Food Insecurity and Unemployment Amongst Immigrants in the United States

Abstract

Immigrants can be more vulnerable to economic downturns and, during those periods, more likely to experience food insecurity (FI) compared to natives. This study examines the effect of the unemployment rate (UR) on the likelihood of being food insecure among diverse groups of immigrant households relative to natives in the U.S. Since unemployment is not randomly determined for households, we create a Bartik instrument by exploiting exogenous spatial variation in industry employment shares interacted with national industry growth rates. Overall, we find a procyclical effect of the UR on household FI. Immigrant noncitizens face greater vulnerability to local labor market downturns than both natives and naturalized citizens, likely due to limited access to assistance programs like SNAP, resulting in higher unemployment-related food insecurity (FI). Noncitizen cohorts from countries with lower human capital or those arriving during adverse economic periods experience particularly elevated FI risk. By contrast, immigrant cohorts with citizenship exhibit FI responses similar to natives during downturns, underscoring the protective role of both naturalization and food assistance program participation as buffers against economic shocks. Higher education partially mitigates the impact of unemployment on FI, particularly for US immigrant noncitizens. This analysis sheds light on the differential resilience of groups of immigrants in the U.S. facing economic downturns. These findings highlight the urgency of developing targeted policy interventions to identify and support at-risk immigrant groups that are disproportionately vulnerable to short-term economic shocks.

Key words: Immigrant, Food Insecurity, Unemployment, Bartik Instrument

JEL codes: J6, Q18, E24, C26

1 Introduction

Immigrant-led households play a crucial role in the U.S. economy, contributing $525 billion in federal taxes in 2021 and comprising 22.6 percent of all self-employed residents in 2022 (American Immigration Council, 2023). Their labor force participation rate was nearly 11 percent higher than that of native-born citizens in 2023 (U.S. Bureau of Labor Statistics, 2023), underscoring their active involvement in the workforce. However, despite these significant contributions, immigrants often face disproportionate economic challenges. They are more likely to face significant unemployment, work in hazardous jobs, earn about 20% less than U.S.-born counterparts, and experience higher poverty rates (Chilton et al. 2009; Kochhar, Espinoza, & Hinze-Pifer, 2010; Liu & Edwards, 2015; Orrenius & Zavodny, 2009). At the same time, when facing economic challenges, immigrant noncitizens are not eligible to access common public assistance programs (e.g., the Supplemental Nutrition Assistance Program (SNAP), unemployment insurance) unless they meet certain requirements [1]. Even after becoming eligible, many either do not apply or receive fewer benefits than natives (Nowrasteh & Orr, 2018). These factors collectively exacerbate their economic vulnerability, placing immigrant households, especially immigrant noncitizens at a heightened likelihood of food insecurity (FI) [2] during economic downturns.

While existing research has established that immigrants are more vulnerable to economic downturns, characterized by unemployment, increasing their likelihood of experiencing FI

[1] Unemployment insurance benefits are only available to authorized workers with the exception of workers in California, Colorado, and New York. Non-citizen immigrants are eligible for SNAP only if they meet specific criteria based on lawful status, length of U.S. residency (5 years), age, disability, or military connection, with many groups—such as undocumented individuals and temporary visa holders—remaining ineligible. https://www.fns.usda.gov/snap/recipient/eligibility/non-citizen

[2] FI occurs when households have a lack of consistent access to enough food for a healthy life (Food Security in the US).

compared to natives (Chaudry & Fortuny, 2010; Orrenius & Zavodny, 2009), much of this work lacks a robust causal identification strategy. For example, Flores-Lagunes et al. (2018) find that immigrants experienced higher FI incidence but less severity during the Great Recession. Potochnick and Arteaga (2018) show that FI increased for all households with children post-recession, with sharper rises among immigrant citizens but no significant differences between noncitizens and U.S.-born households. While informative, these studies primarily report correlations and often overlook endogeneity concerns (Huang, Kim, & Birkenmaier, 2016). Identifying the causal impact of the unemployment rate (UR) on household FI is particularly challenging as unobservable local shocks or household characteristics may simultaneously affect both the local unemployment and FI. Our contribution is to address this challenge by introducing a Bartik instrument for local unemployment.

The primary objective of this study is to measure the differential impact of local unemployment on household FI across immigrant citizenship groups and native households in the United States, with particular attention to how differences in eligibility for assistance programs like SNAP shape vulnerability to economic shocks. We combine annual MSA-level UR data from the U.S. Bureau of Labor Statistics (BLS) with household-level Current Population Survey (CPS) Food Security Supplement (FSS) data from 2004 to 2019, focusing on metropolitan households and omitting much of the agricultural and rural population. We specify several linear probability models to estimate the effect of MSA-level employment on household FI, decomposing the effect by households' immigration citizenship, cohorts of arrival and other factors that may mediate the effect of unemployment on FI.

To address endogeneity concerns, we employ a shift-share (Bartik) identification strategy (Bartik, 1991; Goldsmith-Pinkham, Sorkin, & Swift, 2020), which capture local exposures to national employment shocks through variation in industry composition Using monthly CPS data, we construct our baseline instrument by interacting 2003 MSA-level industry employment shares with national industry growth rates from 2004–2019. We further construct an immigrant citizenship-specific Bartik instrument—our preferred specification for estimating heterogeneous effects—as it holds industry composition fixed while allowing shocks to vary by immigrant status. Both instruments hold the same identification strategy assumption that initial local industry shares are exogenous to unobserved determinants of FI, conditional on controls.

Our identification strategy appears valid on several grounds. First, it satisfies the relevance condition: the Bartik instrument—defined as the inner product of local industry shares and national industry employment growth rates—is strongly correlated with MSA-level unemployment, as confirmed by statistical tests. Second, the exclusion restriction is plausibly satisfied. The instrument is constructed using 2003 industry shares, measured prior to observed household FI outcomes, reducing the risk of reverse causality or confounding by contemporaneous shocks. Multiple pieces of evidence support the instrument's validity. Industry shares display strong persistence over time and are uncorrelated with pre-period household FI, suggesting exogeneity to local shocks directly influencing FI. One potential concern is endogenous migration—immigrant households may move to higher-income MSAs in response to better industry opportunities (Dostie, 2022), potentially biasing estimates. Indeed, some dominant industries correlate with local demographic and economic characteristics. However, results remain robust when we exclude these industries from the instrument. Additionally, overidentification tests indicate that alternative shift-share instruments yield consistent estimates, reinforcing the assumption that all instruments identify the same parameter. Overall, unobserved confounding and household sorting are unlikely to undermine the validity of our identification strategy.

Our analysis yields several important findings. We begin by documenting a procyclical relationship between local labor market conditions and household FI. Specifically, our IV estimates indicate that a one percentage point decrease in the local UR leads to a 1.1–1.2 percentage point increase in the likelihood of household FI. This effect is more than twice as large as estimates from Ordinary Least Squares (OLS) and significantly exceeds prior findings. For example, Nord, Coleman-Jensen, and Gregory (2014) report that a one percentage point increase in the MSA-level UR corresponds to a 0.5 percentage point rise in FI prevalence. Additionally, we find that noncitizen immigrant households are 1.7 percentage points more likely to experience FI than their native-born counterparts, conditional on observable characteristics.

We further document that both noncitizen and citizen immigrants are more likely to experience FI than natives, with noncitizens facing the greatest vulnerability. Using the immigrant citizenship-specific Bartik IV, we find a rise in unemployment increases the likelihood of FI by 1.5 percentage points more for noncitizen households than for natives—a substantially larger effect than the corresponding OLS estimate. This underscores the importance of accounting for heterogeneous labor market shocks across citizenship groups. Consistent with prior literature (Orrenius & Zavodny, 2009), our findings suggest that noncitizen immigrants, who often have limited access to public assistance programs, are particularly vulnerable to economic downturns and exhibit heightened sensitivity to labor market fluctuations. Moreover, the predicted probabilities of FI reveal that noncitizen immigrants experience higher FI rates than natives when URs exceed 5.8%[3]. In contrast, immigrant citizens show only a modestly higher likelihood of FI relative to natives, concentrated in periods when URs range from 6.4% to 7.6%. These results reinforce the notion that noncitizen immigrants are disproportionately exposed to adverse

[3] In a healthy economy, unemployment rates typically range between 3% and 5%.

economic conditions due to both labor market disadvantage and restricted access to safety net programs. (Orrenius & Zavodny, 2009).

Upon controlling for the effects of immigrant citizenship status, distinct patterns emerge across different immigrant arrival cohorts. Noncitizen immigrants from the pre-1970, 1980–1989, and 2000–2009 arrival cohorts display significantly greater sensitivity to increases in unemployment compared to native-born households, while immigrant cohorts with citizenship exhibit response patterns statistically indistinguishable from those of natives. This pattern underscores the buffering role of citizenship during downturns. Variation among noncitizen cohorts likely reflects cohort-specific selection and the enduring impact of arrival-time economic conditions, which shape long-term labor market vulnerability. In particular, the 1980–1989 noncitizen cohort—largely composed of immigrants from economically disadvantaged regions in Latin America and Asia (Abramitzky et al., 2021)—shows a heightened likelihood of FI during economic downturns. Their arrival coincided with an era marked by restrictive immigration policies [4], potentially compounding their economic challenges. The 2000-2009 cohort of immigrants without citizenship demonstrates a pronounced vulnerability to FI in the face of great economic downturns, a situation likely exacerbated by their immediate exposure to the challenges of the post-9/11 immigration policy changes and the GR upon arrival.

Our subsample analysis reveals that while higher education, particularly at the Bachelor's degree or above, mitigates the impact of unemployment on FI. However, it does not consistently offset the additional risk of FI faced by immigrants relative to natives. Notably, higher education appears more protective for immigrant noncitizens than for immigrant citizens when compared to natives. This pattern highlights the widespread challenges in the labor market immigrants face,

[4] During the 1980s, the United States underwent significant changes in its immigration policy, including the Refugee Act of 1980, the Immigration Reform and Control Act (IRCA) of 1986, and the Diversity Visa (DV) Program, etc.

regardless of education, supporting the view that both low and high-skilled immigrants are more susceptible to economic fluctuations over time than natives (Liu & Edwards, 2015; Orrenius & Zavodny, 2009). Additionally, our results suggest that access to food assistance programs can help mitigate the negative impacts of unemployment on FI does not fully protect noncitizens.

Overall, our findings indicate that changes in unemployment disproportionately impact immigrant citizen groups, particularly in terms of FI, compared to natives. This effect is most pronounced among immigrant non-citizens, a group with limited or no access to public assistance. Our analysis underscores the potential advantages of expanding work-based public assistance programs, such as SNAP and unemployment benefits. Such measures are especially relevant for vulnerable immigrant non-citizens, who are often excluded from many government safety net programs[5].

The remainder of this paper is structured as follows. Section 2 describes the data sources. Section 3 outlines the empirical methodology, elaborates on the identification strategy, and explains the construction of the Bartik instruments. Section 4 presents the estimation results and conducts robustness checks for the Bartik instrument. Section 5 discusses the findings and their potential policy implications. Section 6 concludes.

2 Data and Descriptive Statistics

Our analysis utilizes a repeated cross-sectional dataset constructed from the U.S. Bureau of Labor Statistics (BLS) and the Current Population Survey (CPS) spanning the years 2004 to 2019. The CPS is the most extensive monthly household survey in the U.S., conducted by the BLS and the U.S. Census Bureau (Flood et al., 2022), sampling approximately 50,000 households each month.

[5] Recently, several states have begun to provide unemployment benefits to unauthorized workers: Colorado, California, and New York (Visram, 2023; Wilson, 2023).

This survey provides detailed information on household characteristics, including immigration status, citizenship, and employment. Each December, a subset of households that participate in the CPS also complete the Food Security Supplement (FSS). The FSS collects data on household food conditions over the past year and classifies households into four categories: food secure, marginally food secure, low food secure, and very low food secure. Following prior studies (Berning, Cleary, & Bonanno, 2023; Potochnick & Arteaga, 2018), we define FI as a binary indicator[6], coding households as food secure (0) if they fall into the first two categories and food insecure (1) if they fall into the latter two. To account for local labor market conditions, we incorporate annual, seasonally unadjusted URs for metropolitan statistical areas (MSAs) from 2004 to 2019, obtained from the U.S. Bureau of Labor Statistics (BLS). MSAs, defined based on commuting patterns, more accurately reflect functional labor markets than states (Molloy, Smith & Wozniak, 2011). These UR data are matched with household information based on MSA of residence and CPS year, restricting our dataset to metropolitan households, thus excluding rural and agricultural households.

We restrict the sample to individuals aged 18 to 65[7], the conventional working-age population, to focus on those typically active in the labor force. Of these households, 15.4% (n = 49,082) are identified as immigrant households. We classify married immigrant households as those in which both the head and spouse/partner were born outside the U.S., regardless of whether they originate from the same or different countries. Similarly, households where both the head and spouse/partner are U.S.-born are classified as native households. We exclude mixed-nationality

[6] Following Mykerezi and Mills (2010) and Coleman-Jensen et al. (2022), we also explore alternative definitions of food insecurity based on severity: (1) any affirmative response (marginally, low, or very low food security) and (2) very low food security only. Estimates using these alternative measures are reported in Appendix Table E.1.

[7] To ensure generalizability, the main analysis includes all households regardless of the head's or spouse's labor force status. A robustness check restricting to households with heads in the labor force yields similar results (Appendix Table D.1), supporting the broader sample's validity.

households, where the head and spouse differ in immigrant status[8]. Because eligibility for assistance programs differs between noncitizens and naturalized citizens, we divide immigrant households into two groups: noncitizens (n = 23,347; 48%) and naturalized citizens (n = 25,735; 52%). To account for variation in arrival contexts (Abramitzky et al., 2021; Borjas, 1995), we further classify households into six arrival cohorts: 1969 or earlier, 1970–1979, 1980–1989, 1990–1999, 2000–2009, and 2010–2019. The age restriction (18–65) results in smaller sample sizes for the earliest and most recent cohorts.

Summary statistics in Table 1 highlight the differences between native and immigrant households. Immigrant households, particularly noncitizens and post-1990 arrivals, are less likely to conduct interviews by phone relative to natives. They generally have higher rates of marriage and children under 18, particularly among noncitizens and recent arrival cohorts. Immigrant households also tend to have younger, more male-dominated. Educational attainment varies: noncitizens are more likely to lack a high school diploma, while immigrant citizens are more likely to hold advanced degrees, reflecting labor market segmentation (Bandyopadhyay & Grittayaphong, 2020). Income disparities are evident, with immigrant households earning less on average than natives and are more likely to fall below 185% of the poverty line, though naturalized citizens fare better than noncitizens. Poverty rates are lower among earlier arrivals but higher among those arriving after 1970. Noncitizens also participate in SNAP at higher rates than both natives and immigrant citizens.

Figure 1 presents trends in unemployment and FI over the study period. Panel A demonstrates a clear correlation between household FI and UR: native households consistently

[8] As a robustness check (Appendix Table D.1), we restrict the sample to married immigrant households with same-country spouses to reduce cultural heterogeneity. We also conduct a sensitivity analysis including mixed-nationality households (foreign- and native-born spouses), classifying them as immigrant citizen households to assess the role of citizenship in program eligibility and food access.

report the lowest and most stable FI rates, while noncitizen immigrants experience the highest, particularly during downturns. Immigrant citizens resemble natives during stable periods but show elevated FI during recessions. Panel B illustrates variation in FI across different immigrant cohorts, with earlier cohorts (1969 or earlier) generally experiencing lower FI rates compared to natives, while later cohorts (1980-1989, 1990-1999, 2000-2009) exhibit higher vulnerability, especially during economic downturns.

3 Empirical Methods

Our primary objective is to estimate the effect of unemployment in local labor market on household FI, first across all households, and then by nativity and citizenship status—comparing noncitizens, naturalized citizens, and natives. We estimate a battery of regressions designed to estimate the causal effect of unemployment on FI using Bartik instruments. This section introduces the empirical specifications and our identification strategy.

3.1 Empirical Models

We start our empirical analysis by estimating the following benchmark regression model for all households using our repeated cross-sectional data from 2004 to 2019:

$$y_{imt} = \alpha + \beta UR_{mt} + \gamma Imm_{imt} + \boldsymbol{\delta X}_{imt} + \pi L_{imt_0} + \omega_m + \theta_t + \epsilon_{imt} \quad (1)$$

where y is the binary FI status of household i, in metropolitan statistical area (MSA) m in year t. The vector UR_{mt} is the unemployment rate in MSA m in year t. Imm_{imt} is household i immigrant status which takes a value of zero for natives. We control for household and household head characteristics X from CPS monthly data including a vector of household demographic characteristics such as interview type (phone or in-person), marriage status, the number of children under 18; and household head characteristics including gender, age, education attainment, years since immigration, the square of years since immigration and residual household income.

Following Gould and Moav (2016), the residual household income, representing unobserved skills, is calculated as the residual from a Mincer-like regression of wage (regressing the natural log of the midpoint of the household's family income[9] category on the head's years of schooling, age, age squared, marital status, continent of origin fixed effects, MSA & year fixed effects, applying CPS person-level weights). This controls for potential omitted variable bias due to unobserved skills that may contribute to FI disparities. As suggested by Goldsmith-Pinkham, Sorkin, & Swift (2020), we also control for location demographic and socioeconomic characteristics, at the initial research period denoted as L_{imt_0}. Demographic controls from the 2003 CPS monthly data include racial composition, nativity, education levels, gender, marital status, household size, number of children, and median age. Socioeconomic controls from the 2003 CPS ASEC include poverty rate, median income, homeownership, public housing, and SNAP receipt rates. Finally, MSA fixed-effects (ω_m) are included to account for time-invariant but spatial-variant omitted variables correlated with both household FI and UR. Year fixed-effects (θ_t) capture variations in FI and the average UR over time that are not explained by other time-varying covariates.

We use a linear probability model (LPM) to estimate Equation (1) and other equations. While nonlinear models such as logit or probit can capture the bounded and nonlinear nature of binary outcomes and address issues like heteroskedasticity (Friedman, 2012), the LPM[10] offers straightforward interpretation: coefficients can be read as marginal effects of covariates on the probability of FI.

[9] Because weekly earnings are unknow for 86% of the sample, we use family income midpoints as a proxy for economic standing. Mean residual income by immigrant subgroup is reported in Table 1.

[10] We use the LPM for its interpretability, tractability, and compatibility with instrumental variable methods such as two-stage least squares (2SLS), which we employ to address endogeneity. As Wooldridge (2010) notes, the LPM is well-suited for estimating marginal effects and identifying causal relationships. Unlike probit or logit models, it accommodates interaction terms and fixed effects without introducing incidental parameter bias (Ai and Norton, 2003; Greene, 2004).

Following prior research showing that citizenship influences FI (Kalil & Chen, 2008), we specify a model that allows the effect of unemployment on FI to vary by nativity and citizenship status—distinguishing among native, immigrant naturalized citizen, and noncitizen households.

$$y_{imt} = \alpha + \beta_0 UR_{mt} + \beta_1 UR_{mt} \times D_{imm}^{noncit} + \beta_2 UR_{mt} \times D_{imm}^{cit} + \gamma_1 D_{imm}^{noncit} + \gamma_2 D_{imm}^{cit} + \boldsymbol{\delta X}_{imt} + \pi L_{imt_0} + \omega_m + \theta_t + \epsilon_{imt} \quad (2)$$

In this specification, D_{imt}^{noncit} and D_{imt}^{cit} are binary indicators for immigrant noncitizens and naturalized citizens, respectively. Our primary coefficients of interest, β_1 and β_2, captures differences in household FI responses to local labor market UR_{mt} for immigrant noncitizen and citizen households, respectively, relative to native households (the omitted group). So, predicted FI gap between immigrant noncitizens and natives is $\hat{\beta}_1 \cdot UR_{mt} + \hat{\gamma}_1$, and between naturalized citizens and natives is $\hat{\beta}_2 \cdot UR_{mt} + \hat{\gamma}_2$. The model also controls for household and household head characteristics *X*, local factors (*L*), MSA- and year-fixed effects.

We next specify a model capturing the effect of unemployment on FI for the six immigrant arrival cohorts, isolating differences in immigrants due to changes in immigration policy and economic conditions over time (Abramitzky et al., 2021; Borjas, 1995):

$$y_{imt} = \alpha + \beta_0 UR_{mt} + \sum_{c=1}^{6} \beta_c \, UR_{mt} \times D_{imm}^{c} + \sum_{c=1}^{6} \lambda_c D_{imm}^{c} + \boldsymbol{\delta X}_{imt} + \pi L_{imt_0} + \omega_m + \theta_t + \epsilon_{imt} \quad (3)$$

In this Equation (3), D_{imm}^{c} is an indicator for whether the household head's immigration year falls into one of six (j = [1,…,6]) arrival cohorts from 1969 or earlier to 2019. The coefficent $\hat{\beta}_c$ captures the differential responses to local URs across immigrant cohorts of arrival and native households. Furthermore, the combined term $\hat{\beta}_c \cdot UR_{mt} + \hat{\gamma}_c$ estimates the difference in the predicted FI gap between each immigrant cohorts and natives. Because eligibility for U.S. citizenship depends on residence duration, which varies by naturalization pathway, citizenship status may influence cohort-specific outcomes. To isolate these effects, we estimate Equation (3) separately by citizenship category.

3.2 Empirical Strategy, Identification, and Inference

Several factors may bias OLS estimates of the relationship between local unemployment and household FI. First, unobserved household traits—such as skills, resilience, or informal support—may influence both UR and FI, causing omitted variable bias (Munshi, 2003; Gould and Moav, 2016). Second, households may sort across labor markets based on affordability, job prospects, or access to benefits, introducing selection bias if correlated with FI (Cadena & Kovak, 2016). Third, local shocks—such as changes in safety nets, housing markets, or governance—may confound both outcomes. Fourth, reverse causality may arise if food-insecure households relocate or adjust labor supply under hardship. Finally, labor market indicators may be endogenous to population composition, itself shaped by food security dynamics.

To mitigate these concerns, we control for a rich set of covariates. We include residual household income to account for unobserved household traits and labor market attachment. The local demographic characteristics (e.g., racial composition, education levels) and local economic indicators (e.g., poverty rate, SNAP participation, homeownership rate) measured at the initial research period partially capture time-invariant unobserved local shocks that may confound the relationship. A full set of MSA and year fixed effects absorb time-invariant regional differences and national shocks.

Despite these controls, endogeneity concerns persist. Time-varying unobserved shocks at the MSA level—such as changes in governance, safety nets, or labor supply-side conditions—may still bias estimates. Reverse causality and endogenous household sorting across labor markets further complicate identification. To address these issues, we implement a shift-share instrumental variable (or called Bartik IV) strategy, which interacts initial industry employment shares (exposure) with national industry growth (shocks), following Goldsmith-Pinkham, Sorkin, and Swift (2020). The plausibility of share exogeneity for our Bartik IV requires that differential exposure to national shocks—arising from variation in industry shares in initial period[11]—does not systematically cause differential changes in the household FI outcome, except through the endogenous variable (Borusyak, Hull & Jaravel, 2025).

Bartik IV Identification

To construct this Bartik IV, we first compute the 2003 local industry employment shares for household heads aged 18 and older who usually work at least 30 hours per week ($s_{m,k,2003}$) across MSA. We then calculate the national industry employment growth[12] ($g_{k,t}$) from 2004 to 2019 using CPS monthly data. The instrument is the interaction of the initial local industry shares and the national industry growth. The Bartik instrument for the UR in MSA m and year t is given as:

$$B_{m,t} = \sum_j^{13} s_{m,k,2003} * g_{k,t} = \sum_j^{13} \frac{E_{m,k,2003}}{E_{m,2003}} * \frac{E_{k,t} - E_{k,t-1}}{E_{k,t-1}} \quad (4)$$

Here, local industry employment share $s_{m,k,2003}$ is constructed by dividing the number of people employed in industry *k* in MSA *m* in year 2003 ($E_{m,k,2003}$) by total MSA employment ($E_{m,2003}$). National employment growth across industries and years is calculated as $g_{k,t}$, where $E_{k,t}$ is the number employed in industry k in year *t*. We conduct a leave-one-out procedure[13] to estimate

[11] Alternatively, Borusyak, Hull, and Jaravel (2022) assumes the aggregated shocks are exogenous, while the cross-sectional shares may be endogenous.
[12] We use employment growth instead of unemployment growth because CPS data more accurately capture employment, and the two measures are highly correlated.
[13] We estimate Equation (4) separately for each location g, excluding all observations from that location m when constructing the national industry growth rate $g_{k,t}^{(-g)} = \frac{(E_{k,t} - E_{m,k,t}) - (E_{k,t-1} - E_{m,k,t-1})}{E_{k,t-1} - E_{m,k,t-1}}$.

national growth rate $g_{k,t}$ across industries, excluding each MSA's own data when constructing its Bartik instrument. This adjustment prevents mechanical correlation with local shocks by ensuring that MSA m's employment does not influence the national trends used in its instrument, isolating variation driven by national rather than local conditions. Based on industrial classification using the North American Industry Classification System (NACIS), industries in the monthly CPS data are disaggregated into 13 categories[14].

We use $B_{m,t}$ as an instrument to separately estimate Equations (1) - (3) via two-stage least-squares (2SLS). To explain the identification process, we consider Equation (1). The complete identification model comprises the first-stage regression (as shown in Equation (5)), the second-stage regression (originally presented in Equation (1), and now shown in Equation (6)), and the exclusion restrictions specified in Equation (7). The details of these components[15] are as follows:

$$UR_{mt} = \lambda_0 B_{m,t} + \lambda_1 Imm_{imt} + \zeta X_{imt} + \omega_m + \mu_{imt} \tag{5}$$

$$y_{imt} = \alpha + \beta \widehat{UR}_{mt} + \gamma Imm_{imt} + \boldsymbol{\delta X}_{imt} + \pi L_{imt_0} + \omega_m + \epsilon_{imt} \tag{6}$$

$$0 = \text{cov}\left(B_{m,t}, \epsilon_{imt} | Imm_{imt}, X_{imt}, \omega_m\right) \tag{7}$$

There are two main requirements for our instrument to be valid. First, the relevance assumption implies the Bartik instrument causes variation in the MSA level URs, which means λ_0 in Equation (6) is statistically different from zero. Second, the exclusion restrictions (main

[14] The 13 industries include: Agriculture, Forestry, Fishing, and Hunting; Mining; Construction; Manufacturing; Wholesale and Retail Trade; Utilities; Transportation and Warehousing; Information; Finance, Insurance; Real Estate, and Rental and Leasing; Professional and business services; Educational; Health and Social Services; Arts, Entertainment, Recreation; Accommodation, and Food Services; Other Services (Except Public Administration); Public Administration.

[15] We do not use time fixed effect or local demographic controls interacted with time dummies in 2SLS using Bartik IV. Column 6 of Appendix Table F.1 shows that including year fixed effects absorbs too much time series variation in the national shock embedded in the Bartik IV weakening the first stage (F = 0.069). This aligns with Graham and Makridis (2023), who find that year fixed effects eliminate most identifying variation in Bartik designs.

identifying assumption) in Equation (7) requires that conditional on controls, $B_{m,t}$ does not affect household-level FI (y_{imt}) directly, but only through UR_{mt}. In other words, the Bartik instrument does not correlate with the error term ϵ_{imt} in Equation (7).

Bartik IV Validity

Building on Goldsmith-Pinkham, Sorkin, and Swift (2020), our Bartik instrument is conceptually valid, and its relevance assumption is statistically tested. Figure 2 shows a binned scatter plot of the residualized instrument against residualized MSA UR from the first-stage regression. The alignment of binned points around the regression line indicates a strong, statistically significant relationship, even after controlling for covariates. This statistical relevance arises from the instrument's construction as the inner product of local industry shares and national industry employment growth—both plausibly linked to local labor market conditions, proxied by the UR.

In terms of the exclusion restriction, our identification strategy assumes that unobserved shocks to household FI are uncorrelated with local industry composition at the MSA level, conditional on controls. This assumption is plausible, as the industry shares used to construct the instrument are lagged and measured in 2003—prior to the start of the analysis period (2004–2019)—and are therefore predetermined with respect to FI outcomes. Consistent with this logic, we find strong persistence in local industry structure over time: Figure A.1 shows that 2003 MSA-level industry shares correlate above 0.97 with the MSA-level average industry shares across 2004–2018, further reducing concerns about endogeneity from contemporaneous or unobserved shocks. To formally assess endogeneity, we conduct a Durbin–Wu–Hausman test comparing OLS and 2SLS estimates. The test strongly rejects exogeneity ($p < 0.001$), indicating that OLS is inconsistent and the IV strategy is appropriate.

Two key threats remain to our identification strategy. First, although the Bartik instrument relies on predetermined variation, industry shares may still be endogenous if shaped by structural or historical factors—such as concentrated poverty, immigration patterns, or local institutions—that also affect FI trends (Borusyak, Hull, and Jaravel, 2025). If these factors correlate with unobserved local conditions or persistent poverty, the exclusion restriction may be violated. Second, non-random sorting—particularly of immigrants—into industries and locations may reflect unobserved factors related to both FI and local unemployment. For example, if vulnerable groups migrate to areas with expanding sectors (e.g., construction), shocks specific to these populations could bias estimates.

Building on Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2025), we conduct diagnostic tests to assess the validity of the shift-share instrument, focusing on the exogeneity of initial industry shares conditional on observed household and local characteristics. For instance, in our research context, controlling for local foreign-born share and median income helps ensure that the instrument captures variation in industry composition across MSAs, rather than reflecting differences in immigrant sorting or income intensity.

Firstly, we conduct a falsification test—similar to the pre-trends test in Autor, Dorn, and Hanson (2013)—to examine whether our Bartik instrument predicts FI prior to the study period. Specifically, we regress pre-period household FI (e.g., 2000–2002) on the Bartik IV. The lack of a significant relationship between the instrument and pre-period FI (Table A.1) supports the assumption that unobserved shocks to FI are uncorrelated with local industry composition. This also mitigates concerns that initial period shares may reflect structural or historical factors—such as persistent poverty—that could jointly shape industry composition and FI.

Furthermore, we conduct balance tests to examine the relationship between our instrument and observable variables that may correlate with the error term. Following Goldsmith-Pinkham, Sorkin, and Swift (2020), we assess whether initial local industry shares—particularly for the top five most heavily weighted industries[16]—are systematically related to MSA-level characteristics in the base period (2003). Regressions in Appendix Table B.2 yield high R-squared values; for example, local characteristics explain 57% of the variation in the 2003 industry shares, suggesting that much of its cross-sectional variation reflects local conditions. The most heavily weighted industries are significantly correlated with demographic and economic indicators such as racial composition, education levels, immigrant share, poverty and income, while the overall Bartik instrument is primarily correlated with income distribution. Because these variables may proxy for unobserved factors (e.g., endogenous sorting), this raises concerns about omitted variable bias, even after adjusting for these observed confounders (Altonji, Elder, and Taber, 2005; Oster, 2019). Among the top five industries, Wholesale and Retail Trade carries the highest Rotemberg weight, where confounding risk appears greatest.

Given that the most heavily weighted industries in the Bartik instrument are correlated with certain local controls, they pose the highest risk of omitted variable bias. To assess this risk, we conduct a robustness check that sequentially excludes the top five Rotemberg-weighted industries. As shown in Table C.2[17], our results remain stable. Moreover, our estimates are robust to the inclusion of either household-level or MSA-level demographic controls shown in Section 4. To further evaluate the exclusion restriction, Table A.2 shows weak and insignificant correlations

[16] Goldsmith-Pinkham, Sorkin, and Swift (2020) argue that confounding is most likely in industries with the largest Rotemberg weights—i.e., the top five contributors to exposure design Appendix B provides further detail on the construction of these weights.

[17] Further details are provided in Section 4.3. To address concerns that our results may be driven by a single dominant industry, we re-estimate the main 2SLS specification (Table 3, column 7), sequentially omitting each of the most heavily weighted industries from the construction of local industry shares, following Goldsmith-Pinkham, Sorkin, and Swift (2020) and Jiang, Kennedy, and Zhong (2023).

between the Bartik IV and MSA-level net migration, suggesting no meaningful relationship between local labor demand shocks and migration patterns. Together, these findings support the validity of our instrument, indicating that potential unobserved shocks or sorting are unlikely to violate the exclusion restriction.

Additionally, we examine the sensitivity of our estimates to how industry shares are combined. Following Goldsmith-Pinkham, Sorkin, and Swift (2020), Figure B.2 presents a visual diagnostic of the overidentification test, plotting industry-specific IV estimates ($\widehat{\beta_k}$)—each using a single industry share as a separate instrument[18]—to assess whether they yield statistically similar estimates. The results show that the overidentification test effectively "passes": the estimates lie approximately along a single ray from the origin, indicating that most individual shares identify a common parameter—particularly those with high F-statistics and large Rotemberg weights. This supports the exogenous shares assumption, suggesting that each individual share, or any linear combination thereof, serves as a valid instrument underpinning the Bartik design.

In our 2SLS estimates, we report standard errors using the AKM procedure (Adão, Kolesár, and Morales, 2019). In shift-share designs, standard errors can be understated when industry shares are correlated across regions, leading to residual correlation not fully captured by geographic clustering. For example, MSAs with similar industry structures may experience correlated shocks despite being geographically distant. The AKM method addresses this by allowing arbitrary correlation across units with similar exposure profiles and clustering over time. These corrected standard errors are reported in Table 2[19].

Immigrant citizenship-specific Bartik IV

[18] Further details on the overidentification test are provided in Figure B.1 & B.2 of Appendix B.

[19] We report AKM-adjusted standard errors for the baseline 2SLS model (Table 3), following Adão, Kolesár, and Morales (2019). For models with interaction terms, which AKM does not accommodate, we use MSA-clustered standard errors (Appendix Table F.1).

Our Baseline Bartik IV that interacts MSA-level industry shares with national industry employment growth implicitly assumes that all citizenship groups are equally affected by national industry shocks. But this may not hold in immigrant labor markets where employment opportunities differ by immigrant citizenship status (Smith, 2006; Orrenius & Zavodny, 2009; Liu & Edwards, 2015). For instance, industry growth may benefit native-born workers more than non-citizen immigrants due to legal barriers, language differences, or occupational sorting. Using a pooled national growth rate may introduce measurement error and bias in estimates of heterogeneous effects on FI. To address this concern, we follow Jiang, Kennedy, and Zhong (2023) in constructing a citizenship-specific Bartik IV that interacts local industry shares with national growth rates calculated separately by citizenship group. This approach captures group-specific labor demand shocks and mitigates bias from unobserved heterogeneity. Moreover, it clarifies whether disparities in FI reflect true vulnerability to unemployment or are confounded by unobserved factors.

We define the citizenship-specific Bartik IV by interacting MSA-level industry shares with citizenship-specific national industry growth rates, where $g \in \{0,1,2\}$ (0=native, 1=immigrant noncitizen; 2=immigrant citizen), our citizenship-specific Bartik IV is:

$$B_{m,t}{}^{\mathrm{g}} = \sum_{j}^{13} s_{m,k,2003} * g_{k,t}{}^{\mathrm{g}} \tag{8}$$

The key innovation in Equation (8) is the use of group-specific national employment growth in industry k ($g_{k,t}{}^{\mathrm{g}}$), which departs from the baseline specification in Equation (4). $B_{m,t}{}^{\mathrm{g}}$ denotes the Bartik instrument for MSA m, year t, for citizenship-specific group g. $s_{m,k,2003}$ is still the share of industry k in MSA m in base year 2003.

The citizenship-specific Bartik IV further improves the estimation of interaction effects. The second stage equation from the 2SLS model using the new Bartik IV is:

$$y_{imt} = \alpha + \beta_0 \widehat{UR_{mt}}^g + \beta_1 \widehat{UR_{mt}}^g \times D_{imm}^{noncit} + \beta_2 \widehat{UR_{mt}}^g \times D_{imm}^{cit} + \gamma_1 D_{imm}^{noncit} + \gamma_2 D_{imm}^{cit} + \boldsymbol{\delta X}_{imt} + \omega_m + \epsilon_{imt} \quad (9)$$

Comparing the baseline specification in Equation (2), the key innovation in the new specification is that the $\widehat{UR_{mt}}^g$ and its interactions are instrumented using citizenship-specific Bartik IV $B_{m,t}{}^{g}$, where national industry growth rates vary by immigrant citizenship status $g \in \{0,1,2\}$. This allows the instrumented local unemployment rate $\widehat{UR_{mt}}^g$ to capture group-specific labor market exposure, aligning more closely with each subgroup's employment opportunities rather than applying a single value per MSA. As a result, the estimated coefficient β in Equation (9) captures the causal effect of group-specific unemployment risk—driven by national shocks relevant to each group—on FI. This approach strengthens identification by exploiting within-MSA, between-group variation and relaxing the assumption that all groups respond similarly to aggregate labor demand shocks. It is our preferred specification, as it relies on weaker identifying assumptions and provides more credible evidence of heterogeneous effects by aligning the instrument more closely with the labor market realities faced by each group.

This new instrument design is consistent with the core logic of baseline Bartik IV identification. Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022) show that identification in Bartik-style designs primarily comes from variation in industry shares rather than national shocks. Our citizenship-specific Bartik instrument modifies only the shock component—allowing national growth rates to vary by immigrant status—while holding industry composition fixed[20]. The primary identifying assumption is a relaxed version of the baseline exclusion restriction:

[20] Since both instruments has the same identification assumption for exogenous local industry composition, the checks for misspecification and instrument validity of Bartik instrument use the baseline Bartik IV like Table B.2 and information in Appendix B.

conditional on observables, differences in FI across groups within an MSA reflect variation in exposure to group-specific national labor demand shocks, given fixed local industry composition.

4 Results

4.1 The Effect of Unemployment on Household FI

4.1.1 Analysis for All households

We begin by examining the response of household FI to UR in MSAs[21]. Table 2, columns (1) - (3) report the results of our linear probability model (OLS) weighted by CPS 2003 population[22] counts with standard errors clustered at the MSA level. Column (1) includes no controls; Column (2) adds MSA and year fixed effects; and column (3) introduces household-level controls. Across specifications, a 1% increase in the UR is associated with a statistically significant 0.6 % increase in the probability of FI—a slightly stronger effect than found in prior state-level studies (Nord et al., 2014; Potochnick & Arteaga, 2018). Noncitizen immigrants are significantly more likely to experience FI than natives, though the gap narrows from 8.7 to 1.7% after adjusting for demographics. In contrast, naturalized citizens do not differ significantly from natives in their likelihood of being food insecure.

The 2SLS estimates using our baseline Bartik instrument are presented in Columns (4) - (7) with standard errors and F-statistics estimated following Adão, Kolesár and Morales (2019). The first-stage F-statistics reported in the last rows are well above the typical rule of thumb of 10 for weak instruments (Stock, Wright, & Yogo, 2002). Column (4) does not include controls, and columns (5) - (6) include household-level demographic controls as well as location fixed effects.

[21] We also report the results of Table 2 with all controls in Appendix Table F.1.
[22] Following Goldsmith-Pinkham, Sorkin, and Swift (2020), we use initial-period MSA population as regression weights to ensure that identifying variation reflects predetermined exposure to industry shocks, not post-treatment population shifts or sampling design. We also report 2SLS results for Equation (1) and (2) using CPS household food security weights (Table D.2), which remain robust and consistent.

Column (7) introduces a range of local characteristics measured at MSA level in initial period 2003 as suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020). After correcting for bias of OLS estimates, the marginal effects of the UR on FI range from 1.2% to 1.1% with different bundles of controls, which is statistically higher than the estimated marginal effects from OLS. Meanwhile, noncitizen immigrant households 1.7% more likely to experience FI than natives.

As we previously mentioned, the inclusion of the large number of effective local controls provides an empirically demanding test of the possibility that the composition of local households is correlated with the composition of the local employment growth (e.g., the UR) in a way that drives both FI and UR. Nevertheless, we find little changes in the estimated marginal effect of the UR on FI after adding the local demographic controls.

4.1.2 Analysis by Immigrant Citizenship Status

Citizenship status often proxies eligibility for food assistance programs like SNAP and is a strong predictor of FI (Kalil & Chen, 2008; Potochnick & Arteaga, 2018). We therefore test whether local URs have differential effects on FI for immigrant subgroups—citizens and noncitizens—relative to natives (Table 3). Our OLS estimates (columns 1 – 3) show a higher UR is significantly associated with a higher likelihood of FI among immigrant noncitizens, citizens and natives. Specifically, a 1% increase in the UR associated with a 1.2% - 1.9% higher probability of immigrant noncitizen household experiencing FI, 0.7% - 1.1% for immigrant citizens, and 0.4% - 0.8% for natives. In addition, a 1% increase in UR is associated with 0.8% - 1.1% greater probability of FI for immigrant noncitizens relative to natives, and 0.2% - 0.3% for immigrant citizens relative to natives.

The 2SLS estimates using the citizenship-specific Bartik IV better capturing group-specific labor demand shocks (columns 4–7) support the finding that immigrant noncitizen households exhibit greater sensitivity to unemployment than native households. Specifically, a 1 percentage point rise in unemployment causes a 2.3–2.7% rise in FI among immigrant noncitizens, compared to 0.8–0.9% among natives, as more controls are added. This implies a differential effect of approximately 1.5% – 1.8%. In contrast, the estimated effect for immigrant citizens, at 1.2% – 1.6%, is not significantly different from that observed for natives. Notably, when employing the citizenship-specific Bartik IV, we find that immigrant noncitizens are 1.5 percentage points more likely to experience FI in response to unemployment than natives—a statistically larger estimate than the OLS counterpart[23]. The improved significance arises because the citizenship-specific Bartik instrument enhances the credibility of our heterogeneity estimates by better aligning the instrument with the labor market conditions faced by each group.

Based on our 2SLS estimates, we plot and contrast the predicted probabilities of FI between immigrant and native households across varying URs (see Figure 3). The "Immigrant Noncitizen vs Native" line has a steeper positive slope than the "Citizen vs Native" line. There exists a wider disparity in the incidence of household-level FI between immigrant noncitizens and natives compared to that between immigrant citizens and natives across various URs, with notable statistical significance observed when the UR is between 6% and 12.2%. Overall, Figure 3 demonstrates that immigrant noncitizen households exhibit a higher vulnerability to FI compared to U.S.-born households whenever the MSA-level UR surpasses 5.8%. Additionally, when the UR increases between 6.4% and 7.6%, immigrant citizens are significantly more susceptible to FI than natives.

[23] The 2SLS estimates using baseline Bartik IV as a robustness check are reported in Appendix Table F.2.

4.1.3 Analysis by Immigrants' Cohorts of Arrival

We next evaluate heterogenous responses of household FI between immigrant cohorts of arrival and natives, distinguishing among various immigrant citizenship statuses. Table 4 presents the 2SLS estimation results from citizenship-specific Bartik IV incorporating the full set of control variables. Specifically, the analysis detailed in column (1) is confined to the sample comprising both immigrant noncitizens and native-born households. Conversely, the analysis shown in column (2) is restricted to the sample that includes immigrant citizens and native-born households. The interaction terms reveal important cohort heterogeneity.

Among noncitizens, the earliest cohort (pre-1970) exhibits a significant and sizable effect: a 1 percentage point increase in unemployment raises the probability of FI by 2.7% relative to natives at 0.8%. This suggests that long-settled immigrants may face compounded risks, potentially due to aging, limited social mobility, or declining labor market attachment. Relative to natives, households in the 1980–1989 and 2000–2009 cohorts also experience statistically significant increases in FI of 2.4 and 1.4 percentage points, respectively, in response to an economic downturn, as proxied by a rise in the UR. In contrast, estimated differential effects for the 1970–1979 and 1990–1999 cohorts are smaller and not statistically distinguishable from zero. Notably, the most recent cohort (2010–2019) exhibits a negative but statistically insignificant heterogeneous effect relative to natives, suggesting either greater resilience or selection into more stable sectors. Among immigrant citizens, cohort-specific heterogeneity is less pronounced. Across all citizenship cohorts, the estimated differential effects relative to natives are not statistically significant, indicating no meaningful divergence in FI responses to unemployment.

Figure 4 illustrates the predicted FI gap between various immigrant cohorts and natives across different citizenship categories and URs using citizenship-specific Bartik IV. The results highlight the varying resilience and vulnerabilities among immigrant cohorts. For most noncitizen cohorts (Panel A), the FI gap widens as UR increases, except for the 2010–2019 cohort, for which the estimated difference relative to natives remain statistically insignificant across all levels of economic conditions. The 1980–1989 cohort exhibits the highest sensitivity to changes in the UR, with a significantly greater likelihood of FI than natives when the UR exceeds 6.1%. The 1960–1969 cohort appears second most vulnerable, but only during severe economic downturns, when the UR rises above 11%. The 2000–2009 cohort shows a more pronounced likelihood of FI than natives when the UR exceeds 5.8%. Although the average estimated effects of UR on FI for the 1970–1979 and 1990–1999 cohorts are not statistically different from those for natives, both cohorts experience elevated FI risk relative to natives within specific UR intervals: 7.8%–9.3% for the 1970–1979 cohort and 3.5%–15% for the 1990–1999 cohort. Among immigrant citizens (Panel B), predicted FI gaps relative to natives appear to vary by arrival cohort; however, the predicted probabilities FI gaps across the full range of URs do not differ significantly from those of natives, reinforcing the absence of meaningful divergence in FI responses between citizens and natives.

4.2 Heterogeneous Effects Across Different Subsamples by Household Characteristics

To examine mechanisms behind the unemployment–FI relationship, we assess heterogeneity by household education and SNAP participation. Education may buffer unemployment risk or enhance access to resources, while SNAP may cushion the effects of unemployment on food access. We estimate Equation (2) using 2SLS with a citizenship-specific Bartik IV, separately across subsamples defined by the household head's education and a binary indicator for SNAP receipt in the past year.

Table 5 presents the estimates of how the effects of immigrant citizenship status relative to natives vary by education level. Among native households, the estimated effect of a 1 % increase in the MSA-level UR is the largest for those with less than high school education (2.1%) and steadily decreases to just 0.2% for those with graduate or professional degrees. This pattern indicates that higher education provides a protective buffer against labor market shocks. The interaction terms indicate that immigrant noncitizens experience a significantly stronger effect of unemployment on FI than natives, but only within the associate degree or less-than-bachelor groups (2.1%), with no significant differences observed at lower or higher education levels. For immigrant citizens, the estimated differential effects are smaller and mostly statistically insignificant at 5% percentage level, except at the graduate levels, where the effect is slightly larger than for natives. These findings suggest that education moderates the impact of unemployment on FI and that immigrant noncitizens with mid-level education may be particularly vulnerable—possibly reflecting precarious job types or limited access to safety nets even when moderately educated. The elevated vulnerability among immigrant citizens with graduate degrees may reflect factors such as labor market mismatch, concentration in more cyclical sectors, or persistent barriers that limit the full protective returns to education despite naturalization.

Given that immigrant noncitizens are largely ineligible for SNAP, while immigrant citizens and native-born households are generally eligible, access to the social safety net may influence how unemployment affects FI. To examine this, we estimate 2SLS models by SNAP receipt status (Table 6). Results show clear differences: for native-born households not receiving SNAP, a 1% increase in the local unemployment rate raises the probability of FI by 0.8%. Among SNAP recipients, the effect is smaller (0.5 points) and not statistically significant, suggesting SNAP buffers against economic shocks. In contrast, immigrant noncitizens show a 1.4% higher likelihood of FI than natives when not receiving SNAP, and 1.7% higher when receiving SNAP. Although we cannot precisely identify SNAP-eligible individuals, these findings imply that SNAP offers limited protection for immigrant noncitizens during downturns. Immigrant citizens fall in between: their additional likelihood of FI is small and statistically insignificant across both SNAP and non-SNAP groups, suggesting that once naturalized, their responses to unemployment resemble those of natives. Overall, the results indicate that while SNAP helps mediate the unemployment–FI relationship, it does not fully shield noncitizens, underscoring the role of social support in shaping heterogeneous policy impacts by citizenship status.

4.3 Robustness Check

Firstly, we implement alternative Bartik instruments, as recommended by Goldsmith-Pinkham, Sorkin, and Swift (2020), to test the robustness of our estimates to assumptions about instrument construction and mechanical correlation. Specifically, columns (1) and (2) of Appendix Table C.1 report our benchmark 2SLS estimates using baseline Bartik IV from Equation (1) with and without the full set of controls. Columns (3) and (4) present results using an alternative Bartik instrument constructed from demeaned national industry growth rates[24]. This approach addresses concerns about normalization bias, which can arise when local industry shares sum to one and estimates become sensitive to the choice of omitted industry. Removing the average national growth rate across industries isolates industry-specific shocks, reducing the influence of aggregate trends. This yields slightly larger unemployment effects on FI (2.2%–2.9%) compared to our baseline estimates (1.1%–1.2%), suggesting that the demeaned specification better captures relative industry-specific shocks and strengthens the robustness of our strategy. Columns (5) and (6) use an alternative Bartik instrument based on interactions between industry shares and year dummies. This specification yields time-series variation in unemployment similar to our baseline Bartik IV, with estimated effects that are closely aligned. This reinforces the stability of our identification strategy

[24] Specifically, on the baseline leave-one-out approach, we subtract the average growth rate across industries from each industry's growth rate in each time period to remove the average shock across industries.

and suggests that local industry composition alone provides sufficient cross-sectional variation to serve as a valid instrument.

Given that individual industry share instruments may be weak, Goldsmith-Pinkham, Sorkin, and Swift (2020) recommend testing the sensitivity of estimates to alternative combinations of shares. Our primary identification concern is whether industry shares are conditionally exogenous to household FI across MSAs. Following Rotemberg (1983), we decompose the Bartik estimator into a weighted average of just-identified IV estimates, where each industry share serves as a distinct instrument. We compute Rotemberg weights to identify which industries most strongly influence the estimator[25]. Table B.1 shows that Wholesale and Retail Trade; Manufacturing; Information; Finance, Insurance, Real Estate, Rental and Leasing; and Public Administration are the five most influential industries. To ensure that our results are not driven by any single industry, we re-estimate the main 2SLS specification (Table 2, column 7), sequentially excluding each of these top-weighted industries from the local industry shares. The results, presented in Table C.2, remain robust across these alternative specifications, lending support to the identifying assumptions.

We conduct several robustness checks on different subsamples in Table D.1, re-estimating the 2SLS models from column (7) of Table 2 using baseline Bartik IV and column (7) of Table 3 using the Citizenship-Specific Bartik IV. First, we restrict the sample to households where the head is in the labor force (Columns 1–2). Second, we refine the definition of married immigrant households by limiting the sample to couples from the same country of origin, reducing heterogeneity in cultural background, dietary preferences, and acculturation (Columns 3–4). Third, we include mixed-nationality households (one foreign-born, one native-born), which were

[25] Appendix B details the construction and interpretation of these weights.

excluded from the main analysis, and classify them as immigrant citizen households to ensure broader representativeness. Across all specifications, the estimated average effect of local unemployment and its heterogeneous impact by citizenship status remain statistically similar and robust across subsamples.

5 Discussion

Our study estimates the impact of local unemployment on FI across native, naturalized citizen, and noncitizen immigrant households in the U.S. To address potential endogeneity, we use a shift-share IV strategy that interacts MSA-level industry shares with national industry growth rates, including an alternative specification that allows growth to vary by immigrant status. Robustness checks with alternative instruments and misspecification tests support our identification strategy. We evaluate whether noncitizen immigrants—who face limited access to SNAP and the social safety net—are especially vulnerable to economic downturns or not. We also explore heterogeneity by arrival cohort and assess mediating pathways by stratifying the sample by education and SNAP participation.

Comparing the results with the literature, our 2SLS estimates confirm that deteriorating economic conditions, characterized by higher UR, worsen household FI (Cho, Kreider, & Winters, 2022). However, our estimated effects are higher than those of previous work as we address potential downward bias via the Bartik instrument and control for unobserved sub-state level shocks through MSA fixed effects. Our estimates indicates that a 1 percentage point increase in the MSA UR would lead to 1.1 percent increase in the likelihood of FI for all households, which is higher than the OLS estimates reported in the literature. Nord, Coleman-Jensen, and Gregory (2014) predict a 1% increase in the highest monthly UR at the national level is associated with a 0.5% increase in the prevalence of household FI.

When examining variation by immigrant citizenship status, we find that unemployment has a markedly greater impact on immigrant noncitizens than on natives, while the effect for immigrant citizens is, on average, not statistically different from that for natives. The estimated larger effect among noncitizen immigrants, who have limited access to safety net programs like SNAP, suggests greater vulnerability to local labor market downturns. This is consistent with Kalil and Chen (2008) and Potochnick and Arteaga (2018) who find that citizenship is correlated with household FI. Moreover, we find that immigrant noncitizens become more likely to experience FI as the UR rises, and this increase is steeper than for immigrant citizens. Despite advantages such as longer U.S. residency and eligibility for nutrition-assistance programs, immigrant citizens are still more likely than natives to experience FI when local unemployment rises to 6.4 – 7.6%—well above the 4 % level typically viewed as full employment.

Controlling for citizenship status, we find that the effect of unemployment on FI varies across immigrant arrival cohorts. Noncitizen immigrants from the pre-1970, 1980–1989, and 2000–2009 cohorts exhibit greater sensitivity to rising URs compared to natives, whereas all cohorts with citizenship show responses that are statistically similar to those of natives. This suggests a buffering effect of citizenship during economic downturns. Contributing factors likely include lower skill levels, restrictive immigration policies at the time of arrival, and adverse economic conditions upon entry, which may help explain why different noncitizen immigrant cohorts exhibit varying responses of FI to changes in the UR. Pre-1970 noncitizens are especially likely to experience FI when local unemployment exceeds 11%, reflecting compounded disadvantages from aging, slower assimilation, weaker labor market attachment (Borjas, 2015), and limited access to assistance programs. Post-1970 saw an influx of low-skilled immigrants, particularly from Mexico, facing significant disadvantages (Van Hook, Landale, & Hillemeier, 2013). The 1980-1989 cohort, primarily from poorer regions in Latin America and Asia, arrived under stricter immigration policies (Abramitzky et al., 2021), while many in the 1990-1999 cohort were unauthorized and vulnerable to economic instability (Passel & Suro, 2005). The 2000–2009 cohort entered during the Great Recession, making them particularly vulnerable to early economic shocks. Interestingly, the 2010–2019 cohort is either less likely or no more likely to experience FI compared to natives. This relative resilience may reflect positive selection effects (Berning, Norris, & Cleary, 2023), as this cohort largely comprises highly educated immigrants from India and China, who may be better positioned to withstand economic downturns.

We further explore potential mediating pathways by stratifying the sample by education level and SNAP participation. While higher education reduces the impact of unemployment on FI, it does not fully eliminate the gap between immigrants and natives. This reflects structural vulnerabilities in the immigrant labor market, including concentration in cyclical industries, limited work authorization, and lower demand for foreign-acquired skills (Batalova et al., 2008; Kochhar et al., 2010; Liu & Edwards, 2015; Orrenius & Zavodny, 2009). Our results show that immigrant noncitizens with Bachelor degrees or above are relatively protected from unemployment shocks, while those with mid-level education—such as an associate degree—remain more vulnerable, likely due to employment in cyclical sectors (Orrenius & Zavodny, 2009). Among naturalized citizens, individuals with a Bachelor degree or higher face a greater risk of FI during rising unemployment than similarly educated natives, possibly due to labor market mismatches or persistent barriers limiting returns to education even after naturalization (Anita, 2022). These patterns underscore the need for targeted policies to address structural labor market disadvantages and gaps in the safety net, especially for noncitizens and moderately educated immigrants. Additionally, while limited data on household income and SNAP eligibility constrain a precise assessment of SNAP's role, our findings suggest that SNAP helps buffer the impact of unemployment on FI but does not fully protect noncitizens. This highlights the need for stronger social supports, including unemployment insurance. Policymakers may consider program design changes to better support eligible families, including immigrant noncitizens, during economic downturns.

6 Conclusion

Our primary contribution is to identify the causal effect of local labor market unemployment on household FI and to examine how this impact varies by citizenship status, highlighting greater vulnerability among noncitizen immigrants relative to native-born and naturalized citizens. To address endogeneity from unobserved shocks, we employ a Bartik instrument—interacting initial industry shares with national industry growth rates—to exploit exogenous variation in local labor demand. We extend this approach by allowing growth rates to vary by citizenship status to capture differential exposure. We find that a clear and statistically significant increase in the likelihood of FI in response to rising local unemployment, with an effect nearly twice as large as the OLS estimate (1.1 vs. 0.6 percentage points).

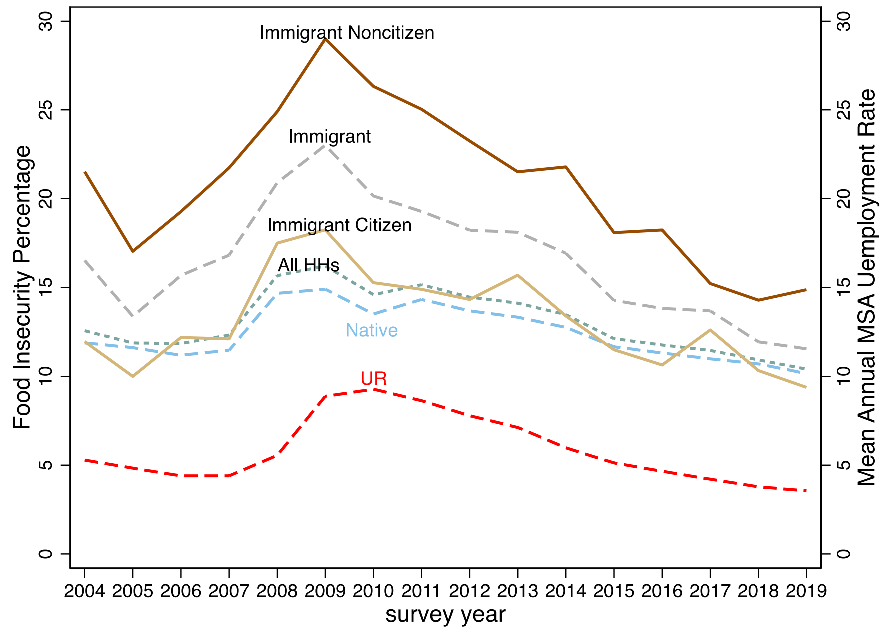
Looking more closely at our sample, we find outcomes vary considerably among immigrant subgroups. Unemployment has a larger impact on FI for noncitizen immigrants than for both naturalized citizens and native-born individuals, likely due to more limited access to safety net programs such as SNAP. These findings are consistent with evidence that SNAP mitigates economic hardship and underscore how exclusion from public assistance heightens noncitizens' vulnerability during downturns (Bitler & Hoynes, 2016). Immigrant cohort differences in the effect of unemployment on FI are pronounced among noncitizens, with those arriving in the pre-1970, 1980–1989, and 2000–2009 periods showing greater sensitivity than natives. In contrast, all cohorts of naturalized citizens exhibit responses statistically similar to those of native-born individuals, highlighting the importance of legal status, human capital and arrival timing in shaping vulnerability to economic shocks (Abramitzky et al., 2021; Borjas, 1995; Van Hook, Landale, & Hillemeier, 2013). Additionally, higher education—particularly at the bachelor's level or above—help mitigate the impact of unemployment on FI, especially among U.S. immigrant noncitizens. However, this mitigating effect appears less pronounced for immigrant citizens relative to natives, likely due to skill underutilization or structural barriers limiting educational returns after naturalization (Anita, 2022). Finally, improving access to food assistance programs may help mediate the negative effect of short-term shocks like unemployment on FI but does not fully protect noncitizens.

In summary, our study offers significant insights into the disparate impacts of unemployment on immigrant households in comparison to native-born households. Understanding these disparities is critical for identifying which groups stand to benefit most from targeted policy interventions. While our findings are most applicable to metropolitan areas—given the MSA-level dataset does not fully capture rural or agricultural contexts—they underscore the importance of inclusive safety net policies. However, traditional public assistance programs often fail to support immigrant families during recessions, as many immigrants—particularly noncitizens—are excluded from unemployment insurance and means-tested transfers (Orrenius & Zavodny, 2009). To better support families facing hardship, federal programs such as SNAP should consider expanding access for noncitizens by simplifying eligibility criteria, streamlining the application process, and addressing language barriers. At the state level, additional support could include extending unemployment benefits to workers without work authorization, as seen in initiatives undertaken by Colorado, California, and New York (Visram, 2023; Wilson, 2023).

Evidence from prior research (Browning & Crossley, 2001; Fu, Huang, & Liu, 2023) underscores the role of enhanced unemployment insurance (UI) in stabilizing household consumption and reducing FI. Unemployment insurance is a critical fiscal tool that stabilizes the economy during downturns. Its temporary expansion during the COVID-19 pandemic demonstrated both the effectiveness of enhanced benefits and the need for more inclusive coverage. This highlights the case for comprehensive reform to extend UI to all workers, regardless of immigration status (Kallick et al., 2022). Paired with improvements to SNAP—which offers limited protection for immigrant noncitizens—such reforms would reduce disparities and promote a more equitable economic recovery.

Tables and Figures

Panel A. Immigrant Citizen Status



Panel B. Immigrant Arriving Cohorts

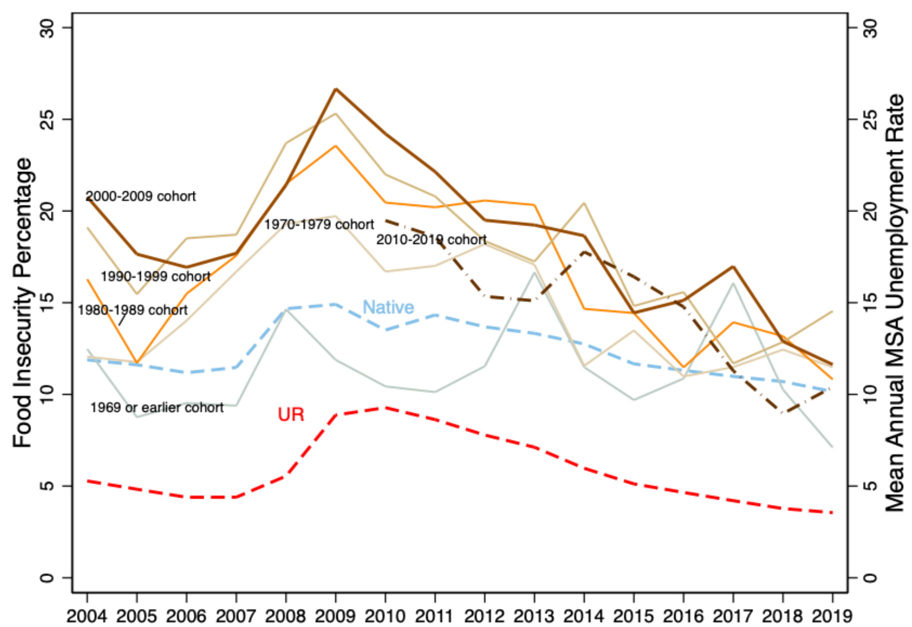


Figure 1. The UR and FI Trends over Time by Groups.

Note: The left y-axis displays the household FI rates (percentage) across different groups over time, while the right y-axis represents the annual UR (percentage) at the MSA level, shown as the red dashed line.
Source: Authors' calculations, U.S. Bureau of Labor Statistics and Current Population Survey.

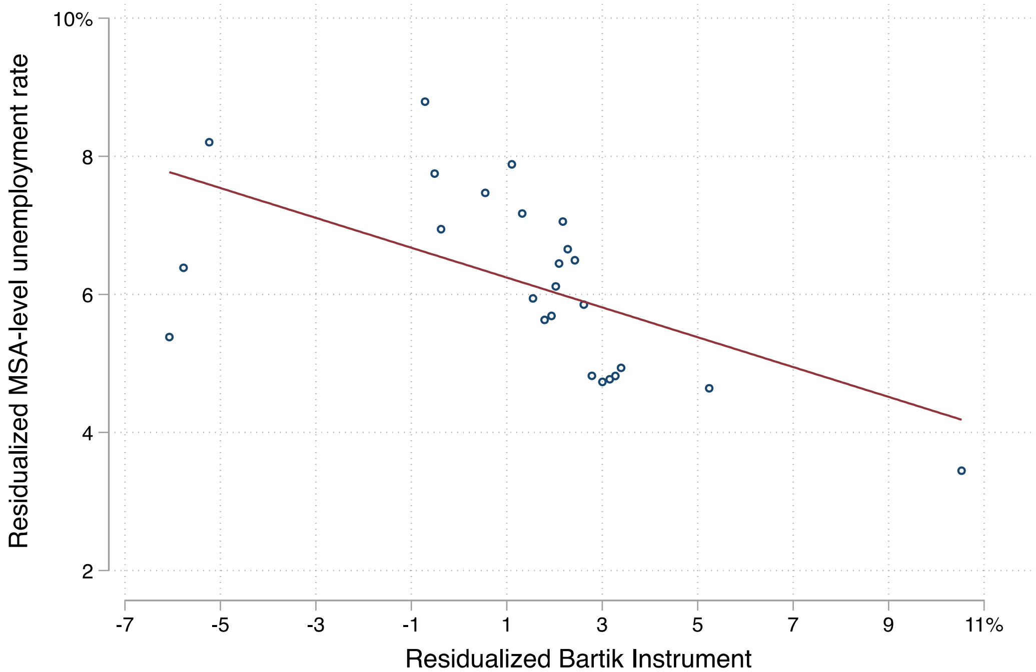


Figure 2. First Stage Effect of Bartik Instrument on the UR.

Note: The residualized variables on the y- and x-axis are generated by the regression of the MSA UR on Bartik instrument with full set of the same control variables, as in the IV estimations of the effect of UR on household FI. We bin the residualized Bartik instrument into equal-sized intervals, compute the mean of both residuals within each bin, and plot these averages in a scatterplot. The red line represents the best linear fit, estimated via OLS regression of the y-residuals on the x-residuals. Its slope corresponds to the first-stage coefficient on the Bartik instrument. Residualization accounts for household and individual demographics, local economic characteristics, and MSA fixed effects. X-axis values are percentage-point deviations from the mean after residualization. Negative values occur when national industry employment declines, even if weights are positive. The '11%' marks the upper bound after binning the residualized instrument.
Source: Authors' calculations, U.S. Bureau of Labor Statistics and Current Population Survey.

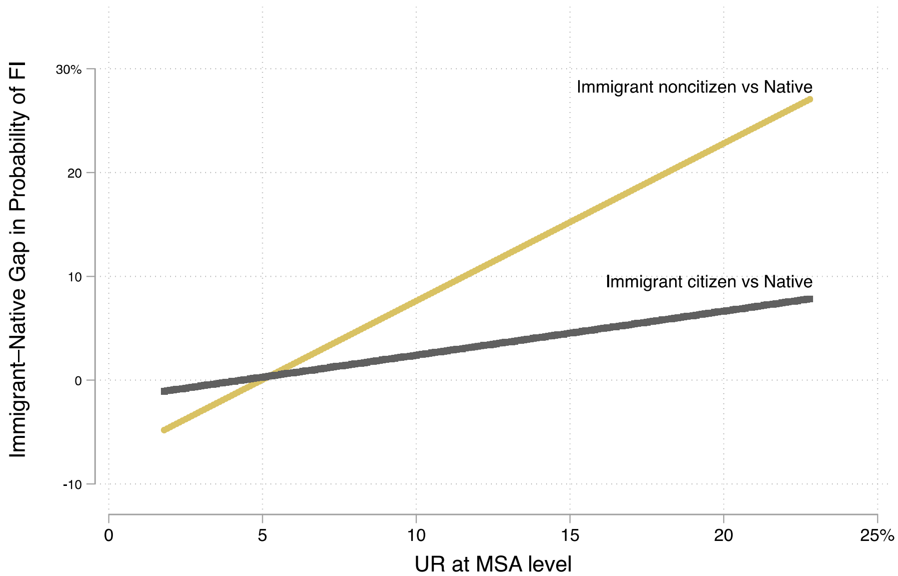


Figure 3. Difference in Probability of FI Between Immigrant Citizen Statuses and Natives.
Note: The y-axis variable is the predicted FI gap between immigrant (noncitizens or citizens) and native households. The value on the yellow line is calculated as $\hat{\beta}_1\ UR_{mt} + \widehat{\gamma_1}$ from Equation (2). Here, $\hat{\beta}_1$ is the estimated difference in the effect of UR on the FI of immigrant noncitizen households compared to native households. And $\widehat{\gamma_1}$ represents the predicted difference in the incidence of FI between immigrant noncitizens and natives when UR is 0. The black line is calculated as $\hat{\beta}_2 * UR_{mt} + \widehat{\gamma_2}$ from Equation (2) where $\hat{\beta}_2$ is the predicted difference in the effect of UR on the FI of immigrant citizens versus native households and $\widehat{\gamma_2}$ is the predicted gap of the incidence of FI between immigrant citizens and natives when UR is 0. The predicted values used to plot this figure are reported in Table 3.

A. Immigrant noncitizen subgroup

B. Immigrant citizen subgroup

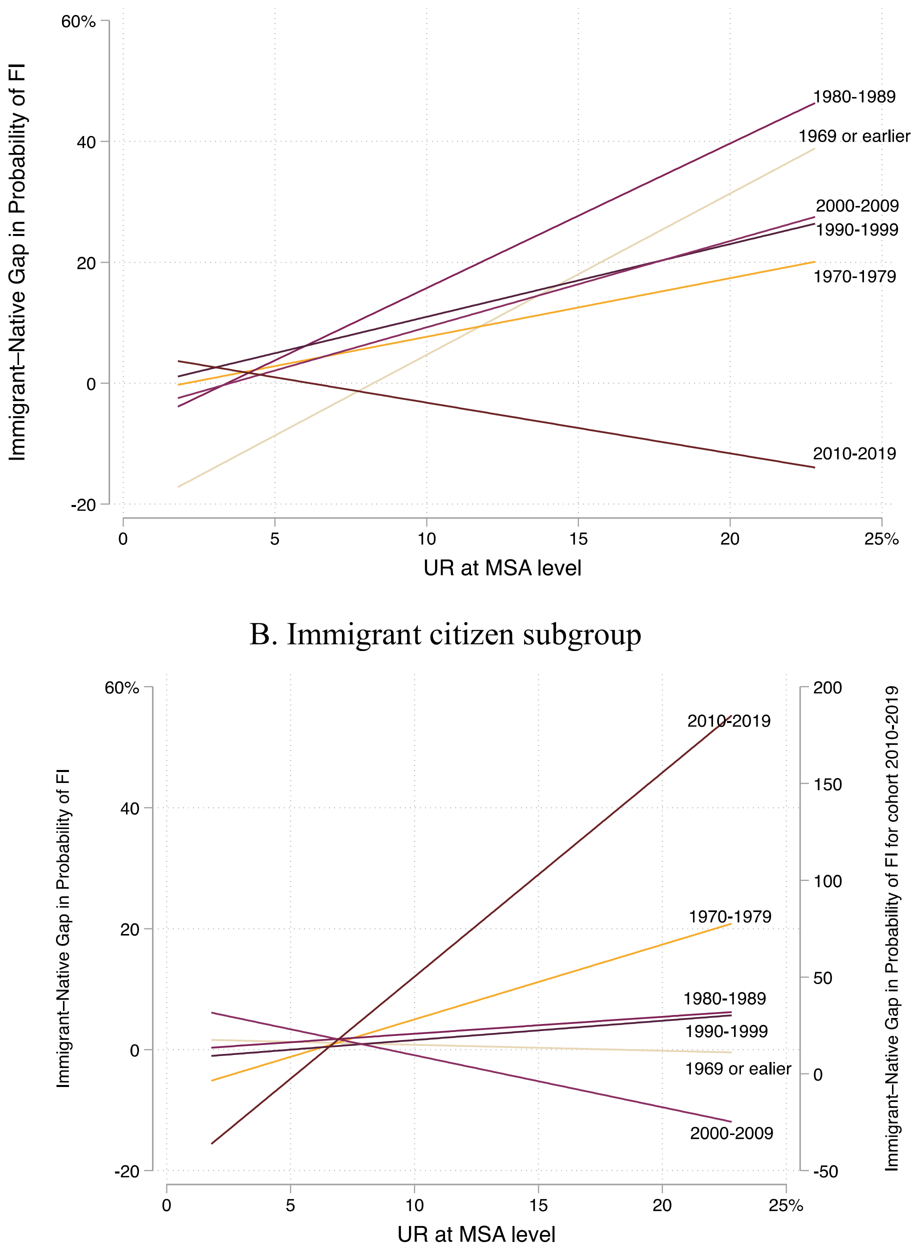


Figure 4. Difference in Probability of FI Between Immigrant Cohorts and Natives Across Different Immigrant Citizenship Statuses

Note: Figure 4 shows the predicted FI gap among immigrant cohorts by citizenship status and native. UR values range from 1.8 to 22.9 percentage points. The lines reflect the sum of the predicted differences in UR's marginal effect between each cohort and natives, and the predicted difference in FI probability when UR = 0. The predicted values are from Table 4. In Panel B, the "2010-2019" citizen cohort shows a significantly higher FI likelihood than natives, so it's plotted on a separate right y-axis.

Table 1. Summary Statistics by Immigration Status.

			Immigrant citizenship		Immigrant Cohorts					
	Native	Imm	Noncitizen	Citizen	1969 or earlier	1970-1979	1980-1989	1990-1999	2000-2009	2010-2019
Interview type (share)										
Telephone	0.55	0.49	0.46	0.52	0.55	0.52	0.50	0.49	0.46	0.47
In person	0.32	0.41	0.44	0.38	0.32	0.38	0.40	0.41	0.44	0.43
Married	0.48	0.53	0.49	0.57	0.33	0.52	0.55	0.56	0.53	0.50
Number of children <18	0.62	0.89	1.01	0.79	0.29	0.62	0.89	1.08	0.97	0.73
Female	49.54	46.43	45.29	47.47	52.9	46.37	43.82	47.2	47.58	42.97
Age Head	44.3	42.64	39.19	45.77	55.42	50.68	46.11	41.27	37.63	35.18
Education Level										
Below HS degree	0.06	0.24	0.35	0.15	0.14	0.25	0.26	0.27	0.25	0.14
HS degree	0.24	0.22	0.22	0.21	0.20	0.19	0.22	0.23	0.23	0.17
Associate degree	0.31	0.18	0.13	0.23	0.31	0.22	0.20	0.17	0.15	0.14
BA degree	0.25	0.20	0.15	0.25	0.21	0.20	0.19	0.19	0.20	0.28
Adv degree	0.14	0.16	0.15	0.16	0.15	0.14	0.12	0.14	0.17	0.27
Residual Wage	0.07	0.001	-0.07	0.07	0.09	0.14	0.07	0.01	-0.078	-0.2
Years of immigration	0	18.36	12.52	23.66	44.97	33.47	25.8	16.08	8.1	1.92
Above 185% poverty line	0.76	0.57	0.46	0.67	0.72	0.67	0.58	0.53	0.52	0.59
Received SNAP	0.09	0.10	0.13	0.07	0.07	0.07	0.09	0.11	0.12	0.09
Observations	269,724	49,082	23,347	25,735	2,601	5,245	10,551	14,161	12,479	4,045

Note: The sample is from the 2004 to 2019 CPS FSS. Individual characteristics including interview type, married status, gender, age, education level, residual wage and years of immigrations are for respondents who identify as head of household. "Imm" means immigrant. The residual wage is defined as the residual from a regression of the log midpoint of household income on the head's education, age, age squared, marital status, continent of origin, MSA, and year fixed effects, using CPS person-level earning weights.

Table 2. The Effect of UR on Household FI.

	OLS			Bartik IV			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UR_{MSA}	0.0094***	0.0076***	0.0064***	0.0120***	0.0117***	0.0106***	0.0106***
	(0.00086)	(0.0021)	(0.0018)	(0.000)	(0.000)	(0.000)	(0.000)
Immigrant noncitizen	0.0870***	0.0905***	0.0169***	0.0864***	0.0904***	0.0172***	0.0172***
	(0.0102)	(0.0105)	(0.0045)	(0.0099)	(0.0104)	(0.0046)	(0.0046)
Immigrant citizen	0.0095**	0.0158***	0.0038	0.0089**	0.0155***	0.0042	0.0042
	(0.0043)	(0.0038)	(0.0039)	(0.0043)	(0.0039)	(0.0040)	(0.0040)
Constant	0.0613***	0.0800***	0.1387***	0.0453***	0.0558***	0.1175***	-3.5229***
	(0.0073)	(0.011)	(0.0139)	(0.0086)	(0.0104)	(0.0162)	(0.1113)
Observations	318,806	318,806	318,806	318,806	318,806	318,806	318,806
Controls							
Household	NO	NO	YES	NO	NO	YES	YES
Local	NO	NO	NO	NO	NO	NO	YES
MSA FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	NO	NO	NO
Standard Error							
MSA Cluster	YES	YES	YES	NO	NO	NO	NO
AKM (2019)	NO	NO	NO	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES
K-P rk Wald F-Statistic	—	—	—	221.789	243.946	243.401	243.401
R-squared	0.011	0.015	0.146	0.010	0.014	0.145	0.145

Note: This table reports estimates of Equation (1), controlling for household characteristics and local characteristics and MSA, year fixed effects. Columns (1)-(3) show ordinary least squares (OLS) results, while columns (4)-(8) present two-stage least squares (2SLS) estimates using a Bartik instrumental variable (IV). Additionally, standard errors and F-statistics for 2SLS models from Columns (4)-(5) and (7)-(8) are estimated following Adão, Kolesár and Morales (2019), also allowing for correlation in industry shares through time. Statistical significance is indicated by ***p<0.01, **p<0.05, and *p<0.1.

Table 3. The Effect of UR on Household FI: Analysis by Immigrant Citizenship Status.

	OLS			Citizenship-Specific Bartik IV			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
UR_{MSA}	0.0077***	0.0051***	0.0044***	0.0089***	0.0086***	0.0082***	0.0082***
	(0.0008)	(0.0015)	(0.0014)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
Immigrant noncitizen × UR_{MSA}	0.0106***	0.0108***	0.0079***	0.0176***	0.0175***	0.0152***	0.0152***
	(0.0015)	(0.0013)	(0.0016)	(0.0027)	(0.0028)	(0.0023)	(0.0023)
Immigrant citizen × UR_{MSA}	0.0027***	0.0025***	0.0025**	0.0067	0.0059	0.0042	0.0042
	(0.0009)	(0.0007)	(0.0011)	(0.0073)	(0.0073)	(0.0061)	(0.0061)
Immigrant noncitizen	0.0200***	0.0224***	-0.0311***	-0.0240	-0.0199	-0.0754***	-0.0754***
	(0.0067)	(0.0062)	(0.0102)	(0.0214)	(0.0220)	(0.0136)	(0.0136)
Immigrant citizen	-0.0070	0.0005	-0.0098*	-0.0330	-0.0209	-0.0183	-0.0183
	(0.0046)	(0.0040)	(0.0055)	(0.0481)	(0.0478)	(0.0410)	(0.0410)
Constant	0.0717***	0.0957***	0.1512***	0.0644***	0.0763***	0.1339***	-4.2963***
	(0.0061)	(0.0086)	(0.0129)	(0.0057)	(0.0057)	(0.0124)	(0.1703)
Observations	318,733	318,806	318,806	318,733	318,733	318,733	318,733
Controls							
Household	NO	NO	YES	NO	NO	YES	YES
Local	NO	NO	NO	NO	NO	NO	YES
MSA FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	NO	NO	YES
MSA Cluster	YES	YES	YES	YES	YES	YES	NO
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES
K-P rk Wald F-Statistic	—	—	—	24.538	25.640	25.497	22.527
Adjust R-squared	0.011	0.016	0.146	0.011	0.014	0.145	0.145

Note: This table reports estimates based on Equation (2), controlling for household characteristics, local characteristics and MSA, year fixed effects. Columns (1)-(3) present ordinary least squares (OLS) results, while columns (4)-(6) present two-stage least squares (2SLS) estimates using a citizenship-specific Bartik IV; the corresponding second-stage specification is shown in Equation (9). A small number of observations (n = 73; <0.001%) from OLS to 2SLS are dropped due to missing national industry-by-citizenship employment data, resulting in a slightly smaller estimation sample. Standard errors, clustered at the MSA level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. The Effect of UR on Household FI: Analysis by Immigrant Cohorts of Arrival.

	Immigrant Noncitizen	Immigrant Citizen
VARIABLES	(1)	(2)
UR_{MSA}	0.008***	0.008***
	(0.001)	(0.001)
Imm Cohort 1969 or earlier × UR_{MSA}	0.027**	-0.001
	(0.014)	(0.013)
Imm Cohort 1970-1979 × UR_{MSA}	0.010	0.012
	(0.014)	(0.008)
Imm Cohort 1980-1989 × UR_{MSA}	0.024***	0.003
	(0.004)	(0.015)
Imm Cohort 1990-1999 × UR_{MSA}	0.012	0.003
	(0.008)	(0.005)
Imm Cohort 2000-2009 × UR_{MSA}	0.014***	-0.009
	(0.003)	(0.010)
Imm Cohort 2010-2019 × UR_{MSA}	-0.008	0.105*
	(0.020)	(0.055)
Imm Cohort 1969 or earlier	-0.220*	0.018
	(0.117)	(0.087)
Imm Cohort 1970-1979	-0.020	-0.074
	(0.115)	(0.045)
Imm Cohort 1980-1989	-0.082*	-0.002
	(0.043)	(0.100)
Imm Cohort 1990-1999	-0.011	-0.016
	(0.041)	(0.051)
Imm Cohort 2000-2009	-0.050*	0.077
	(0.030)	(0.071)
Imm Cohort 2010-2019	0.052	-0.552*
	(0.116)	(0.288)
Constant	-4.246***	0.000
	(0.151)	(1.281)

	(1)	(2)
Observations	293,023	295,434
Controls		
Household	YES	YES
Local	YES	YES
MSA FE	YES	YES
Year FE	NO	NO
MSA Cluster	YES	YES
2003 Population weighted	YES	YES
F-Statistic	[30.16-189.19]	[16.78-149.60]
Adjust R-squared	0.152	0.144

Note: This table reports estimates of Equation (3), controlling for household characteristics, local characteristics and MSA fixed effect. Column (1) show the 2SLS estimates for immigrant noncitizen and native households using the citizenship-specific Bartik IV. Column (2) reports analogous estimates for immigrant citizen and native households. The last row shows the range of first-stage F-statistics for each endogenous variable, indicating that the instruments are sufficiently strong to identify each endogenous component individually. Standard errors, clustered at the MSA level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Heterogeneous Effects of UR on Household FI Across Education Levels by Immigrant Citizenship Statuses.

	Below high school	High school	Associate or less than bachelor	Bachelor	Graduate or professional
VARIABLES	(1)	(2)	(3)	(4)	(5)
UR_{MSA}	0.021***	0.014***	0.009***	0.004***	0.002
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)
Immigrant noncitizen × UR_{MSA}	0.009	0.013	0.021***	0.011	-0.001
	(0.007)	(0.009)	(0.004)	(0.008)	(0.005)
Immigrant citizen × UR_{MSA}	-0.023	0.003	-0.001	0.010*	0.023***
	(0.015)	(0.014)	(0.013)	(0.005)	(0.006)
Immigrant noncitizen	-0.007	-0.062	-0.134***	-0.043	0.016
	(0.050)	(0.059)	(0.026)	(0.060)	(0.028)
Immigrant citizen	0.169*	-0.007	-0.004	-0.041	-0.124***
	(0.091)	(0.076)	(0.095)	(0.042)	(0.040)
Constant	0.000	13.035***	-11.963***	0.000	-2.205***
	(13.865)	(0.376)	(0.475)	(5.388)	(0.347)
Observations	27,129	75,895	92,976	77,994	44,739
Controls					
Household	YES	YES	YES	YES	YES
Local	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES
Adjust R-squared	0.081	0.113	0.115	0.071	0.053
Methods	2SLS	2SLS	2SLS	2SLS	2SLS

Note: This table reports estimates based on Equation (2), separately for subsamples defined by education levels. All regressions control for household characteristics, local characteristics and MSA fixed effects. Each column presents two-stage least squares (2SLS) estimates using the citizenship-specific Bartik instrument. Standard errors, clustered at the MSA level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Heterogeneous Effects of UR on Household FI Across SNAP Receipt by Immigrant Citizenship Statuses.

	Received SNAP	Not Received SNAP
VARIABLES	(1)	(3)
UR_{MSA}	0.005	0.008***
	(0.004)	(0.001)
Immigrant noncitizen × UR_{MSA}	0.017**	0.014***
	(0.007)	(0.002)
Immigrant citizen × UR_{MSA}	0.011	0.004
	(0.031)	(0.008)
Immigrant noncitizen	-0.093	-0.060***
	(0.058)	(0.011)
Immigrant citizen	-0.055	-0.015
	(0.209)	(0.054)
Constant	0.297***	0.078***
	(0.055)	(0.008)
Observations	28,025	290,708
Controls		
Household	YES	YES
Local	YES	YES
MSA FE	YES	YES
Year FE	NO	
MSA Cluster	YES	YES
2003 Population weighted	YES	YES
Adjust R-squared	0.023	0.095
Methods	2SLS	2SLS

Note: This table reports estimates based on Equation (2), separately for subsamples defined by SNAP Receipt. All regressions control for household characteristics, local characteristics and MSA fixed effects. Each column presents two-stage least squares (2SLS) estimates using the citizenship-specific Bartik instrument. Standard errors, clustered at the MSA level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Online Appendix (Not for Print)

Appendix A. Instrument Validity and Exclusion Restriction Checks

To support the validity of our identification strategy, we conduct a pre-trend test in Table A.1 examining whether the baseline Bartik instrument is correlated with FI prior to the main analysis period. Specifically, we regress the average FI rates from 2000 to 2002 at the MSA level on the Bartik instrument, which is constructed using 2003 initial industry shares interacted with post-2004 national industry growth rates. Since the Bartik instrument is based on future national shocks and predetermined local industry composition, it should not predict pre-period FI outcomes. A significant relationship would suggest that unobserved factors affecting household food security could be correlated with the industrial structure of MSAs, thus violating the exclusion restriction. Conversely, a lack of significant correlation would support the assumption that unobserved shocks to household FI are uncorrelated with local industry composition. Table A1 reports the results of the pre-trend test. Across specifications with and without clustered standard errors, the Bartik instrument is not significantly associated with pre-period FI rates. These findings provide evidence consistent with the exogeneity of the instrument and reinforce the validity of our empirical strategy.

Furthermore, Table A.2 investigates the relationship between the Bartik instrument and net migration flows across U.S. metropolitan areas for two periods: 2010–2014 and 2014–2018. The regression results indicate weak and statistically insignificant correlations, with R-squared values below 0.01. The Bartik instrument is only marginally significant in the earlier period. These findings suggest that migration patterns at the metropolitan level are not systematically related to the instrument, lending support to the identifying assumption that household sorting is unlikely to bias the estimates via endogenous migration responses to local labor demand shocks.

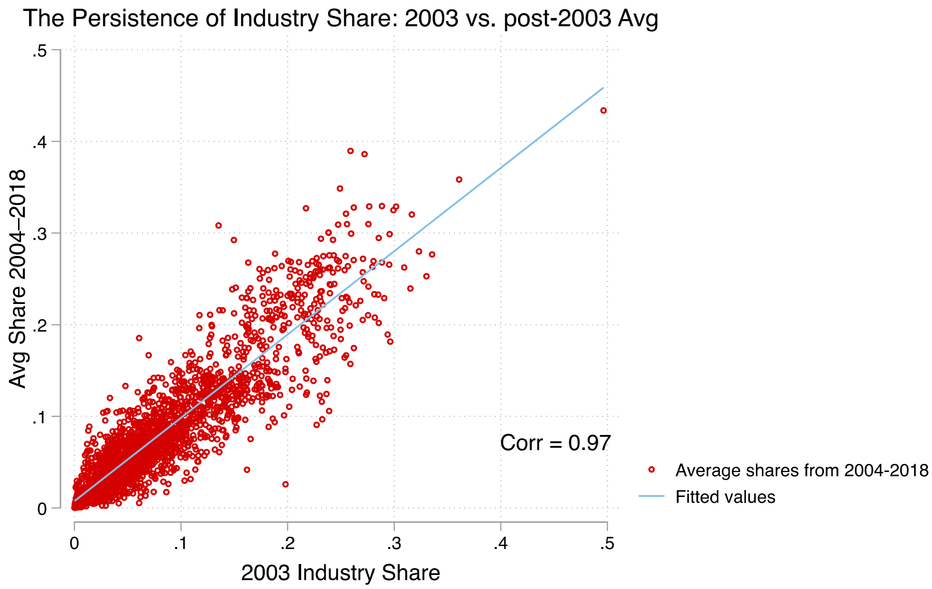

Figure A1. The persistence of Industry Share: 2003 vs. Post-2003 Average

Table A.1. Pre-trend FI and baseline Bartik Instrument.

VARIABLES	OLS (1)	Clustered SE (2)
Bartik Instrument	0.012	0.012
	(0.007)	(0.008)
Constant	0.094***	0.094***
	(0.011)	(0.011)
Observations	211	211
R-squared	0.012	0.012
N	211	211

Note: This table presents the relationship between pre-trend (2000-2002) MSA level household FI rates and Bartik instrument. Both Columns (1) and (2) have no added controls but Column (2) clusters standard errors at the MSA level. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Correlation between Bartik Instrument and Net Migration Flows (2010–2018).

	2010-2014	2014-2018
VARIABLES	(1)	(2)
Bartik IV	3.008*	3.022
	(1.677)	(2.095)
Constant	-4.806 *	-4.930
	(2.695)	(3.324)
Observations	207	207
R-squared	0.006	0.003
MSA Cluster	YES	YES
N	207	207

Note: This table presents simple regressions of net migration (in thousands) on the Bartik instrumental variable. The dependent variable, net migration, is computed from metro-to-metro migration data sourced from the U.S. Census Bureau for the periods 2010–2014 and 2014–2018. Standard errors clustered by MSA are shown in parentheses. ***p<0.01, **p<0.05, *p<0.1.
Source: US Census Bureau & IPUMS CPS.

Appendix B. Shift-share (Bartik) Instrument Critiques

Decomposing the Bartik Estimator and Estimating the Rotemberg Weight.

Following Rotemberg, 1983, we decompose the Bartik estimator which is numerically equivalent to a generalized method of moments (GMM) estimator into a weighted combination of just-identified estimates based on each instrument with the guidance of Goldsmith-Pinkham, Sorkin, and Swift (2020). Since our Bartik instrument treats local industry shares as instruments and the national growth rates as a weight matrix, the Bartik instrument estimator can then be decomposed into a set of estimators using each of the local shares, and a set of "Rotemberg" weights associated with each of these estimates. To be specific, we use a simplification of our two-stage least squares estimator to illustrate the process:

$$UR_{lt} = \lambda B_{lt} + \mu_{lt} \tag{10}$$

$$y_{lt} = \beta \widehat{UR}_{lt} + \epsilon_{lt} \tag{11}$$

Equation (10) represents the first stage, while Equation (11) corresponds to the second stage. B_{lt} is the Bartik instrument, and $\widehat{UR}_{lt}$ is the predicted MSA-level unemployment rate obtained from the instrument on UR. y_{lt} is household FI. For the sake of simplicity, we assume that only one household is observed in each location, for only one time period (t = 1), and that the exclusion restriction holds. Let l denote the number of locations and X to denotes the $l \times 1$ stacked vector of UR_{lt} which is endogenous in Equation (11). Recall that our Bartik instrument $B_{lt} = \sum_k^K s_{lk} \times g_{kt}$, where s_{lk} is the share of employment in industry k and location l; g_{kt} is the national growth rate. Let Z denote the $l \times k$ stacked vector of local industry shares and G denote the $k \times 1$ stacked vector of industry national growth rate. Now our constructed Bartik instrument B_{lt} will be $l \times 1$

defined as $B = ZG$. Finally, then IV estimator of the effect of economic fluctuations on FI using Bartik instrument is:

$$\hat{\beta}^{bartik} = \frac{B'Y}{B'X} = \frac{G'Z'Y}{G'Z'X} \tag{12}$$

Following the decomposition process of the Bartik instrument estimator suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020), $\hat{\beta}^{bartik} = \sum_{k=1}^{K} \hat{\alpha}_k \times \hat{\beta}_k^{bartik}$, where $\hat{\beta}_k^{bartik}$ is the just-identified estimates using local share of industry k as the instrument, and $\hat{\alpha}_k$ is the Rotemberg weight for the corresponding estimator ($\sum \hat{\alpha}_k = 1$).

For a given k, the just identified estimate is:

$$\hat{\beta}_k^{bartik} = \frac{{Z_k}'Y}{{Z_k}'X} \tag{13}$$

where ${Z_k}'$ is the k^{th} column of Z. Based on $\hat{\beta}^{bartik}$ and $\hat{\beta}_k^{bartik}$, the Rotemberg weight $\hat{\alpha}_k$ is:

$$\hat{\alpha}_k = \frac{g_{kt}{Z_k}'X}{\sum_{k=1}^{K} g_{kt}{Z_k}'X} = \frac{\hat{\lambda}g_{kt}{Z_k}'X}{\hat{\lambda}B'X} = \frac{X_k^{bartik'}X}{X_k^{bartik'}X} \tag{14}$$

where the second equality comes from the definition of the Bartik instrument: $B_{lt} = \sum_k^K s_{lk} \times g_{kt}$, $\hat{\lambda}$ is the estimated first stage coefficient, X^{bartik} is the fitted value for the local unemployment rate in first stage, and $X_k^{bartik'}$ is the value in the k^{th} column of X^{bartik} which is predicted using the k^{th} component of the Bartik instrument. Importantly, the Rotemberg weight can be negative.

We assess the influence of each industry share on parameter estimates by decomposing the identifying variation in our Bartik instrument, as suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020). They argue that a just-identified two-stage least squares approach using Bartik instruments can be viewed as a GMM estimator, where local industry shares serve as instruments and national industry growth rates form the weight matrix. Building on Rotemberg (1983), we decompose the Bartik estimator into a weighted combination of just-identified instrument variable estimators, with each industry share serving as a separate instrument. The weights, known as Rotemberg weights, are based on the covariance between each instrument's fitted value and the endogenous variable, summing to 1 and potentially being negative. This decomposition enhances transparency by revealing the contribution of different industries to the estimate and identifying which high-weight instruments are most sensitive to misspecification.[26]

We summarize the decomposition of the Bartik instrument in Table B.1. Panels A and B report the variation in Bartik instruments among industries and years. a small number of industries dominate the identifying variation. Specifically, the top five industries—"Wholesale and Retail Trade ", "Manufacturing", "Information", "Finance, Insurance, Real Estate, and Rental and Leasing", "Public Administration" account for 98% (= 2.156 / 2.196) of the positive weight in the estimator, as shown in Panel A of Table B. This concentration suggests that biases in the top five industries could significantly impact the overall estimator. The heavy influence of the "Wholesale and Retail Trade " and "Manufacturing", is particularly notable, consistent with discussions of the Bartik instrument in the context of the automobile industry (e.g., Bound and Holzer (2000, pg. 24)). Furthermore, when summing Rotemberg weights across years, we observe that the identifying variation is concentrated around the GR (2007-2009) and the economic recovery of 2012-2013. These periods are critical, as URs likely had a significant impact on household finances, influencing food consumption and FI status.

Panel C summarizes the distribution of Rotemberg weights[27]. Panel D shows the correlation between the Rotemberg weights ($\widehat{\alpha_k}$), industry national employment growth rate ($\widehat{g_k}$),

[26] Andrews, Gentzkow, and Shapiro (2017) also interpret these Rotemberg weights as sensitivity-to-misspecification elasticities, which provides a formal, quantitative language to describe the relative importance of different moments (or industries in our analysis) for determining the value of specific parameters.
[27] Goldsmith-Pinkham, Sorkin, and Swift (2020) suggest that negative Rotemberg weights can arise due to outlying point estimates, which raises the possibility, though not necessarily implying, non-convex weights in the just-identified instrumental variable estimator. In such cases, the overall Bartik estimate may lack a LATE-like interpretation as a weighted average of treatment effects.

the just identified coefficient estimates ($\widehat{\beta_k}$), the first stage F- statistics of the industry share ($\widehat{F_k}$) and the variance of local industry shares ($Var(z_k)$). This panel shows that Rotemberg weights are weakly and negatively correlated with national industry growth rates, suggesting that the growth rates do not meaningfully drive the identifying variation. In contrast, Rotemberg weights are positively correlated with the variance of local industry shares, meaning industries with greater cross-MSA variation receive more weight. Additionally, the variance in MSA-level industry shares is weakly correlated—or not correlated at all—with national growth rates. Together, these patterns indicate that the identifying variation in the Bartik instrument primarily stems from cross-sectional differences in local industry shares, not from potentially endogenous national growth trends.

We additionally present Figures B.1 and B.2 to assess heterogeneity in the industry-specific IV estimates ($\widehat{\beta_k}$), following the approach of Goldsmith-Pinkham et al. (2020). Figure B1 plots the relationship between Rotemberg weights and the first-stage F-statistics. Figure B2 visualizes the dispersion of the $\widehat{\beta_k}$ estimates around the overall 2SLS coefficient. As shown, the industries with the largest Rotemberg weights tend to have $\widehat{\beta_k}$ values close to the overall IV estimate, suggesting that the identifying variation is not driven by extreme or outlying sectors. While some industries exhibit negative Rotemberg weights and appear as outliers, Appendix B.1 (Panel C) shows that these account for 35% of the total weight. Importantly, as shown in Panel E, the mean $\widehat{\beta_k}$ is very similar across industries with positive and negative weights, indicating that treatment effect heterogeneity is limited. This suggests that the Bartik IV is not aggregating fundamentally different or contradictory industry-specific effects.

In line with the interpretation in Goldsmith-Pinkham et al. (2020), these findings indicate that our instrument passes the overidentification test: the identifying variation comes from internally consistent sectors, and the weighted estimate is not driven by outliers or offsetting effects.

Therefore, our IV estimate can be reasonably interpreted as a weighted average treatment effect—that is, a LATE-like parameter under standard assumptions.

Table B.1. Summary of Rotemberg Weights with 2003 as Initial Year (Initial Controls)

Panel A: Top 5 Rotemberg weight industries					
	$\widehat{\alpha_k}$	g_k	$\widehat{\beta_k}$	95% CI	Ind Share
Wholesale and Retail Trade	0.754	-3.543	0.044	(.,.)	14.346
Manufacturing	0.708	-3.446	0.044	N/A	13.213
Information	0.435	-6.822	0.046	(.,.)	3.102
Finance, Insurance, Real Estate and Rental and Leasing	0.173	-4.182	0.045	(.,.)	8.276
Public Administration	0.086	-28.082	0.057	(0,0)	5.120
Panel B: Variation across years in $\widehat{\alpha_k}$					
	Sum	Mean			
2004	-0.043	-0.003			
2005	0.295	0.023			
2006	-0.036	-0.003			
2007	0.228	0.018			
2008	0.431	0.033			
2009	-0.283	-0.022			
2010	0.033	0.003			
2011	0.143	0.011			
2012	0.272	0.021			
2013	0.277	0.021			
2014	0.163	0.013			
2015	-0.160	-0.012			
2016	-0.176	-0.014			
2017	-0.207	-0.016			
2018	-0.013	-0.001			
2019	0.075	0.006			
Panel C: Negative and positive weights					
	Sum	Mean	Share		
Negative	-1.196	-0.171	0.353		
Positive	2.196	0.366	0.647		
Panel D: Correlations of Industry Aggregates					
	$\widehat{\alpha_k}$	g_k	$\widehat{\beta_k}$	$\widehat{F_k}$	Var(z_k)
$\widehat{\alpha_k}$	1				
g_k	-0.080	1			
$\widehat{\beta_k}$	-0.056	0.929	1		
$\widehat{F_k}$	-0.012	0.236	0.224	1	
Var(z_k)	0.174	-0.085	0.051	-0.204	1
Panel E: Estimates of β_k for positive and negative weights					
	α-weighted Sum	Share of overall β	Mean		
Negative	-0.055	-1.240		0.054	
Positive	0.099	2.240		0.047	

Note: This table reports the summary statistics about the Rotemberg weights. In all cases, we report statistics about the aggregated weights with leave-one-out growth rates, where aggregation across years is performed at the industry level, as described in Appendix B. $\widehat{\alpha_k}$ denotes Rotemberg weights for each industry. g_k is the national industry growth rate, $\widehat{\beta_k}$ is the coefficient from the just identified regression—specifically, $\hat{\beta}_k^{bartik}$ estimated from Equation (12). $\widehat{F_k}$ represents the first stage F-statistics corresponding to each industry share. Var(z_k) captures the cross-sectional variation in industry shares. Following the guidance of Goldsmith-Pinkham, Sorkin, and Swift (2020), we utilize the weak instrument robust confidence interval approach, as outlined by (Chernozhukov & Hansen, 2008), to calculate the 95% confidence interval within a range spanning from -10 to 10 (N/A or (.,.) indicates that it was not possible to successfully define the confident interval). Ind Share is the industry share.

Table B.2. Relationship Between Industry Shares and MSA Demographic Shares.

	Wholesale and Retail Trade	Manufacturing	Information	Finance, Insurance; Real Estate, and Rental and Leasing	Public Administration	Bartik (2003 shares)
Share of White	0.447	0.604	0.242	1.139	-1.520	-5.657
	(0.193)	(2.078)	(0.226)	(0.360)	(0.822)	(12.676)
Share of black	0.566	-2.072	0.496	1.037	-0.539	11.003
	(0.211)	(2.083)	(0.287)	(0.414)	(0.830)	(12.104)
Share of Foreign Born	0.273	-0.993	-0.326	0.043	1.087	5.800
	(0.214)	(1.002)	(0.249)	(0.303)	(0.469)	(7.525)
high school	0.302	-0.100	-1.352	1.645	-1.405	11.618
	(0.461)	(1.770)	(0.492)	(0.781)	(1.151)	(13.263)
Associate or less than Bachelor	1.465	0.887	-0.787	1.577	-1.617	-3.910
	(0.409)	(1.914)	(0.405)	(0.676)	(1.011)	(12.588)
Share of Bachelor or more	0.375	0.197	-0.407	3.135	-3.189	-5.504
	(0.573)	(2.125)	(0.464)	(0.744)	(1.214)	(15.553)
Share of Male	0.430	-1.389	-0.121	0.572	-1.859	8.869
	(0.316)	(1.085)	(0.337)	(0.512)	(0.789)	(7.927)
Share of Married	0.391	-2.007	0.395	0.373	1.298	7.698
	(0.302)	(1.786)	(0.289)	(0.507)	(0.694)	(9.931)
Mean Household Size	1.113	1.221	1.337	1.744	-3.022	-28.225
	(0.553)	(3.976)	(0.545)	(0.828)	(1.785)	(22.030)
Mean Household Children Number	-1.387	1.954	-1.319	-0.743	0.456	9.686
	(0.568)	(3.616)	(0.516)	(0.870)	(1.625)	(19.994)
Median Age	0.045	-1.217	-0.076	0.375	0.206	6.598
	(0.354)	(1.031)	(0.274)	(0.450)	(0.810)	(7.470)
Poverty rate	-0.755	0.763	-0.977	-1.479	1.577	14.029
	(0.444)	(1.965)	(0.489)	(0.732)	(1.082)	(12.392)
Median household income	-1.300	-1.024	-0.395	-1.454	3.346	21.830
	(0.310)	(1.577)	(0.243)	(0.469)	(0.796)	(9.420)
Homeownership rate	0.044	0.129	-0.481	-0.387	0.765	3.501
	(0.244)	(1.153)	(0.286)	(0.405)	(0.485)	(7.364)
Public Housing rate	0.103	-0.849	0.005	0.637	-0.810	6.703
	(0.265)	(1.000)	(0.280)	(0.455)	(0.518)	(6.094)
Receiving SNAP rate	-0.028	0.440	0.166	0.183	0.275	-8.830
	(0.317)	(1.505)	(0.434)	(0.558)	(0.833)	(9.142)

Population Weighted	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.71	0.52	0.55	0.47	0.72	0.57
N	211	211	211	211	211	211

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Each column reports results of a single regression of a 2003 industry share on 2003 MSA demographics. The final column is our constructed Bartik instrument. Results are weighted by 2003 population. Standard errors in parentheses.

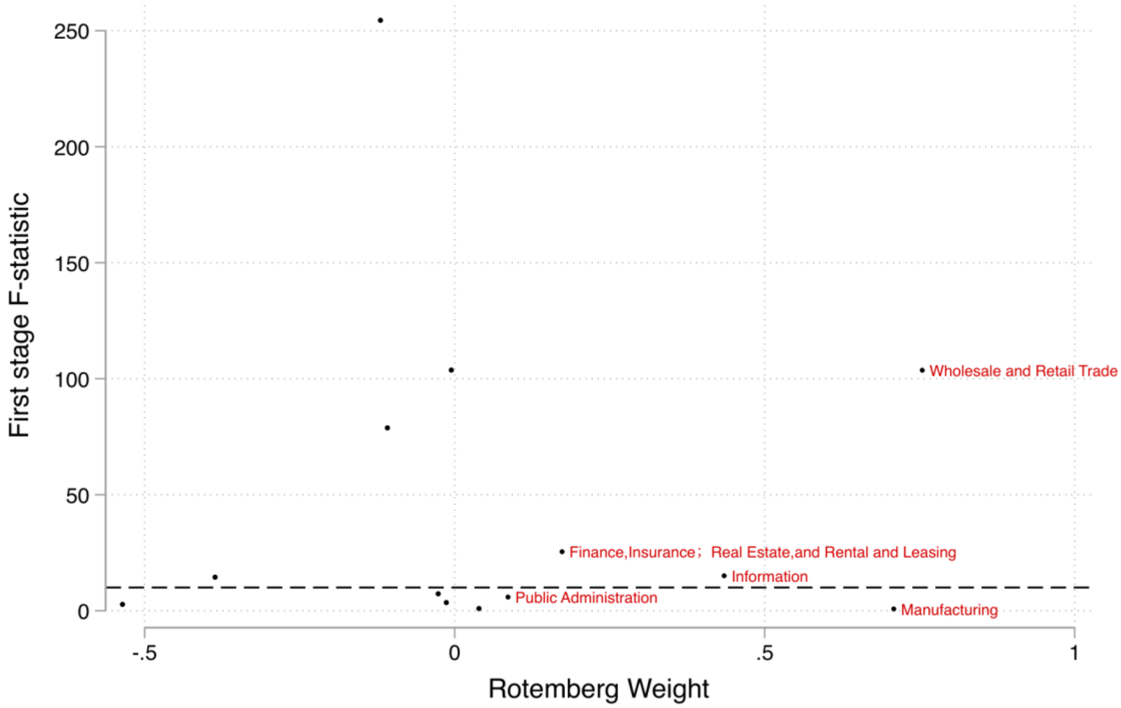

Figure B.1. First stage versus Rotemberg weights.

Note: First stage versus Rotemberg weights. This figure plots each instrument's Rotemberg weight against the first- stage F-statistic. Each point represents the estimates for an instrument, where instruments are aggregated across time period. The labeled industries correspond to the five highest Rotemberg weight industries from Table B1 . The dashed horizontal line is equal to 10.

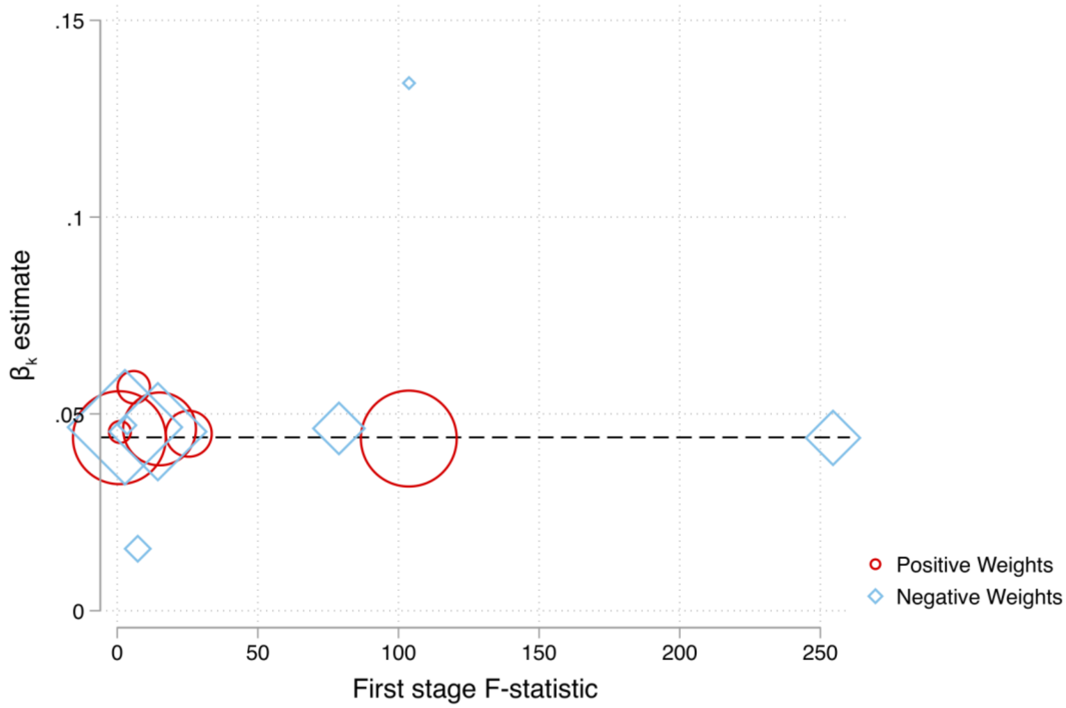

Figure B.2. Heterogeneity of $\widehat{\beta_k}$

Note: This figure is for visualizing the overidentification tests. It plots the relationship between each instrument's $\widehat{\beta_k}$, first stage F-statistics and the Rotemberg weights.. Each point is a separate instrument's estimates (industry share). The figure plots the estimated $\widehat{\beta_k}$ for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall $\hat{\beta}$ reported in the column (8) in the TSLS (Bartik) row in Table 3.

Appendix C. Robustness Check of Bartik Instrument

Table C.1. The Effect of UR on Household FI Using Alternative Bartik Instruments

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Instrument	*Baseline*	*Baseline*	*Simple demeaning growth rate*	*Simple demeaning growth rate*	*Share-Year Dummy Interaction Instrument*	*Share-Year Dummy Interaction Instrument*
UR_{MSA}	**0.012*** **	**0.011*** **	**0.029*** **	**0.022*** **	**0.010*** **	**0.008*** **
	(0.002)	**(0.001)**	**(0.005)**	**(0.004)**	**(0.001)**	**(0.002)**
Immigrant noncitizen	0.086***	0.017***	0.083***	0.018***	0.087***	0.017***
	(0.010)	(0.005)	(0.009)	(0.004)	(0.010)	(0.005)
Immigrant citizen	0.009**	0.004	0.005	0.005	0.009**	0.004
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Constant	0.045***	-3.523***	-0.059**	-3.442***	0.056***	-3.223***
	(0.009)	(0.111)	(0.030)	(0.114)	(0.006)	(0.260)
Observations	318,806	318,806	318,806	318,806	318,806	318,806
R-squared	0.010	0.145	-0.007	0.137	0.007	0.146
Household characteristics	NO	YES	NO	YES	NO	YES
Local characteristics	NO	YES	NO	YES	NO	YES
MSA FE	NO	YES	NO	YES	NO	YES
Year FE	NO	NO	NO	NO	NO	YES
MSA Cluster	YES	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES
K-P rk Wald F-Statistic	263.83	263.34	74.167	28.870	910,000	11,000

Notes: The table reports estimate of Equation (1) using alternative Bartik instruments with household controls, MSA demographic controls, and MSA and year fixed effects. Columns (1) and (2) use the baseline Bartik instrument which is calculated by the interaction between industry shares and leave-one-out national growth rate described in the section 3. Columns (3) and (4) use a version of the Bartik instrument with different growth rates coming from demeaning the industry growth rates. Column (5) and (6) uses a version of the Bartik instrument that use the interaction of industry shares with year dummy. Standard errors clustered at the MSA level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2. The Effect of UR on Household FI, Excluding Each Top Industry

VARIABLES	No Wholesale and Retail Trade	No Manufacturing	No Information	No Finance, Insurance; Real Estate, Rental and Leasing	No Public Administration
	(1)	(2)	(3)	(4)	(5)
UR_{MSA}	0.010***	0.011***	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Immigrant noncitizen	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Immigrant citizen	0.004	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-3.527***	-3.524***	-3.523***	-3.523***	-3.522***
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Observations	318,806	318,806	318,806	318,806	318,806
R-squared	0.145	0.145	0.145	0.145	0.145
demographic characteristics	YES	YES	YES	YES	YES
Local characteristics	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES
Year FE	YES	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES
Methods	2SLS	2SLS	2SLS	2SLS	2SLS

Notes: The table reports estimate of Equation (1) using alternative baseline Bartik instruments by excluding each top industry, controlling for household, MSA characteristics, and MSA fixed effects. Standard errors clustered at the MSA level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D. Robustness Check for Different Groups

Table D.1. Robustness Check for Different Subsamples

VARIABLES	Labor Force		Immigrant HHs from same countries		Mixed immigrant HHs	
	No Interaction	Interaction	No Interaction	Interaction	No Interaction	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
UR_{MSA}	0.011***	0.008***	0.010***	0.008***	0.011***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant noncitizen × UR_{MSA}		0.017***		0.014***		0.015***
		(0.002)		(0.002)		(0.002)
Immigrant citizen × UR_{MSA}		0.005		0.004		0.003
		(0.007)		(0.007)		(0.003)
Constant	0.118***	-4.069***	0.120***	0.000	-3.228***	0.000***
	(0.016)	(0.174)	(0.016)	(1.283)	(0.106)	(3.984)
Observations	254,869	254,809	315,375	315,305	335,104	334,987
R-squared	0.134	0.134	0.146	0.146	0.134	0.144
demographic characteristics	YES	YES	YES	YES	YES	YES
Local characteristics	YES	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES
Methods	2SLS-Baseline Bartik IV	2SLS-Citizenship - Specific Bartik IV	2SLS-Baseline Bartik IV	2SLS-Citizenship - Specific Bartik IV	2SLS-Baseline Bartik IV	2SLS-Citizenship - Specific Bartik IV

Notes: This table presents robustness checks across subsamples. Odd-numbered columns use the baseline Bartik IV (without UR–citizenship interaction), while even-numbered columns use the Citizenship-Specific Bartik IV (with interaction). Columns (1)–(2) restrict the sample to households with heads in the labor force; (3)–(4) focus on married immigrant households with spouses from the same country; (5)–(6) include mixed households, classified as native. Standard errors are clustered at the MSA level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2. Robustness Check for Comparing 2003 population weights and CPS-FSS weights

	No Interaction		Interaction	
VARIABLES	2003 pop weight	CPS FSS weight	2003 pop weight	CPS FSS weight
UR_{MSA}	0.011***	0.011***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant noncitizen × UR_{MSA}			0.015***	0.013***
			(0.002)	(0.004)
Immigrant citizen × UR_{MSA}			0.004	0.007
			(0.006)	(0.005)
Constant	-3.520***	-3.127***	-4.296***	-3.785***
	(0.110)	(0.080)	(0.170)	(0.216)
Observations	318,806	318,806	318,733	318,733
R-squared	0.145	0.145	0.145	0.145
demographic characteristics	YES	YES	YES	YES
Local characteristics	NO	NO	YES	YES
2003 Population weighted	YES	NO	YES	NO
CPS-FSS weighted	NO	YES	NO	YES
MSA FE	YES	YES	YES	YES
Year FE	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES
Methods	2SLS-Baseline Bartik IV	2SLS-Baseline Bartik IV	2SLS-Citizenship -Specific Bartik IV	2SLS-Citizenship -Specific Bartik IV

Note: This table reports robustness checks using alternative sample weights for 2SLS estimates, with and without an interaction between UR and citizenship. Columns (1)–(2) exclude the interaction and use the baseline Bartik IV. Columns (3)–(4) include the interaction and use the Citizenship-Specific Bartik IV. Standard errors clustered at the MSA level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix E. Alternative definitions of FI.

Food insecurity is measured using the Household Food Security Survey Module (HFSSM), which includes 10 adult-focused and 8 child-specific questions assessing a household's ability to maintain adequate food access. Affirmative responses are summed into a raw score and converted into 29 discrete Rasch scores (ranging from 0.0 to 9.3), which classify households into four categories: food secure, marginally food secure, low food secure, and very low food secure.

Given the HFSSM's three-stage design with screening questions, we use alternative definitions of FI to capture its intensity. Following USDA guidelines (Coleman-Jensen et al., 2022), households with one or two affirmative responses are "marginally food secure," while those with three or more are "food insecure." Very low food security applies to households reporting reduced food intake and meal skipping in three or more months. In addition to the standard binary FI measure (low or very low food secure), we analyze two alternative thresholds: (1) at least one affirmative (including marginal cases) and (2) very low FI (severe insecurity only).

Table E.1 shows that the effect of rising URs on FI weakens as the severity of FI increases. The estimated coefficients are largest for the broadest definition—"at least one affirmative"—and progressively smaller for standard FI and very low FI for all groups. This pattern suggests that unemployment shocks primarily expand the incidence of moderate food-related hardship rather than deepening existing severe deprivation. When we focus on the interaction between local URs and immigrant citizenship status, noncitizen immigrants consistently exhibit greater sensitivity to rising unemployment than natives across all definitions. Importantly, the size of the interaction effect $Immigrant\ noncitizen \times UR_{MSA}$ declines with increasing severity of FI: 1.7% for "at least one affirmative", 1.5% for standard FI, and 0.5% for very low FI. This pattern suggests that noncitizens are especially vulnerable to initial or moderate forms of FI during downturns, but the differential effect relative to natives narrows at the most severe level. In contrast, interaction effects for naturalized citizens are small and statistically insignificant, indicating that their responsiveness to unemployment is similar to that of native-born individuals, regardless of FI severity. These findings highlight how noncitizen immigrants face disproportionate exposure to economic shocks, likely due to weaker labor market attachment and more limited access to safety net programs.

Table E.1. Heterogeneous Effects of Unemployment on the Depth of Food Insecurity by Citizenship Status.

	Depth of FI					
	At least one affirmative		FI		Very Low FI	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
URmsa_annual	0.006***	0.011***	0.004***	0.008***	0.002***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant noncitizen × UR_{MSA}	0.008***	0.017***	0.008***	0.015***	0.004***	0.005***
	(0.001)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)
Immigrant citizen × UR_{MSA}	0.004***	0.006	0.003***	0.004	0.001	-0.002
	(0.001)	(0.004)	(0.001)	(0.006)	(0.000)	(0.002)
Immigrant noncitizen	-0.022***	-0.077**	-0.031***	-0.075***	-0.033***	-0.045***
	(0.006)	(0.034)	(0.006)	(0.014)	(0.004)	(0.011)
Immigrant noncitizen	-0.017**	-0.027	-0.010*	-0.018	-0.016***	-0.001
	(0.007)	(0.026)	(0.006)	(0.041)	(0.004)	(0.010)
Constant	0.289***	-3.658***	0.151***	-4.296***	-0.002	-2.286***
	(0.032)	(0.286)	(0.028)	(0.170)	(0.018)	(0.081)
Observations	318,733	318,733	318,733	318,733	318,733	318,733
R-squared	0.207	0.205	0.146	0.145	0.065	0.064
demographic characteristics	YES	YES	YES	YES	YES	YES
Local characteristics	NO	YES	NO	YES	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
MSA Cluster	YES	YES	YES	YES	YES	YES
Method	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: This table presents estimates using three definitions of FI to capture varying depths of food hardship: (1) at least one affirmative response (marginally, low, or very low food secure), (2) FI (low or very low food secure) which is our main definition of FI, and (3) very low FI only. For each definition, the first column reports OLS estimates, and the second column reports 2SLS estimates.

Appendix F. Table including all variates

Table F.1. The Effect of UR on Household FI.

	OLS			2SLS				
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UR_{MSA}	0.009***	0.008***	0.006***	0.012***	0.012***	0.160	0.011***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.634)	(0.001)	(0.001)
Immigrant noncitizen	0.087***	0.090***	0.017***	0.086***	0.090***	0.092***	0.017***	0.017***
	(0.010)	(0.011)	(0.005)	(0.010)	(0.010)	(0.017)	(0.005)	(0.005)
Immigrant citizen	0.010**	0.016***	0.004	0.009**	0.016***	0.014*	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)
Interview, type unspecified			0.010***				0.010***	0.010***
			(0.002)				(0.002)	(0.002)
Interview, In person			0.041***				0.041***	0.041***
			(0.004)				(0.004)	(0.004)
Married			-0.102***				-0.102***	-0.102***
			(0.003)				(0.003)	(0.003)
N of Children under 18			0.028***				0.028***	0.028***
			(0.001)				(0.001)	(0.001)
Female			0.026***				0.026***	0.026***
			(0.002)				(0.002)	(0.002)
Age head			0.005***				0.005***	0.005***
			(0.000)				(0.000)	(0.000)
Age^2			-0.000***				-0.000***	-0.000***
			(0.000)				(0.000)	(0.000)
High school			-0.105***				-0.105***	-0.105***
			(0.005)				(0.005)	(0.005)
Associate or less than bachelor's degree			-0.127***				-0.127***	-0.127***
			(0.005)				(0.005)	(0.005)
BA degree			-0.206***				-0.205***	-0.205***
			(0.004)				(0.004)	(0.004)

Adv degree	-0.237***	-0.236***	-0.236***
	(0.004)	(0.004)	(0.004)
Residual Wage	-0.093***	-0.093***	-0.093***
	(0.003)	(0.003)	(0.003)
Years of Immigration	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
$Years\ of\ Immigration^2$	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Share of White			0.706***
			(0.037)
Share of black			0.677***
			(0.036)
Share of Foreign Born			0.042***
			(0.007)
high school			-0.221***
			(0.016)
Associate or less than bachelor's degree			-0.143***
			(0.015)
Share of Bachelor's degree or more			-0.167***
			(0.012)
Share of Male			0.025***
			(0.001)
Share of Married			0.023***
			(0.004)
Mean Household Size			-0.301***
			(0.022)
Mean Household Children Number			0.309***
			(0.018)
Median Age			-0.028***
			(0.005)
Poverty rate			0.044***

								(0.006)
Median household income								0.025***
								(0.004)
Homeownership rate								0.105***
								(0.004)
Public Housing rate								-0.097***
								(0.004)
Receiving SNAP rate								0.041***
								(0.012)
Constant	0.061***	0.082***	0.139***	0.045***	0.056***	-0.815	0.118***	-3.523***
	(0.007)	(0.011)	(0.014)	(0.009)	(0.010)	(3.703)	(0.016)	(0.111)
Observations	318,806	318,806	318,806	318,806	318,806	318,806	318,806	318,806
R-squared	0.011	0.015	0.146	0.010	0.014	-0.081	0.145	0.145
demographic characteristics	NO	NO	YES	NO	NO	NO	NO	NO
Local characteristics	NO	NO	NO	NO	NO	NO	NO	NO
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	YES	NO	YES	NO	NO	NO
Year FE	NO	YES	YES	NO	NO	YES	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES	YES
K-P rk Wald F-Statistic	—	—	—	221.789	243.946	0.068	243.401	243.401

Note: this table is the same as Table 2 results but report all covariates. Columns (1)-(3) show ordinary least squares (OLS) results, while columns (4)-(8) present two-stage least squares (2SLS) estimates using a Bartik instrumental variable (IV). Standard errors, clustered at the MSA level, are reported in parentheses. Statistical significance is indicated by ***p<0.01, **p<0.05, and *p<0.1.

Table F.2. The Effect of UR on Household FI: Analysis by Immigrant Citizenship Status.

	OLS			Bartik IV				Citizenship-Specific Bartik IV
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UR_{MSA}	0.008***	0.005***	0.004***	0.009***	0.009***	0.009***	0.009***	0.008***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant noncitizen × UR_{MSA}	0.011***	0.011***	0.008***	0.016***	0.016***	0.012***	0.012***	0.015***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Immigrant citizen × UR_{MSA}	0.003***	0.002***	0.003**	0.006	0.006	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)
Immigrant noncitizen	0.020***	0.022***	-0.031***	-0.012	-0.008	-0.056***	-0.056***	-0.075***
	(0.007)	(0.006)	(0.010)	(0.019)	(0.020)	(0.016)	(0.016)	(0.014)
Immigrant noncitizen	-0.007	0.000	-0.010*	-0.026	-0.020	-0.018	-0.018	-0.018
	(0.005)	(0.004)	(0.005)	(0.036)	(0.036)	(0.027)	(0.027)	(0.041)
Constant	0.072***	0.096***	0.151***	0.061***	0.073***	0.131***	-4.069***	0.134***
	(0.006)	(0.009)	(0.013)	(0.006)	(0.006)	(0.012)	(0.174)	(0.012)
Observations	318,806	318,806	318,806	318,806	318,806	318,806	318,806	318,733
Controls								
Household	NO	NO	YES	NO	NO	YES	YES	YES
Local	NO	NO	NO	NO	NO	NO	YES	NO
MSA FE	NO	YES	YES	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES
K-P rk Wald F-Statistic	—	—	—	24.538	25.640	25.497	25.497	22.527
Adjust R-squared	0.011	0.016	0.146	0.011	0.015	0.145	0.145	0.145

Note: This table reports estimates of Equation (2), with household characteristics and local characteristics and MSA, year fixed effect as controls. Columns (1)-(3) show ordinary least squares (OLS) results, while columns (4)-(7) present two-stage least squares (2SLS) estimates using a baseline Bartik instrumental variable (IV). Column (8) shows results using an citizenship-specific Bartik IV constructed by adjusting national industry employment growth across immigrant status. Standard errors, clustered at the MSA level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.