adjusted CES Price Index

When products differ in quality, the correct CES price index must account for quality-adjusted prices:

$$P_{true} = \left[\sum_u (\phi_u p_u)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{C.67}$$

This can be decomposed into two components:

$$\ln P_{true} = \ln P_{SV} + \ln \Phi \tag{C.68}$$

where:

$$\Phi = \left[\sum_u \phi_u^{1-\sigma} s_u \right]^{\frac{1}{1-\sigma}} \tag{C.69}$$

is a quality index that captures how expenditure-weighted average quality changes over time. Taking the log-differential:

$$\Delta \ln P_{true} = \underbrace{\Delta \ln P_{SV}}_{\substack{\text{Standard price} \\ \text{effect}}} + \underbrace{\Delta \ln \Phi}_{\substack{\text{Between-product} \\ \text{composition effect}}} \tag{C.70}$$

C.10.4 What Does the Empirical SV Index Measure?

In our empirical analysis, we construct the standard SV index using only observed prices:

$$\text{SV}_{\text{empirical}} = \sum_u w_u^{SV} \Delta \ln p_u \tag{C.71}$$

This corresponds to $\Delta \ln P_{SV}$ in equation (C.70), which measures price changes *holding the quality composition fixed.*

Distinction Between Standard and Quality-Adjusted Indices. The between-product composition effect (Mechanism 2a)—the shift in expenditure toward lower-quality products—does not appear in the standard SV index. Instead, it appears in $\Delta \ln \Phi$, which requires separate measurement using estimated quality parameters ϕ_u.

What About Within-Product Effects? The within-product mechanism (Mechanism 2b) *does* affect observed prices p_u. The equilibrium pricing formula shows:

What About Within-Product Effects? The within-product mechanism (Mechanism 2b) *does* affect observed prices p_u. The equilibrium pricing formula shows:

$$p_u = \mu_u(\tilde{\sigma}_{\text{eff}}, \bar{\phi}_u, s_{fg}^G) \cdot MC(q_u) \tag{C.72}$$

When the consumer mix changes (ω_{uh} shifts toward immigrants), two things happen:

1. The effective elasticity rises: $\tilde{\sigma}_{\text{eff}} = \sum_h \omega_{uh} \tilde{\sigma}_{g,h}^U \uparrow$ (Mechanism 1)
2. The effective quality changes: $\bar{\phi}_u = \sum_h \omega_{uh} \phi_{ufgh}$ adjusts (Mechanism 2b)

Both effects influence the equilibrium markup μ_u and hence the observed price p_u. Therefore:

$$\Delta \ln p_u = \underbrace{\frac{\partial \ln \mu_u}{\partial \tilde{\sigma}_{\text{eff}}} \frac{\partial \tilde{\sigma}_{\text{eff}}}{\partial L_i}}_{\substack{\text{M1: Elasticity} \\ \text{effect}}} + \underbrace{\frac{\partial \ln \mu_u}{\partial \bar{\phi}_u} \frac{\partial \bar{\phi}_u}{\partial L_i}}_{\substack{\text{M2b: Within-product} \\ \text{quality effect}}} + \underbrace{\delta_g \frac{\partial \ln q_u}{\partial L_i}}_{\substack{\text{M3: Scale} \\ \text{effect}}} \tag{C.73}$$

The empirical SV index $\sum w_u^{SV} \Delta \ln p_u$ captures all three of these within-product mechanisms.

C.10.5 Complete Decomposition Framework

Combining both quality mechanisms and variety effects, the total effect of immigration on the price index is:

$$\begin{aligned}
\frac{d \ln P_{true}}{dL_i} &= \frac{d \ln P_{SV}}{dL_i} + \frac{d \ln \Phi}{dL_i} \\
&= \underbrace{\sum_{u \in \Omega} s_u \left[\frac{\partial \ln p_u}{\partial \tilde{\sigma}_{\text{eff}}} \frac{\partial \tilde{\sigma}_{\text{eff}}}{\partial L_i} + \frac{\partial \ln p_u}{\partial \bar{\phi}_u} \frac{\partial \bar{\phi}_u}{\partial L_i} + \delta_g \frac{\partial \ln q_u}{\partial L_i} \right]}_{\substack{\text{Price effects within existing products} \\ \text{(M1 + M2b + M3)}}} \\
&\quad + \underbrace{\frac{1}{1 - \sigma_g^U} \sum_{u \in \Delta\Omega} s_u}_{\substack{\text{Variety effect} \\ \text{(M1 \& M3 offset)}}} \\
&\quad + \underbrace{\sum_u (1 - \sigma) s_u (\ln \phi_u - \ln \bar{\phi}) \frac{ds_u}{dL_i}}_{\substack{\text{Quality composition effect: } d \ln \Phi / dL_i \\ \text{(M2a: between-product shifts)}}}
\end{aligned} \tag{C.74}$$

where Ω denotes the continuing set of products and $\Delta\Omega$ denotes entering/exiting products.

Interpretation:

- **Price effects within products** (Captured by empirical SV on continuing products):
  - **M1 (Elasticity/Markup):** Higher $\tilde{\sigma}_{\text{eff}}$ compresses markups
  - **M2b (Within-product quality):** Changes in $\bar{\phi}_u$ affect pricing for each product
  - **M3 (Scale):** Higher quantities raise marginal costs
- **Variety effect:** Product entry and exit, with M1 (lower markups discourage entry) and M3 (higher scale encourages entry) offsetting
- **Quality composition effect** (Requires structural estimation): M2a expenditure shifts toward low-ϕ products, not captured by standard SV

C.10.6 Empirical Implementation

To implement this complete decomposition, we use a three-step procedure:

Step 1: Construct Standard SV Index. Using observed prices and quantities:

$$\Delta \ln P_{SV} = \sum_u w_u^{SV} \Delta \ln p_u \tag{C.75}$$

This measures the effect through within-product mechanisms (M1 + M2b + M3).

Step 2: Estimate Quality Parameters. Following Hottman, Redding and Weinstein (2016), we recover product quality from observed market shares:

$$\ln s_{uf} = \frac{1}{\sigma^U - 1} \ln \phi_{uf} + \text{(price and other terms)} \tag{C.76}$$

This allows us to construct the quality index:

$$\Phi_t = \left[\sum_u \phi_u^{1-\sigma} s_{ut} \right]^{\frac{1}{1-\sigma}} \tag{C.77}$$

Step 3: Decompose Total Effect. The quality-adjusted price index change is:

$$\Delta \ln P_{true} = \Delta \ln P_{SV} + \Delta \ln \Phi \tag{C.78}$$

We can then attribute each component to specific mechanisms by running regressions:

$$\Delta \ln P_{SV,c} = \alpha_1 \cdot \text{Immigration}_c + \text{controls} \quad \text{(Within-product effects)} \tag{C.79}$$

$$\Delta \ln \Phi_c = \alpha_2 \cdot \text{Immigration}_c + \text{controls} \quad \text{(Between-product composition)} \tag{C.80}$$

Example Decomposition. Suppose immigration causes the quality-adjusted price index to fall 6%:

- Standard SV effect ($\Delta \ln P_{SV}$): -4%
  - M1 (Elasticity): -3% (markup compression)
  - M2b (Within-product): -0.5% (consumer mix effects)
  - M3 (Scale): $+1.5\%$ (higher MC, partially offsetting)
  - Variety: -2% (net entry/exit effects)
- Quality composition effect ($\Delta \ln \Phi$): -2%
  - M2a (Between-product): Expenditure shifts to cheaper goods
- Total effect ($\Delta \ln P_{true}$): -6%

The empirical SV index measures the -4%, not the full -6%. The between-product composition effect (-2%) requires structural estimation of quality parameters.

C.10.7 Why This Distinction Matters

This decomposition is crucial for three reasons:

1. Measurement. Standard price indices (BLS CPI, SV index) attempt to measure "constant-quality" inflation by:

- Hedonic adjustments
- Product matching over time

- Quality controls

These methods aim to capture $\Delta \ln P_{SV}$ (within-product price changes) while excluding $\Delta \ln \Phi$ (between-product quality shifts). However, demographic changes like immigration can shift the relevant consumption basket, making $\Delta \ln \Phi$ economically important even if statisticians try to exclude it.

2. Welfare. The two quality mechanisms have different welfare implications:

- **M2a (Between-product):** Immigrants voluntarily choose cheaper products. This reflects optimal choice given their budget constraints and preferences. The welfare loss is captured by the expenditure function.

- **M2b (Within-product):** The same product becomes effectively lower quality as the consumer base shifts. This may involve forced quality degradation or reduced service quality, with potentially different welfare implications.

3. Policy. Understanding which mechanism dominates guides policy responses:

- If M2a dominates: Immigration affects aggregate price indices through basket composition. Policies might focus on ensuring product variety and market access.

- If M1/M2b dominate: Immigration affects prices through competitive pressure and markup compression. Policies might focus on market structure and firm responses.

Connection to Empirical Tables. Our empirical analysis proceeds in stages:

- Table ?? reports the total effect on standard SV price indices ($\Delta \ln P_{SV}$)

- Table ?? shows estimated quality parameters ϕ_f decline with immigrant exposure

- Table ?? constructs the quality composition effect ($\Delta \ln \Phi$) using structural estimates

- Table ?? presents the complete decomposition attributing effects to each mechanism

Appendix D Discussion

D.1 Summary of Mechanisms

Our framework identifies three interconnected mechanisms (with Mechanism 2 subdivided into two channels):

- **M1 (Elasticity/Markup):** Immigration raises effective demand elasticity through household composition, compressing markups
- **M2a (Between-Product Composition):** Expenditure shifts toward lower-quality products, affecting the quality index Φ
- **M2b (Within-Product Quality):** Consumer mix changes affect effective product quality, embedded in equilibrium prices
- **M3 (Scale):** Population growth raises costs through increasing marginal cost of production

The net price effect combines all mechanisms. Empirically, M1, M2a, and M2b collectively dominate M3, yielding price declines despite population increases.

D.2 Empirical Implementation

Each theoretical mechanism maps directly to specific empirical patterns.

Mechanism 1 (Elasticity and Markup Effect): Predicts that state-level demand elasticities ($\tilde{\sigma}_g^U$ and σ_g^F) should increase with immigration, which Table ?? confirms through structural estimation. The mechanism also predicts markup compression, consistent with the negative price effects documented in Table ??. This effect is captured in the standard SV price index.

Mechanism 2a (Between-Product Quality Composition): Predicts that immigration shifts expenditure toward lower-quality products. Table ?? verifies this through:

- Declining estimated quality index Φ in high-immigration counties
- Increased consumption of private-label products (inherently lower quality)
- Heterogeneous price responses across the quality distribution

This effect requires constructing the quality index Φ using structural estimates and does not appear in standard SV indices.

Mechanism 2b (Within-Product Quality Effect): Predicts that the effective appeal $\bar{\phi}_u$ of each product changes as the consumer mix shifts. Table ?? documents declining estimated appeal parameters ϕ_f in response to immigrant demand, consistent with this mechanism. This effect operates through equilibrium pricing and is captured in the standard SV index.

Mechanism 3 (Scale Effect): Predicts upward price pressure from increased market size, but our empirical analysis demonstrates that Mechanisms 1, 2a, and 2b collectively dominate this force. The offsetting of scale effects with markup compression explains why variety effects are muted (Table ??).

An important empirical regularity is that firm market shares remain stable despite substantial price and quality adjustments. The model explains this pattern through coordinated adjustment: firms simultaneously reduce prices (Mechanism 1) and quality (Mechanisms 2a/2b) in proportions that leave quality-adjusted prices approximately constant. This finding implies that markup changes operate primarily through elasticity mechanisms rather than through shifts in market power, since market shares remain stable in equilibrium.

D.3 Limitations and Extensions

The model abstracts from several features to maintain analytical tractability. We assume firms charge uniform prices to all consumers, though price discrimination between natives and immigrants is feasible in principle. Quality and appeal parameters are treated as exogenous, though firms may endogenously adjust product characteristics in response to changing demand composition. The framework is static, focusing on long-run equilibrium rather than transition dynamics. We adopt a partial equilibrium approach, abstracting from general equilibrium effects on wages, input prices, and firm entry at the firm level (as distinct from product-level entry/exit which we model explicitly).

Despite these simplifications, the framework provides a coherent structural interpretation of how immigration affects prices through demand composition effects. All three mechanisms operate simultaneously in the model, each corresponding to distinct empirical patterns in the data. The framework demonstrates that immigration's price effects operate primarily through changes in the composition of both households and products, rather than through simple scaling of existing demand patterns.