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. The effect for immigrants is approximately twice as large compared to natives. Immigrant noncitizens, particularly those from countries with constrained human capital or those who faced adverse economic conditions upon arrival, grapple with heightened FI challenges. The heterogeneity noted across subsamples underscores poverty level and engagement in food assistance programs as potential buffers against FI during economic recessions. Higher education, especially graduate degrees, 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 fluctuations. It further underscores the pressing need to identify and support those at-risk immigrant cohorts that are most vulnerable to short-term economic disruptions.

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, immigrants 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 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 food insecurity (FI) compared to natives (Chaudry & Fortuny, 2010; Orrenius & Zavodny, 2009), much of this work lacks a robust causal identification strategy. For instance, Flores-Lagunes et al. (2018)

[1] Unemployment insurance benefits are only available to authorized workers with the exception of workers in California, Colorado, and New York. To be eligible for SNAP, immigrants typically must have established residency for five years. Although, there are exceptions for certain groups of immigrants.
[2] FI occurs when households have a lack of consistent access to enough food for a healthy life (Food Security in the US).

analyzed the differential in FI rates and severity among immigrant and non-immigrant populations throughout the phases of the Great Recession (GR). Their findings suggest that while immigrants endure a greater incidence of FI relative to non-immigrants, the severity of FI within immigrants is generally less pronounced. Furthermore, Potochnick and Arteaga (2018) observed that FI rates have increased for all households with children during and after the GR period. While this increase has been more pronounced for households of immigrant citizens who on average experience lower FI rate, it has not differed significantly between immigrant noncitizens and their U.S.-born counterparts. Despite these insights, the current literature largely examines correlations, often neglecting the potential for endogeneity. Identifying the causal impact of the unemployment rate (UR) on household FI is particularly challenging as unobservable drivers of economic conditions may affect both household-level variables (income, wealth etc.) contributing to FI as well as the UR.

In this study, we measure the differential impact of unemployment on FI between immigrant and native households[3] in the United States. 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 status, citizenship, and other factors that may mediate the effect of unemployment on FI.

[3] Married households with both head and spouse/partner as immigrants are classified as immigrant households; the same applies to native households. For single households, the classification depends on the head's status. Further details on these definitions will be provided in the data section.

To address endogeneity concerns, our identification approach builds upon the theoretical foundation of shift-share or Bartik instruments (Bartik, 1991; Goldsmith-Pinkham, Sorkin, & Swift, 2020), which measure local exposures to fluctuations in employment via the exogenous concentration of employment in different industries. Our construction of the Bartik instrument uses detailed employment data from the monthly Current Population Survey (CPS) data. To construct our instrument, we first generate industry-specific employment shares from an initial pre-research year (2003), which details cross-sectional variation in the local (MSA-level) labor market composition. Subsequently, we interact the employment shares with the time-varying national employment growth rate (from 2004 - 2019) to derive our instrument.

Our identification approach is intuitively plausible for two reasons. First, it is likely to satisfy the relevance assumption since our instruments are constructed by the inner product of industry shares and the national employment growth rate which are correlated with labor market demand measured by the UR in each MSA. Second, the exclusion restriction of our Bartik instruments is also credible. Our instruments are composed of local industries using data from 2003, prior to the time when household food consumption decisions and food security status are determined in our sample. They are unlikely to be correlated with unobserved shocks that simultaneously affect the UR, household food consumption, or FI during the research period. We estimate our model using two-stage least squares (2SLS) regression.

Our analysis yields several important findings. We identify a procyclical trend in household FI and a distinct impact of unemployment on FI between natives and immigrants. Using our instrumental variable (IV) approach, a 1% reduction in unemployment correlates with a 1% rise in FI, slightly exceeding Ordinary Least Squares (OLS) and previous literature estimates. Nord, Coleman-Jensen, and Gregory, (2014) find a 1% increase in the highest national monthly UR is associated with a 0.5% percent increase in the prevalence of FI. Our results further demonstrate that immigrants experience twice the increase in FI resulting from a 1% increase in unemployment compared to natives, at 1.6% versus 0.8%. In line with our expectations, immigrants exhibit greater vulnerability within the labor market compared to natives, subsequently leading to a heightened likelihood of economic adversity (Chaudry & Fortuny, 2010; Orrenius & Zavodny, 2009). Furthermore, we also find immigrants face greater likelihood of FI than those with U.S.-born natives once the MSA UR rises above the threshold of 2.6%.[4]

The results further indicate that both noncitizen immigrants and citizen immigrants are more likely to experience FI compared to natives, with noncitizens facing the greatest challenges. Unemployment is found to increase the likelihood of FI by 1.2% more for noncitizen households than for natives, with no significant difference between immigrant citizens and natives. This indicates noncitizen immigrants, who typically have limited access to government safety nets, are more susceptible to economic hardship and exhibit greater sensitivity to labor market fluctuations (Orrenius & Zavodny, 2009). Additionally, the predicted probability of FI confirms that immigrants without citizenship suffer higher levels of FI than natives across a wide range of the UR (3.4%-22.8%). In contrast, there is evidence of slightly higher likelihoods of FI for immigrant citizens than natives when the URs are between 3.5% and 16.3%. Altogether, this shows that immigrant noncitizens who typically lack access to many government safety net programs are more likely to experience economic hardship and are more sensitive to labor market fluctuations than natives (Orrenius & Zavodny, 2009).

[4] A healthy economy usually maintains the URs between 3% and 5%.

Upon controlling for the effects of immigrant citizenship status, distinct patterns emerge across different immigrant arrival cohorts. These variations likely capture the enduring influences of the selection mechanisms inherent to specific periods, where cohorts may consist of differently skilled workers. Additionally, the prevailing economic conditions during their time of arrival seem to play a pivotal role, emphasizing the lasting effects of initial disadvantages faced by these cohorts upon entering the U.S. labor market. FI among immigrant cohorts with citizenship who arrived between 1970 and 1979 are positively affected by unemployment, possibly attributable to the large number of Mexican immigrants during this period who had low skills and undocumented status (Passel & Suro, 2005; Van Hook, Landale, & Hillemeier, 2013). The 1980-1989 noncitizen cohort, which is predominantly comprised of individuals from economically disadvantaged regions in Latin America and Asia (Abramitzky et al., 2021), exhibits a similar trend. Their arrival coincided with a period characterized by stringent migration policy constraints[5]. This confluence of origin and policy backdrop likely contributed to the specific vulnerabilities faced by this group in the U.S. labor market. The 2000-2009 cohort of immigrants without citizenship, on the other hand, 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 graduate level, reduces the impact of unemployment on FI, it does not consistently minimize the additional probability of FI that immigrants face when compared to natives. Moreover, higher education is more effective in reducing FI for immigrant noncitizens than for immigrant citizens when compared to natives. This pattern highlights the widespread challenges immigrants face, regardless

[5] 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.

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). Among households at or below 185% of the poverty line, the analysis shows no significant difference in the effects of unemployment on FI between immigrants and natives, highlighting the central role of poverty levels in mediating this impact (Loopstra & Tarasuk, 2013). Additionally, our results suggest that access to food assistance programs can help mitigate the negative impacts of unemployment on FI, especially for vulnerable immigrant noncitizens who are often ineligible for many government safety net benefits.

Overall, our findings indicate that changes in unemployment disproportionately impact immigrants, 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[6]. 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[7].

The remainder of this paper is structured as follows. Section 2 discusses the data source. Section 3 outlines the empirical methodology, elaborates on the identification strategy, explains the construction of the Bartik instruments, and provides a decomposition of these instruments. In Section 4, we present the estimation results and conduct robustness checks for the Bartik instrument. Finally, Section 5 discusses the findings and their potential policy implications.

[6] Noncitizens are eligible for SNAP, such as those who have worked in the United States for a certain amount of time (with 5 years of residency) or have come into the United States with a particular immigration status.
[7] Recently, several states have begun to provide unemployment benefits to unauthorized workers: Colorado, California, and New York (Visram, 2023; Wilson, 2023).

2 Data and Descriptive Statistics

Our analysis utilizes a repeated cross-sectional dataset constructed from the U.S. BLS and the 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. 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 food conditions and behaviors over the past year through a set of questions, classifying households into categories of food security: food secure, low food secure, or very low food secure. For the purpose of this study, following previous literature (Berning, Cleary, & Bonanno, 2023; Potochnick & Arteaga, 2018), we define food security as a binary variable: food secure (0) and food insecure (1), with the latter category encompassing both low and very low food security. To account for economic conditions, we integrate seasonally unadjusted yearly UR for metropolitan statistical areas (MSAs) from 2004 to 2019. 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.

Our final sample consists of 332,612 households, limited to those headed by individuals aged 18 to 65, a demographic particularly vulnerable to fluctuations in unemployment[8]. Of these households, 14.5% (n = 48,310) are identified as immigrant households. We classify married immigrant households as those in which both the head and spouse/partner were born outside the

[8] We further excluded households with heads aged above 65, given that the CPS data does not adequately represent elderly individuals residing in long-term care (LTC) facilities.

U.S. and share the same country of origin, ensuring cultural and acculturation consistency. Similarly, households where both the head and spouse/partner are U.S.-born are classified as native households. We exclude mixed-nationality households and those with differing countries of origin. Immigrant households are further divided into two subgroups based on citizenship: noncitizens (n = 23,748; 49% of immigrants) and citizens (n = 24,562; 51% of immigrants). Immigrant cohorts face varying political and economic conditions depending on their time of arrival in the U.S (Abramitzky et al., 2021; Borjas, 1995). We therefore categorize immigrant households into seven arrival cohorts: 1959 or earlier, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009, and 2010-2019. Given the age restriction of 18 to 65, the earliest and most recent cohorts are relatively smaller.

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, possibly due to limited English proficiency. Immigrants generally have higher rates of marriage and children under 18, especially among noncitizens and later arrival cohorts. Additionally, immigrant households, in general, have a higher proportion of male heads and are younger compared to natives. Education levels vary, with noncitizens having the highest proportion of low educational attainment (below high school), while immigrant citizens exhibit a higher share of advanced degrees, reflecting the demand for both skilled and manual labor (Bandyopadhyay & Grittayaphong, 2020).

Income disparities are evident, with immigrant households earning lower incomes on average than native households and being more likely to fall below 185% of the poverty line. However, immigrant citizens typically have higher incomes than noncitizens and are less likely to be in poverty. Earlier arrival cohorts generally experience lower poverty rates, while more recent arrivals, particularly those after 1970, are more vulnerable to poverty. Noncitizens also have higher participation rates in the SNAP compared to both natives and immigrant citizens[9].

Figure 1 presents trends in unemployment and FI over the study period. Panel A demonstrates a correlation between the prevalence rates of household FI and the fluctuations in the UR, with native households consistently showing the lowest and most stable FI rates. In contrast, immigrant noncitizens exhibit the highest FI rates, particularly during economic downturns. Immigrant citizens, however, display FI rates similar to natives during periods of economic stability but show increased FI during recessions. Panel B illustrates variation in FI across different immigrant cohorts, with earlier cohorts (1959 or earlier, 1960-1969) 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 goal is to quantify the effect of the UR on FI in immigrant populations. 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:

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

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

[9] Immigrant noncitizens can apply for SNAP benefits after a waiting period and meeting certain criteria.

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 wage. Following Gould and Moav (2016), the residual wage, representing unobserved skills, is calculated as the residual from a Mincer-like regression of wage on household head characteristics, with state and year fixed effects. 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 characteristics at the initial research period that are correlated with unobserved shocks, denoted as L_{imt}. These local characteristics, drawn from the 2003 CPS monthly data, include the MSA-level share of white individuals, native households, those with a bachelor's degree or higher, the percentage identifying as male, the percentage married, mean household size, mean number of children, and median age. Finally, MSA- and Year- fixed-effects (ω_m, θ_t) are included to control for time-invariant but spatial-variant omitted variables correlated with both household FI and UR . Year fixed-effects 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). Logit or probit models offer a more nuanced understanding of the non-linear interplay between unemployment and the likelihood of household FI, potentially mitigating biases such as heteroskedasticity and producing probabilities strictly within the [0,1] interval (Friedman, 2012). However, LPM estimates[10] are

[10] As a model diagnostic, 91.5% of the predicted probabilities of FI fall within the 0-1 range in our estimated linear probability model with all controls.

easy to interpret, as they can be treated as ceteris paribus marginal effects of each covariate on the probability of FI.

To examine whether unemployment has a different effect on FI for immigrant and native households, we specify the following model:

$$y_{imt} = \alpha^{imm} + \beta_0^{imm} UR_{mt} * (1 - Imm_{ist}) + \beta_1^{imm} UR_{mt} * Imm_{imt} + \gamma^{imm} Imm_{imt} + \delta^{imm} X_{imt} + \pi^{imm} L_{imt} + \omega_m^{imm} + \theta_t^{imm} + \epsilon_{imt}^{imm} \quad (2)$$

The estimate of $\hat{\beta}_0^{imm}$ and $\hat{\beta}_1^{imm}$ measure the effect of the UR on FI for native households and immigrant households, respectively. The difference of these two estimates, $\hat{\beta}_1^{imm} - \hat{\beta}_0^{imm}$, represents the difference in the effect of the UR on FI of immigrant households relative to natives. The difference in the predicted probability of experiencing FI between immigrant and native households is calculated as $(\hat{\beta}_1^{imm} - \hat{\beta}_0^{imm})\, UR_{mt} + \hat{\gamma}^{imm}$, which we evaluate at the different UR values. The superscript "imm" indicates parameters and coefficients in Equation (2) estimating the different effect on FI for immigrant and native households, distinct from those used in other equations.

Next, following prior research indicating that citizenship influences FI (Kalil & Chen, 2008), we specify a model which allows for the effect of the UR on FI to differ across natives, immigrant citizens, and noncitizen households:

$$y_{imt} = \alpha^{cit} + \beta_0^{cit} UR_{mt} * \left(1 - Imm_{imt}^{noncit}\right) + \beta_1^{cit} UR_{mt} * Imm_{imt}^{noncit} + \beta_2^{cit} UR_{mt} * Imm_{imt}^{cit} + \gamma_1^{cit} Imm_{imt}^{noncit} + \gamma_2^{cit} Imm_{imt}^{cit} + \delta^{cit} X_{imt} + \pi^{cit} L_{imt} + \zeta_m^{cit} MSA_m + \eta_m^{cit} year_t + \epsilon_{imt}^{cit} \quad (3)$$

where Imm_{imt}^{noncit} and Imm_{imt}^{cit} are binary indicators for immigrant noncitizens and citizens, respectively. $\hat{\beta}_0^{cit}$, $\hat{\beta}_1^{cit}$, and $(\hat{\beta}_0^{cit} + \hat{\beta}_2^{cit})$ are estimates of the effect of the UR on the probability of experiencing FI of natives, immigrant noncitizens and immigrant citizens, respectively. The difference in predicted probability of FI between immigrant noncitizens and natives is $\left(\hat{\beta}_1^{cit} - \hat{\beta}_0^{cit}\right) \cdot UR_{mt} + \hat{\gamma}_1^{cit}$, while the difference in predicted probability of FI between immigrant citizens and natives is $\hat{\beta}_2^{cit} \cdot UR_{mt} + \hat{\gamma}_2^{cit}$. The "$cit$" superscript in Equation (3) designates parameters and coefficients unique to model for immigrant citizen status and natives.

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

$$y_{imt} = \alpha^{coh} + \beta_0^{coh} UR_{mt} * \left(1 - Imm_{imt}^{coh1}\right) + \sum_{j=1}^{7} (\beta_j^{coh} * UR_{mt} * Imm_{imt}^{cohj} + \gamma_j^{coh} Imm_{imt}^{cohj})$$

$$+\delta^{coh} X_{imt} + \pi^{coh} L_{imt} + \omega_m^{coh} + \theta_t^{coh} + \epsilon_{imt}^{coh} \quad (4)$$

Imm_{imt}^{cohj} is an indicator variable capturing whether the household head immigration year falls into one of seven (j = [1,…,7]) arrival cohorts from 1960 to 2019. After estimating the Equation (4), $\hat{\beta}_0^{coh}$ represents the estimated impact of the *UR* on FI for natives, $\hat{\beta}_1^{coh}$ captures the corresponding effect for immigrants from the initial cohort, arriving in 1959 or earlier. Furthermore, the combined term $\hat{\beta}_0^{coh} + \hat{\beta}_j^{coh}$ (for j > 1) quantifies the estimated effect of the UR on FI for immigrants from subsequent arrival cohort j (post-1960). As before, the difference in the predicted probability of FI between immigrant arrival cohorts 1959 or earlier and natives is calculated as $\left(\hat{\beta}_1^{coh} - \hat{\beta}_0^{coh}\right) UR_{mt}$ + $\hat{\gamma}_1^{coh}$. The difference in the predicted probability of FI between other cohorts and natives is $\hat{\beta}_j^{coh} \cdot UR_{mt} + \hat{\gamma}_j^{coh}$. Given that immigrants are required to reside in the U.S. for a specific duration to attain citizenship, and this duration varies based on the type of naturalization application, citizenship status might influence certain cohort-specific outcomes in our study. To isolate the distinct impacts of citizenship status on varying cohorts, we conduct separate estimations of Equation (4) for each citizenship category.

3.2 Empirical Strategy, Identification, and Inference

Despite including household-level, individual-level, local controls, and fixed effects, the UR may be endogenous for several reasons. First, unobserved local economic shocks may simultaneously affect the UR, food consumption and FI, leading to biased estimates of the UR effect. Second, food-insecure households may attempt to augment their income, potentially influencing labor supply and reducing the UR, which could lead to the reverse causality as posited by Krogh and Smith (2019) and result in downward bias. Conversely, FI-related health issues may limit employment opportunities, causing upward bias (Gundersen & Ziliak, 2015; Stronks et al., 1997). Third, household sorting based on industry-specific employment opportunities could correlate FI with unobserved shocks in certain demographic profiles.

To address potential endogeneity, we develop a shift-share instrumental variable approach, also referred to as Bartik instruments (Bartik, 1991; Goldsmith-Pinkham, Sorkin, & Swift, 2020). In general, the implied empirical strategy of Bartik instruments asks whether differential exposure measured by local shares of some economic activities (e.g., employment by industries) to common shocks (e.g., employment growth or UR) leads to differential changes in the outcomes. Following Goldsmith-Pinkham, Sorkin, and Swift (2020), we exploit exogenous variations in industry shares across locations and then interact the local variation in industry shares with national growth of employment across industries—our shocks.

To construct this instrument, we calculate household head aged 18 and older who report usually working at least 30 hours per week to first aggregate the local industry composition (local industry employment share) in metropolitan statistical areas for initial period 2003 ($s_{m,k,2003}$). Then, we calculate the annual employment growth[11] across industries at the national level ($g_{k,t}$) from 2004 to 2019 using CPS monthly data. We use the interaction between the share of employment in different industries across MSAs in 2003 and the annual employment growth of industries across years at the national level. The Bartik instrument for the UR in MSA m and year t is given as:

$$B_{m,t} = \sum_{j}^{13} s_{m,k,2003} * g_{k,t} \qquad (5)$$

where local industry employment share $s_{m,k,2003} = E_{m,k,2003} / E_{m,2003}$ and $E_{m\,,k,2003}$ is the number of people employed in industry *k* in MSA *m* in year 2003 and $E_{m,2003}$ is the total number people employed in MSA *m* in 2003. Employment growth across industries and years is calculated as $g_{k,t}$ = ($E_{k,t} -\ E_{k,t-1}$) / $E_{k,t-1}$. In this function, $E_{k,t}$ is the number employed in industry *k* in year *t*. To avoid mechanical correlations between the MSA-level URs and our instrument, we conduct a leave-one-out procedure to estimate national growth rate $g_{k,t}$ across industries separately by dropping all observations in that location. Based on industrial classification using the North American Industry Classification System (NACIS), industries in the monthly CPS data are disaggregated into 13 categories[12].

We use $B_{m,t}$ as an instrument to separately estimate Equations (1) - (4) via two-stage least-squares (2SLS). To explain the identification process, we consider Equation (1). The complete

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[11] The reason why we use employment growth but not unemployment growth is that it is more accurate to assess employment than unemployment using CPS data. Further, unemployment growth is highly correlated with employment growth.

[12] 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.

identification model comprises the first-stage regression (as shown in Equation (6)), the second-stage regression (originally presented in Equation (1), and now shown in Equation (7)), and the exclusion restrictions specified in Equation (8). The details of these components are as follows:

$$UR_{mt} = \lambda_0 B_{m,t} + \lambda_1 Imm_{imt} + \lambda_2 X_{imt} + \delta_m + \delta_t + \mu_{imt} \tag{6}$$

$$y_{imt} = \alpha + \beta \widehat{UR}_{mt} + \gamma Imm_{imt} + \delta X_{imt} + \theta_m + \theta_t + \epsilon_{imt} \tag{7}$$

$$0 = \text{cov}\,(B_{m,t}, \epsilon_{imt} | Imm_{imt}, X_{imt}, \theta_m, \theta_t) \tag{8}$$

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 identifying assumption) in Equation (8) 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).

Building on Goldsmith-Pinkham, Sorkin, and Swift (2020), our Bartik instrument is intuitively valid. The relevance assumption of our Bartik instrument is satisfied since our instrument uses the inner product of industry shares and national employment growth rate which are correlated with labor market demand measured by the UR. In terms of the exclusion restriction, our identification strategy essentially assumes that the industry shares embedded in the Bartik instrument measure the differential exogenous exposure to a common shock[13]. This means that unobserved shocks (ϵ_{imt}) to household-level FI are uncorrelated with the composition (or shares) of different industries in the same MSA of the household because the shares of different industries across locations are pre-determined at the time when household FI is measured. We construct the

[13] Alternatively, Borusyak, Hull, and Jaravel (2022) assumes the aggregated shocks are exogenous, while the cross-sectional shares may be endogenous.

composition of local industries using data collected in 2003 prior to the beginning of our research period (2004 - 2019). As such, our instrument is unlikely to be correlated with unobserved shocks that simultaneously affect the UR, household food consumption and FI. Even though the increase in the probability of household-level FI could affect the UR to keep income and food consumption smooth, it is unlikely to be correlated with the pre-determined composition (or shares) of local industries.

There is still the concern of sorting in which households select into different industries with specific characteristics, which may threaten our identification strategy. In this situation, unobserved shocks to households with particular demographics will increase the likelihood of FI for households that prefer to live in locations with particular industries. For instance, suppose lower skilled (less than high school degree) households work in pro-cyclical industries, like manufacturing, retail, and service industries. When there are unobserved shocks that disproportionately affect these lower skilled households, both household-level FI and UR in these locations will be sensitive to these shocks. If households sort based on being employed in different industries, the exogeneity of our Bartik instrument may be in question.

To investigate the probability of potential endogeneity caused by this household sorting behavior, we follow suggestions by Goldsmith-Pinkham, Sorkin, and Swift (2020) and Graham and Makridis (2023) to regress the MSA level shares of industries on location demographic characteristics at the initial period (year 2003). This relationship reflects how the instrument's cross-sectional variation in the industry share, especially for the overall instrument, is explained by the local characteristics. If we find there are correlations between the shares of industries and the local characteristics which are the potential confounding factors, it may imply that there are omitted variables influencing estimation like households sorting behavior.

Table 2 reports these correlation estimates for the shares of top five industries fixed in the initial period (2003) and initial period MSA-level characteristics[14]. The R-squared values for these regressions are quite high. For instance, the local characteristics explain 47% of the variation in the 2003 total industry shares embedded in the Bartik instrument. This indicates that demographic variation by MSA accounts for a significant portion of the cross-sectional variation in the Bartik instrument. We also find that the construction, manufacturing, utilities, transportation, and warehousing industries, as well as the overall Bartik instrument, are correlated with the share of male, share of white, share of native-born, household size, number of children, and median age. However, observable local characteristics might serve as predictors for unobserved confounders that could potentially bias our estimations. For instance, the share of local manufacturing employment is statistically correlated with the percentage of native-born households. Given that the share of immigrants is simply the complement of the native-born share, it might also indicate the likelihood of immigrant inflows or labor supply shocks. Consequently, our measure of industry share could be associated with these unobserved labor supply shocks. Overall, the correlations between industry shares and local demographics presented in Table 2 indicate the potential occurrence of household sorting, whereby households select industries based on specific characteristics. Furthermore, these correlations suggest that unobserved shocks to particular demographic groups may affect the estimates.

To test the potential threat of household sorting, the results in Section 4 show that our estimates remain robust whether or not we include household-level or MSA-level demographic

[14] Goldsmith-Pinkham, Sorkin, and Swift (2020) argue that focusing on the industries with the largest Rotemberg weights (the top five contributing to the Bartik instrument) highlights where confounding variables are most concerning. We explain Rotemberg weights further in Section 3.4.

control variables. This suggests that even there is household sorting into employment and locations by industry, it is uncorrelated with unobserved shocks to household FI.

3.3 Strength of Bartik Instrument

We empirically examine the relevance of our Bartik instrument by estimating the first-stage regression from Equation (7). We plot the first stage effect of the Bartik Instrument on the MSA using a binned scatter plot of residualized Bartik instrument against the residualized UR (Figure 2). The residualization is generated from the multivariate regression on a full set of controls including the household, individual demographic characteristics and local characteristics, together with MSA fixed effects. Dispersion of binned scatter points around the red regression line in Figure 2 suggests a statistically significant relationship between the Bartik instrument and MSA UR, even with a large number of control variables. As such, the relevance assumption of our Bartik instrument in predicting local URs appears valid.

3.4 Decomposition of the Variations in Bartik Instrument

We also 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[15].

We calculate the Rotemberg weights (details in Appendix Table A.1) on the Bartik estimates with controls, aggregated across time and location, and found that a small number of industries dominate the identifying variation. Specifically, the top five industries—"Construction," "Manufacturing," "Utilities, Transportation and Warehousing," "Finance, Insurance, Real Estate, and Rental and Leasing," and "Information"—account for 96% (= 2.2 / 2.311) 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 "Construction" industry, driven by immigrant labor, is particularly notable, as is the substantial role of the "Manufacturing" industry, 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 during the GR (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.

4 Results

4.1 The Effect of Unemployment on Household FI

4.1.1 Analysis for All households

We first examine the response of household FI to UR in MSAs, without distinguishing between the different effects on native and immigrant households. We use a binary control variable

[15] 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.

(0=native; 1=immigrant) to identify household immigrant status. Table 3, columns (1) - (3) report the results of our linear probability model (OLS) weighted by CPS 2003 population counts with standard errors clustered at MSA level. Column (1) includes no controls, column (2) introduces the year and MSA fixed effect and column (3) includes household controls as well as fixed effects. Our OLS estimates of the marginal effect of the UR on FI are not sensitive to including controls with marginal effects from 0.7% to 0.9%. This indicates that a 1% higher MSA-level UR is statistically significantly associated with a 0.8% increase in the probability of being FI for all households. This estimate is a little higher than state-level evidence from Nord, Coleman-Jensen, and Gregory (2014) and Potochnick and Arteaga (2018). We also found that immigrants statistically tend to be more food insecure than natives. The difference between immigrant and native households ranges from 4.7% to 5.3%.

The 2SLS estimates using our Bartik instrument are reported in Columns (4) - (7). 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. Column (7) introduces a range of local demographic characteristics measured at MSA level in initial period 2003 as suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020). It is worth noting that we do not use time fixed effect or local demographic controls interacted with time dummies when we use Bartik instrument with national growth rates as these may absorb too much time series variation in the instrument (Graham & Makridis, 2023). The marginal effects of the UR on FI range from 1.0% to 1.1% with different bundles of controls, which is higher than the estimated marginal effects from OLS.

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. Overall, after correcting the downward bias of OLS estimates, our 2SLS estimates indicate a 1% increase of the MSA-level UR would increase the probability of household-level FI by 1.0%. The 2SLS results also suggest immigrant households are 4.8% more likely to be food insecure than natives.

4.1.2 Analysis by Immigrant Status

We next examine whether unemployment affects FI of US immigrants differently than natives in the United States by estimating Equation (2). We first report the OLS estimations in Table 4, columns (1) - (3) under different sets of controls. Overall, the UR has a negative and larger effect on FI for immigrant households compared with native households. When there are no controls reported in column (1), a 1% higher MSA-level UR is associated with a 0.8% increase in the probability of being food insecure for native households and a 1.4% increase for immigrant households. With the inclusion of year and MSA fixed effect and household demographic controls, the marginal effect of the UR on FI of natives decreases to 0.6%. For immigrant households, the marginal effect is 1.1% to 1.4%. Altogether, the probability of FI for immigrants is 0.5% - 0.6% higher than natives given a 1% increase in the UR. Overall, the OLS estimation results reveal that when the UR is zero, the difference in FI probabilities between immigrants and natives is 0.9% - 1.6%. Since the predicted FI also depends on the marginal effect of the UR, we test and confirm immigrants are always more likely to be food insecure than natives at various URs.

Columns (4) - (7) report 2SLS estimations. After controlling all covariates, the impact of the UR on FI for immigrants is twice as large compared to natives (0.8% vs 1.6%). This finding exceeds the estimation provided by OLS. We then calculate and compare the predicted probability of being food insecure for immigrant and native households using different UR values. We plot the trend of the predicted differences in the probability of being food insecure between immigrant and native households against different values of UR ranging from 1.8% to 22.9% (the minimum and maximum values of MSA UR in our sample) in Panel A of Figure 3. We see that the differences in the incidence of household-level FI are increasing from 1.5% to 17.9% with the greater UR. Since there are few observed MSAs with UR greater than 13.2%, the 95% CIs are wide with UR higher than 13.2%. After accounting for variations in the data, the results indicate that immigrant households are statistically more likely to be food insecure than native households when the UR exceeds 2.6%[16].

4.1.3 Analysis by Immigrant Citizenship Status

Prior research suggests that citizenship status can act as a symbol of eligibility to receive food assistance and may be a strong predictor of FI (Kalil & Chen, 2008; Potochnick & Arteaga, 2018). As such, we further examine whether unemployment have different effects on natives relative to immigrant citizens and noncitizens (Table 5).

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 1.4% - 1.8% higher probability of immigrant noncitizen household experiencing FI, 0.8% - 1.0% for immigrant citizens, and 0.5% - 0.8% for natives. In addition, a 1% increase in UR is associated with 0.9% - 1.1% greater probability of FI for

[16] However, it is important to note that only 1% of the MSA-level URs in our sample fall below this threshold.

immigrant noncitizens relative to natives, and 0.2% - 0.3% for immigrant citizens relative to natives.

The 2SLS estimates (columns 4 – 7) further support that immigrant noncitizen households exhibit greater sensitivity to unemployment than natives. Specifically, a 1% increase in the UR leads to a 2% rise in their probability of experiencing FI, compared to a 0.8%–0.9% increase for natives. This suggests that the effect on noncitizen immigrants is approximately 1.2% higher than on natives. In contrast, the impact on immigrant citizens, at 1.3%–1.4%, does not significantly differ from that observed in native households.

We use our 2SLS estimates to plot and contrast the predicted probabilities of FI between immigrant and native households across varying URs (see Panel B of 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 within the range of 6% to 10.8%. Overall, Panel B of 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 3.4%. Additionally, when the UR falls between 3.5% and 16.3%, immigrant citizens are more susceptible to FI than natives.

4.1.4 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 6 presents the 2SLS estimation results 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.

Within the noncitizen immigrant group, more recent cohorts, specifically those arriving between 1980–1989 and 2000–2009, each reports a statistically significant 2.3% increase in the probability of FI in response to an economic downturn, as indicated by a decrease in the UR. Meanwhile, the cohort that arrived in 1959 or earlier, which has the longest U.S. residence, experience the most substantial increase in the probability of FI—13.6%—due to the same economic conditions. This unexpected significant rise for earlier cohorts may be due to the small sample size (only 1% of the group) and a higher proportion of low-skilled households in this subgroup. For immigrant citizens, the 1970-1979 cohort is the most vulnerable to adverse economic conditions, with a 2.1% increase in the likelihood of FI. The cohorts from 1980-1989 and 1990-1999 follow with a 1.9% and 1.0% increase in the likelihood of FI, respectively. FI for other cohorts with citizenship is not significantly affected by unemployment. Aside from citizenship status, variation in the migration policy and economic conditions in the period of arrival and countries of origin, may explain the various effects of the UR (Borjas, 1995).

We next compare the effects of unemployment between immigrant cohorts and natives. Noncitizens who arrived in the United States by 1959 or earlier exhibit a 12.8% higher likelihood of FI compared to native households as a result of a 1% increase in unemployment. This may indicate that immigrants who have not acquired citizenship after a prolonged period in the U.S. face additional challenges. Alternatively, it might be attributable to the inadequate sample size within this cohort group[17]. The noncitizen immigrant cohorts from 1980-1989 and 2000-2009 also face higher risks of FI than natives due to unemployment: a 1.5% higher increase in response to a

[17] After limiting the sample age between 18-65 years old, there are 45 noncitizen immigrant households in the 1959 cohort.

1% increase in unemployment. One possible explanation is that the 1980-1989 immigrant cohort contended with migration policy restrictions, challenging labor market conditions, or predominantly hailed from poor countries (Abramitzky et al., 2021; Borjas, 1995). Those arriving between 2000-2009 confronted the GR. For other cohorts of immigrant noncitizens, we do not find significantly higher probabilities of FI compared to natives. Regarding the immigrant citizen group, only the 1970-1979 cohort exhibits a notably higher likelihood (1.2%) of FI compared to natives. Other cohorts of immigrants with citizenship display similar or even less vulnerability to unemployment than natives (cohort 1960-1969).

Figure 4 illustrates the predicted FI gap between various immigrant cohorts and natives across different citizenship categories and URs. 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, which is less likely to experience FI compared to natives when UR exceeds 6.3%. The 1959 or earlier cohort shows the highest sensitivity to UR changes, with significantly greater FI likelihood than natives when the UR exceeds 8%, though this finding may be limited by sample size. The 1960–1969 cohort, despite its vulnerability, does not show significant disparities in FI across URs. The 1980–1989 cohort is the second most vulnerable, particularly within the 3.9% to 18.7% UR range. The 2000–2009 cohort reveals a more pronounced likelihood of FI than natives when UR exceeds 4.1%, while the 1990–1999 cohort faces a higher likelihood of encountering FI relative to natives within a UR span of 2.3% to 11%.

Looking at immigrant citizens (Panel B), we observe different patterns in FI across the corresponding cohort groups. The cohorts 1959 or earlier, 1960-1969 and 2000-2009 with citizenship all exhibit a lower likelihood of FI compared to natives. Regardless of the URs, the 1959 or earlier cohort does not exhibit a statistically significant difference in the probability of FI compared to natives. Interestingly, the 1960-1969 cohort begins to show a significantly reduced likelihood of FI when the UR climbs above 10%. The 2000-2009 cohort also exhibits a significantly reduced propensity for FI in comparison to natives within the UR range of 4% to 9.4%. The 2010-2019 cohort with citizenship displays a heightened, albeit not significant, likelihood of FI when compared to natives. The cohorts 1970-1979, 1980-1989, and 1990-1999 demonstrate greater susceptibility to FI relative to natives at UR thresholds exceeding 6.5%, within the 5.3-18.7% range, and the 4.6-18.3% range, respectively.

4.2 Heterogeneous Effects Across Different Subsamples by Household Characteristics

Unemployment is expected to have a larger effect on low-skilled workers and low-income households[18]. To examine this, we estimate Equations (2) and (3) across subsamples defined by education attainment of household heads, poverty levels, and SNAP participation status. For poverty groups, we identify households with income above or below 185% of the poverty line. We use a binary indicator for households that report receiving SNAP benefits in the past year or not.

We first compare household FI between immigrant and native populations across varying levels of education (odd columns of Table 7). Across all levels of educational attainment, both native-born and immigrant populations are more likely to experience FI as URs rise. For native-born individuals, the effect diminishes from 2.1% to 0.2% as we move from below high school education to graduate education. For immigrants, the effect of unemployment rises to 2.3% as educational attainment reaches a high school degree, then decreases to 1.0% for those with graduate or professional degrees. The effect of unemployment on FI is higher for immigrants than natives at all education levels except below high school. This finding suggests that educational

[18] Note, we identify low-skilled or high-skilled based on educational attainment.

attainment may not be sufficient to mitigate the difference in the likelihood of FI between immigrants and natives.

We further split our immigrant samples by citizenship status (even columns of Table 7). Our results suggest that immigrant noncitizens who attain a graduate or professional degree are not statistically susceptible to unemployment. However, those with a bachelor's degree or lower exhibit a higher vulnerability to unemployment in terms of FI. Comparing the effects of URs on immigrant noncitizens to its native-born counterparts, significant disparities emerge, particularly among those with high school (1.7%) and bachelor's degrees (1.9%). For immigrant citizens, the data indicates that those with a high school education or less remain unaffected by the URs, no different than their native-born counterparts. Yet, immigrant citizens with an associate degree or more advanced qualifications experience a marked increase in FI in response to rising UR, presenting a higher probability compared to native-born households. The results detailed in Table 7 indicate that higher education generally acts as a protective factor against the impacts of unemployment on FI of immigrant noncitizens. However, this protective effect is not evident among immigrant citizens.

Next, we disaggregate the sample by above or below 185% poverty line (Table 8, columns 1 - 4) and split the immigrant sample by citizenship status. For those residing below 185% of the poverty line, an increase in the UR significantly affects the likelihood of experiencing FI (FI): 1.6% for native-born individuals, 2.3% for immigrant noncitizens, and 1.7% for immigrant citizens. Conversely, for households above the 185% poverty threshold, the rise in the UR continues to impact the likelihood of FI, though to a lesser extent: 0.5% for natives and 1% for both immigrant noncitizens and immigrant citizens. When assessing the impact on immigrant relative to native-born households, no significant differences emerge in how the UR affects household FI for both immigrant noncitizens and citizens. This might indicate that once income limitations are accounted for, the disproportionate influence of unemployment on FI between immigrants and natives becomes indistinguishable.

Additionally, we compare households that receive and do not receive SNAP (Table 8, columns 5 - 8). SNAP is available only to U.S. citizens and limited categories of immigrants, so we focus on the comparison of immigrant by citizen status and natives. [19] Among the group that has not received SNAP benefits, elevated URs markedly impact the likelihood of experiencing FI across various populations: 2% for immigrant noncitizens, 1.3% for immigrant citizens, and 0.8% for native-born individuals. Notably, immigrant noncitizens, who often have restricted eligibility for SNAP, are statistically more susceptible to FI due to increases in the UR compared to their native-born counterparts. For those who have received SNAP benefits, only the native-born population demonstrates a statistically heightened likelihood of FI due to unemployment. Further, both immigrant citizens and noncitizens display similar likelihoods of FI as native-born households. Participation in food assistance programs like SNAP may serve as a mitigating factor, tempering the negative impacts of economic cycle on FI, particularly for the more vulnerable immigrant noncitizens.

4.3 Robustness Check

We use three alternative Bartik instruments suggested by Goldsmith-Pinkham, Sorkin, and Swift, 2020) to further test the robustness of our Bartik instrument results. Columns (1) and (2) of Appendix Table B.2 report our benchmark results with and without the full set of controls. Columns (3) and (4) report a version of the Bartik instrument where we normalize the growth rate by demeaning. Specifically, on the baseline leave-one-out approach, we subtract the simple mean

[19] Most lawfully residing immigrant adults cannot receive food stamps on the same basis as citizens until they have been in the U.S. in a specified "qualified" immigrant status for five years.

of growth rates in each time period. The estimates employing alternative Bartik instrument with simple demeaning growth rate perform quite well and show the effect of the UR on household FI in the range of 4.7% to 2.7%, which produces a slightly larger estimate than our baseline model.

Columns (5) and (6) use a restricted version of the Bartik instrument that only exploits the top five industries based on variation in the instruments.[20] The results are similar to the results using baseline Bartik instrument in column (1) and (2), further confirming that the top five industries provide a majority of relevant information for identification in the instrument.

Finally, columns (7) and (8) use a version of the interaction of industry shares with year dummy variables as the Bartik instrument. The use of year dummies in this version of the instrument produces almost the same time-series variation in unemployment as our baseline Bartik instrument. This may suggest that local industry composition (or shares) provides sufficient cross-sectional variation to be used as instruments for unemployment on their own.

5 Discussion

Our study estimates how MSA URs affect household FI of immigrants relative to natives in the United States. We use a shift-share instrumental variable approach to address potential endogeneity of the URs that could bias estimates of their effect on household FI. After identifying the differential effect of unemployment on FI between immigrants and natives, we further explore which types of immigrants are the most vulnerable immigrant populations. Separating the sample by educational attainment, poverty level, and food assistant program participation helps us explore potential mediating pathways.

Comparing the results with the literature, our 2SLS estimates confirm that deteriorating economic conditions, characterized by higher UR, worsen household FI (Cho, Kreider, & Winters,

[20] We have discussed about how to decide these five industries in the Section 3.4.

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 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.

Comparing natives and immigrants, we find the effect of the UR on FI is approximately twice as large for immigrants as for natives (1.6% vs 0.8%). Moreover, when the MSA UR exceeds a 2.6% threshold, immigrant households face heightened vulnerability to FI compared to U.S.-born households. This pattern may also imply that immigrants face more pronounced job losses and diminished incomes during economic downturns than natives (Chilton et al., 2009; Kochhar, Espinoza, & Hinze-Pifer, 2010; Liu & Edwards, 2015; Orrenius & Zavodny, 2009).

We next evaluate the impact of citizenship. Overall, we find the impact of unemployment is markedly higher for immigrant noncitizens compared to natives, whereas the effect of unemployment on immigrant citizens is not distinguishable from that of natives on average. 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 the susceptibility to FI for immigrant noncitizens rises more precipitously with increasing UR than for immigrant citizens. Although immigrant citizens benefit from factors like prolonged residency in the US and eligibility for food assistance programs, they still encounter increased the likelihoods of FI compared to natives when the UR ranges between 3.5% and 16.3%.

When controlling for citizenship status, we find varying impacts of the UR on FI across immigrant cohorts. Noncitizen immigrants from the 1980-1989 and 2000-2009 cohorts and citizen immigrants from the 1970-1979 cohort show heightened sensitivity to rising URs compared to natives. Contributing factors likely include lower skill levels, restrictive immigration policies at their time of arrival, and adverse economic conditions encountered upon entry. For example, 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 was heavily impacted by the GR. Interestingly, the earlier cohorts (pre-1970) and the 2010-2019 cohort are either less likely or not significantly more likely to experience FI compared to natives. This resilience may stem from selection effects (Berning, Norris, & Cleary, 2023): Pre-1970 immigrants predominantly came from wealthier countries like Italy, Germany, and Canada, often possessing higher human capital (Zong, Batalova, & Hallock, 2018). Similarly, the 2010-2019 cohort largely comprised highly educated migrants from India and China, making them less vulnerable to economic shocks.

Examining select subgroups, we find while higher education generally reduces the impact of unemployment on FI, it may not be sufficient to mitigate the disparities between immigrants and natives. This follows the previous literature which suggests that both low-skilled and high-skilled immigrants face greater vulnerability to worse economic conditions compared to natives due to their concentration in cyclical industries, lack of legal work authorization, and reduced demand for their skills during economic downturns (Batalova, Fix, & Creticos, 2008; Kochhar, Espinoza, & Hinze-Pifer, 2010; Liu & Edwards, 2015; Orrenius & Zavodny, 2009). Our findings further point out that immigrant noncitizens with graduate or professional degrees appear less susceptible to unemployment's effects on FI, while those with lower levels of education remain more vulnerable. Interestingly, immigrant citizens with an associate degree or higher face an increased likelihood of FI during periods of rising unemployment compared to their native-born counterparts. These results underscore the need for targeted policies and interventions that address the unique challenges faced by immigrants, particularly those with lower levels of education and noncitizens, in mitigating the risks of FI during economic instability.

When we control for poverty status or participation in food assistance programs, unemployment does not have a differential impact on FI of immigrants relative to natives. This highlights the role of poverty in managing FI disparities even across immigrant status (Chen, Wu, & Jin, 2023; Loopstra & Tarasuk, 2013). The lack of data about specific household income and SNAP receipt precludes us from a more precise assessment of the contribution of SNAP. Still, our findings highlight that expanding access to food assistance programs could help reduce the harmful effects of economic downturns (such as increases in the UR) on FI, especially for vulnerable noncitizen immigrants.

6 Conclusion

Our primary contribution to the literature is to identify a causal effect of unemployment on household FI to explore whether immigrants are more vulnerable than natives. Unemployment has been widely considered to be one of the important determinants of FI. However, it is difficult to examine the plausibly causal evidence of this effect because endogenous shocks may jointly affect both unemployment and household FI. To solve this problem, we use a Bartik instrument for local exposures to fluctuations in UR which exploits exogenous cross-sectional variations in industry shares across locations in an initial period and aggregated time variations in national growth of employment across industries. With the instrument in hand, we find that the impact of the UR on FI for immigrants is notably twice as significant compared to natives (1.6% vs 0.8%).

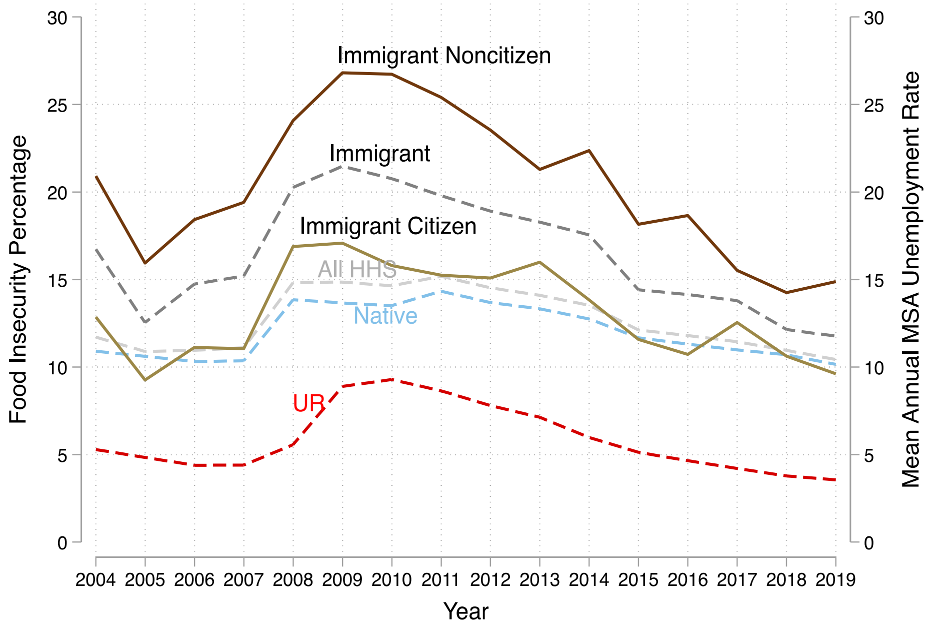
Looking more closely at our sample, we find outcomes vary considerably among immigrant subgroups. FI in immigrant noncitizen households is more affected by unemployment than in native households, while immigrant citizens face the same likelihood as natives. Within each citizenship category (immigrant citizen or noncitizen), the effect of the unemployment on FI varies distinctly across different immigrant arrival cohorts. These finding imply that immigrant cohorts, selected by low human capital or confronted with unfavorable economic conditions upon their initial arrival, exhibit an elevated likelihood of FI in comparison to native (Abramitzky et al., 2021; Borjas, 1995; Van Hook, Landale, & Hillemeier, 2013). Also, higher education, particularly at the graduate level and above, to some extent mitigates the impact of unemployment on FI, especially for US immigrant noncitizens, but may not be as effective for immigrant citizens compared to natives. Additionally, we find that poverty status may be one of the strongest contributors to the effect of UR on FI for both natives and immigrants (Loopstra & Tarasuk, 2013). Finally, improving access to food assistance programs may help mediate the negative effect of short-term shocks like unemployment on FI, especially for immigrant noncitizens.

In summary, our study offers significant insights into the disparate impacts of unemployment on immigrant households in comparison to native-born households. These distinctions are essential for pinpointing which groups would benefit the most from targeted policy instruments. To support families facing hardship, federal programs like SNAP could consider revising eligibility requirements for immigrant noncitizens. Moreover, states can fill gaps in the federal system by offering unemployment benefits to those without work authorization. Such efforts have already been made by Colorado, California, and New York (Visram, 2023; Wilson, 2023). Research, notably by Browning and Crossley (2001) and Fu, Huang, and Liu (2023), confirms that enhanced unemployment insurance (UI) can help stabilize household food consumption and reduce FI. It is important to note that our findings using this MSA-level dataset are more relevant for households in metropolitan areas than for those in agricultural and rural regions.

Unemployment insurance is a key fiscal policy tool, providing necessary economic stimulus during downturns. The one-time expansion program during COVID-19 pandemic highlighted the efficacy of enhancing unemployment benefits and the imperative to expand these benefits inclusively to help both state and national economic resilience. This oversight underscores the potential for a comprehensive reform that extends traditional unemployment insurance to all workers, regardless of immigration status (Kallick et al., 2022). Such efforts not only address immediate inequalities between immigrants and natives during economic downturns but also pave the way for a more inclusive approach to economic recovery.

Tables and Figures

Panel A. Immigrant Citizen Status



Panel B. Immigrant Arriving Cohorts

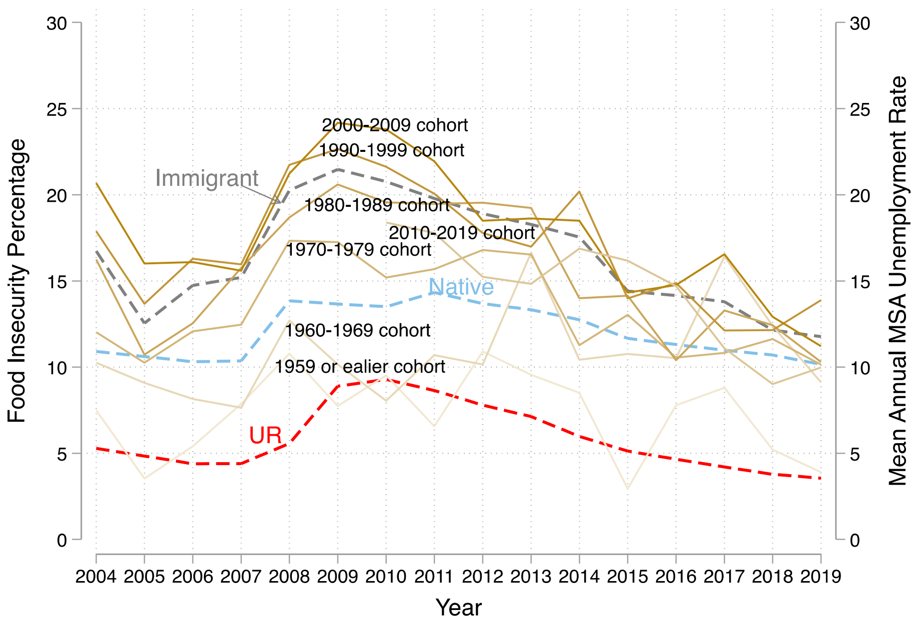


Figure 1. The UR and FI Trends over Time by Groups.

Note: The left y-axis displays the household food insecurity rates (percentage) across different groups over time, while the right y-axis represents the annual unemployment rate (percentage) at the MSA level, shown as the red dashed line.

Source: Authors' calculations, U.S. Bureau of Labor Statistics and Current Population Survey.

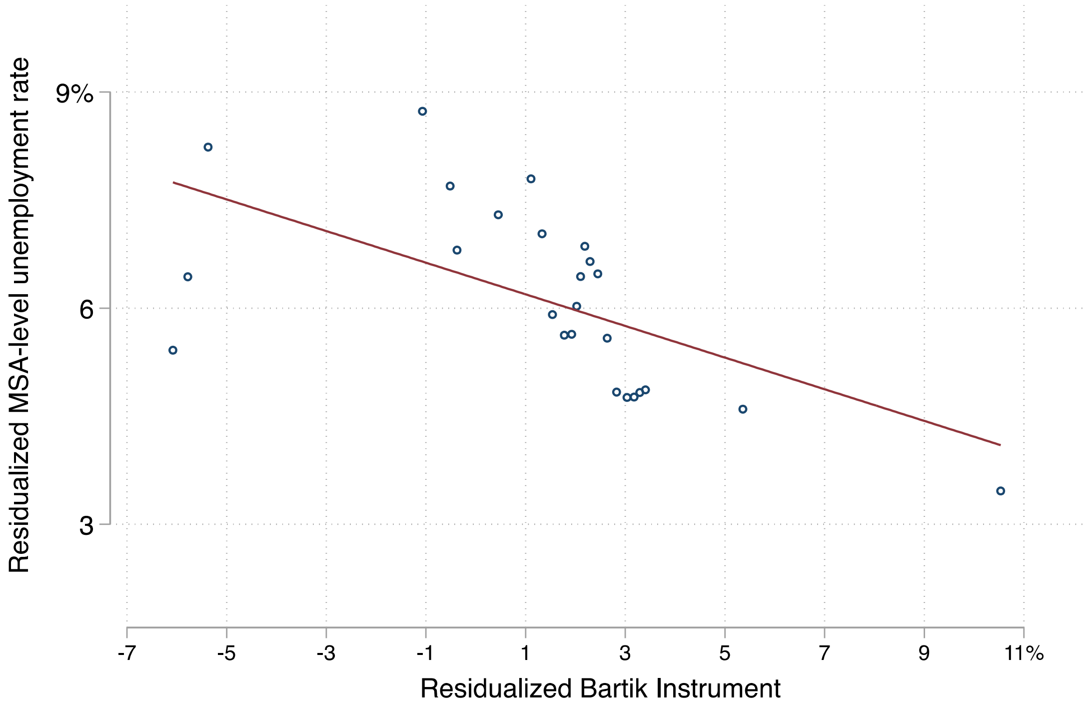


Figure 2. First Stage Effect of Bartik Instrument on the UR.

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 then group the value of residualized Bartik instrument into equal sized bins, compute the mean of instrument and UR residuals within each bin, and create a scatterplot of these data points. Finally, the red line in the graph represents the best linear fit line, which is constructed using an OLS regression of the y-residuals on the x-residuals. The slope of the fit line matches the first-stage regression coefficient on the Bartik instrument.
Source: Authors' calculations, U.S. Bureau of Labor Statistics and Current Population Survey.

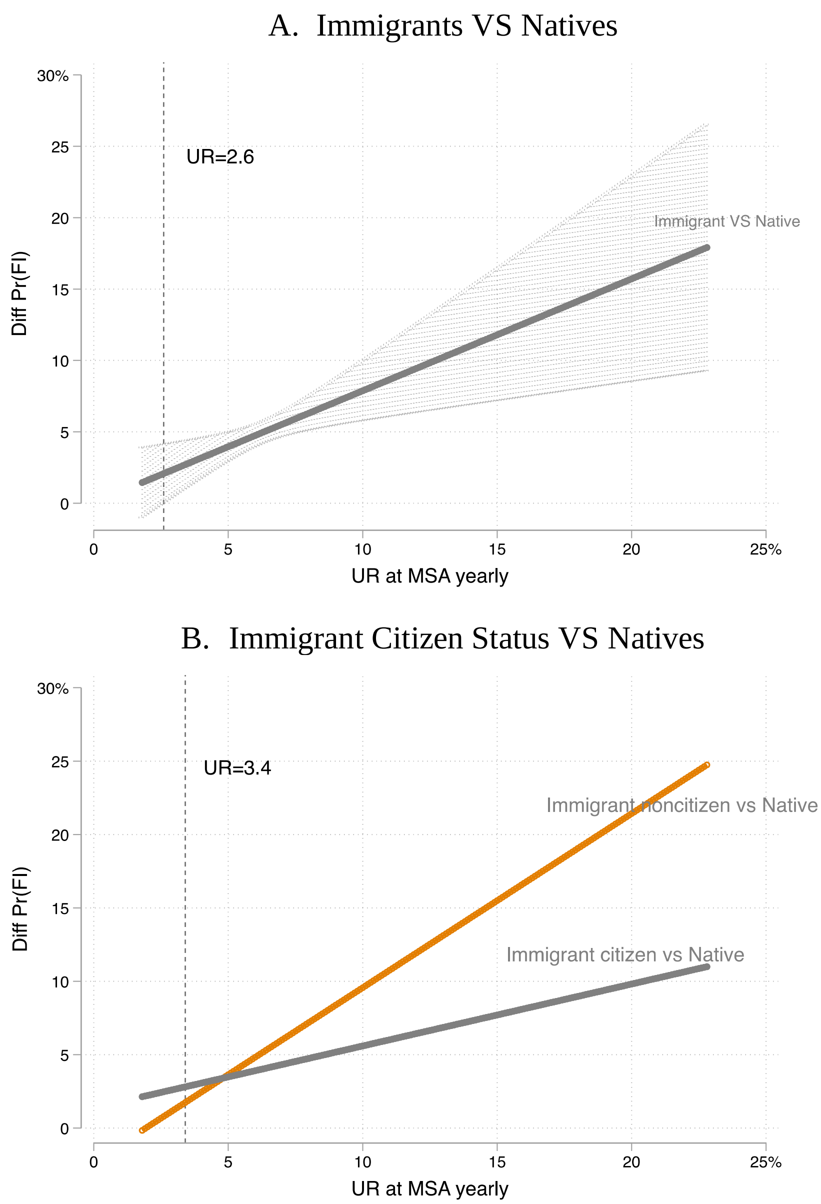
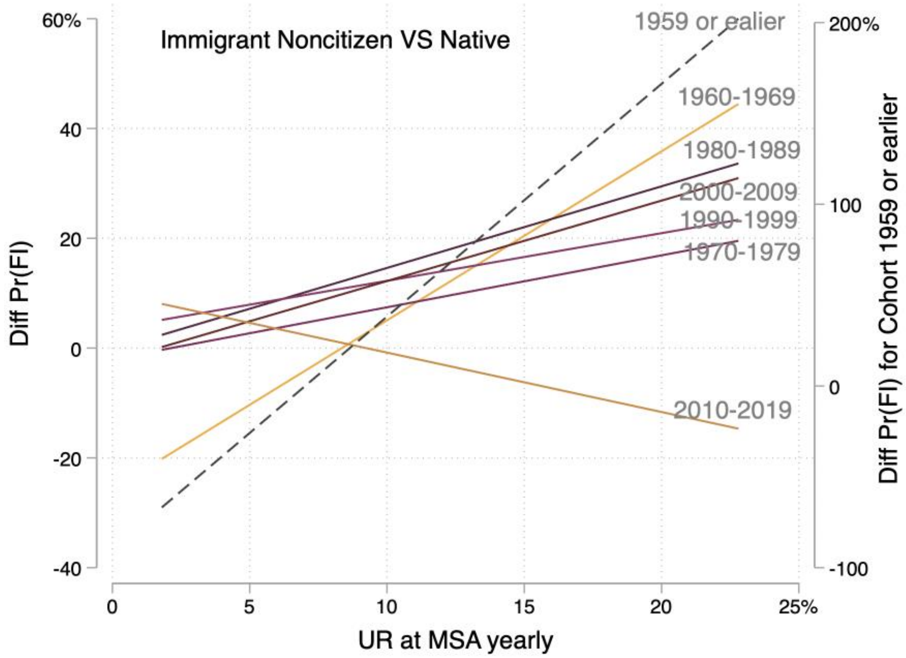


Figure 3. Difference in Probability of FI Between Immigrant and Natives.

Note: The y-axis variable is the difference in the predicted probabilities of being food insecure between immigrant (noncitizens or citizens) and native households. The shadow area in Panel A represents the 95% CI. For Panel A, the y-axis value calculation is $(\hat{\beta}_1 - \hat{\beta}_0)\ UR_{mt} + \hat{\gamma}$ from Equation (2). Here, $\hat{\beta}_1 - \hat{\beta}_0$ is the estimated difference in the effect of UR on the FI of immigrant households compared to native households. And $\hat{\gamma}$ represents the predicted difference in the incidence of FI between immigrants and natives when UR is 0. The predicted values used to plot this figure are reported in Table 4. For Panel B, the value on the orange line is calculated as $(\hat{\beta}_1 - \hat{\beta}_0)\ UR_{mt} + \widehat{\gamma_1}$ from Equation (3). Here, $\hat{\beta}_1 - \hat{\beta}_0$ 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 grey line is calculated as $\hat{\beta}_2 * UR_{mt} + \widehat{\gamma_2}$ from Equation (3) 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 5.

A. Immigrant noncitizen subgroup



B. Immigrant citizen subgroup

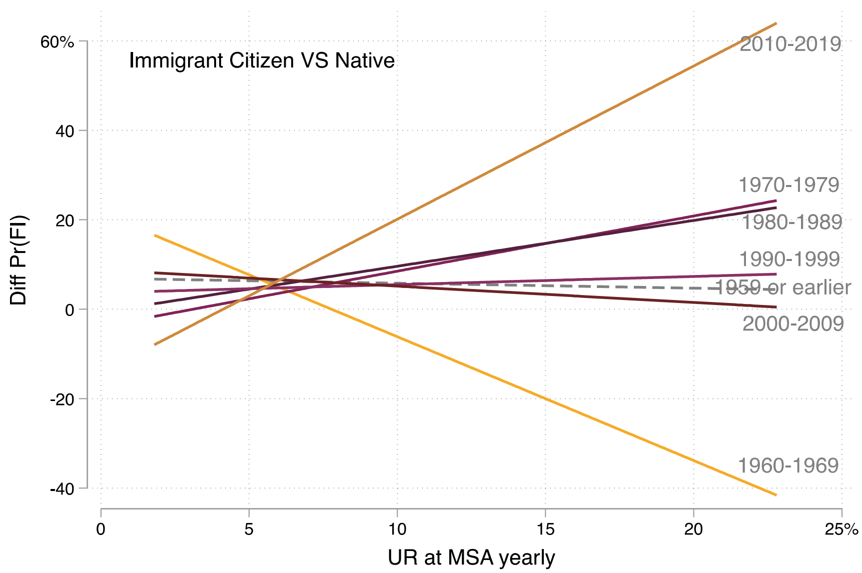


Figure 4. Difference in Probability of FI Between Immigrant Cohorts and Natives Across Different Immigrant Citizenship Statuses

Note: Figure 4 shows the difference in the predicted probabilities of being food insecure 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 6. In Panel A, the "1959 or earlier" noncitizen cohort (dashed line) shows a significantly higher FI likelihood than natives due to limited sample size, so it's plotted on a separate right y-axis.

Table 1. Summary Statistics by Immigration Status.

	Native	Imm	Immigrant citizen status		Immigrant Cohorts						
			Noncitizen	Citizen	1959 or earlier	1960-1969	1970-1979	1980-1989	1990-1999	2000-2009	2010-2019
Interview type (share)											
Telephone	0.55	0.49	0.46	0.52	0.58	0.53	0.52	0.50	0.49	0.46	0.47
In person	0.32	0.42	0.45	0.39	0.28	0.36	0.39	0.41	0.42	0.44	0.44
Married	0.48	0.50	0.47	0.52	0.16	0.32	0.47	0.51	0.53	0.50	0.47
Number of children <18	0.62	0.87	0.99	0.76	0.30	0.59	0.87	0.86	1.06	0.94	0.71
Female	0.50	0.47	0.45	0.48	0.56	0.53	0.47	0.44	0.47	0.48	0.43
Age Head	44.37	42.55	39.14	45.85	58.25	54.39	50.69	46.05	41.20	37.47	35.05
Education Level											
Below HS degree	0.06	0.25	0.35	0.15	0.07	0.17	0.27	0.27	0.28	0.26	0.14
HS degree	0.24	0.22	0.23	0.22	0.19	0.21	0.20	0.23	0.24	0.23	0.18
Associate degree	0.31	0.18	0.13	0.23	0.36	0.30	0.20	0.20	0.17	0.15	0.14
BA degree	0.25	0.20	0.15	0.25	0.24	0.19	0.20	0.19	0.19	0.19	0.28
Adv degree	0.14	0.15	0.14	0.15	0.14	0.13	0.13	0.12	0.13	0.17	0.26
Residual Wage	1.27	1.33	1.43	1.22	1.07	1.08	1.12	1.26	1.37	1.43	1.45
Years of immigration	0	18.10	12.40	23.61	50.89	42.79	33.23	25.48	15.80	7.79	1.93
Above 185% poverty line	0.77	0.58	0.49	0.68	0.77	0.72	0.68	0.60	0.55	0.54	0.59
Received SNAP	0.08	0.10	0.12	0.07	0.06	0.08	0.07	0.09	0.11	0.12	0.09
Observations	284,302	48,310	23,748	24,562	607	1,958	5,133	10,339	14,035	12,387	3,851

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.

Table 2. Correlations of Industry Shares and MSA Demographic Shares.

	Construction	Manufacturing	Utilities; Transportation and Warehousing	Finance, Insurance; Real Estate, and Rental and Leasing	Information	Bartik (2003 shares)
Share of White	-0.579**	2.525***	-0.667**	0.539	-0.014	-19.303***
	(0.231)	(0.681)	(0.335)	(0.450)	(0.222)	(5.673)
Share of Native Born	0.108	1.368**	0.131	-0.172	-0.228	-3.885
	(0.209)	(0.655)	(0.217)	(0.278)	(0.219)	(4.675)
Share of bachelor's degree or above	-0.332	-1.311*	-0.237	0.512	0.423*	8.876*
	(0.277)	(0.787)	(0.310)	(0.364)	(0.219)	(5.313)
Share of Male	1.347***	-0.728	0.418	-0.383	-0.165	6.337
	(0.361)	(0.936)	(0.341)	(0.518)	(0.324)	(9.454)
Share of Married	0.169	-2.583*	-0.168	0.110	0.537	11.157
	(0.409)	(1.445)	(0.556)	(0.612)	(0.345)	(7.830)
Mean Household Size	-2.517***	3.724	-0.217	0.363	1.212*	-45.233***
	(0.665)	(2.357)	(0.687)	(0.950)	(0.646)	(17.205)
Number of Children	1.794**	-0.431	1.036	0.244	-1.535***	32.367**
	(0.750)	(2.487)	(0.876)	(0.913)	(0.576)	(16.208)
Median Age	0.052	-2.312**	0.809*	1.330*	-0.572**	20.108***
	(0.263)	(0.950)	(0.465)	(0.720)	(0.255)	(7.634)
Population Weighted	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.46	0.47	0.23	0.25	0.46	0.47
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.

Table 3. The Effect of UR on Household FI.

	OLS			2SLS-Bartik instrument			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
URmsa	0.009***	0.007***	0.008***	0.011***	0.011***	0.010***	0.010***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Immigrant (0=native)	0.048***	0.053***	0.047***	0.048***	0.053***	0.048***	0.048***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Constant	0.059***	0.076***	0.145***	0.048***	0.057***	0.142***	0.481*
	(0.007)	(0.010)	(0.017)	(0.007)	(0.008)	(0.012)	(0.247)
Observations	332,612	332,612	332,612	332,612	332,612	332,612	332,612
R-squared	0.008	0.013	0.096	0.008	0.012	0.095	0.095
demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Local characteristics	NO	NO	NO	NO	NO	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	YES	NO	YES	YES	YES
Year FE	YES	YES	YES	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES
F-statistics for URmsa	—	—	—	245.31	263.83	263.34	263.34

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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

	OLS			2SLS-Bartik instrument			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. URmsa × Native	0.008***	0.005***	0.006***	0.009***	0.009***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
b. URmsa × Immigrant	0.014***	0.011***	0.011***	0.018***	0.018***	0.016***	0.016***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Diff:							
b-a	0.006***	0.006***	0.005***	0.009***	0.009****	0.008***	0.008**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Immigrant	0.009*	0.014***	0.016***	-0.010	-0.005	0.000	0.000
	(0.005)	(0.004)	(0.004)	(0.018)	(0.018)	(0.017)	(0.017)
Constant	0.069***	0.090***	0.157***	0.063***	0.073***	0.155***	0.463**
	(0.006)	(0.008)	(0.015)	(0.005)	(0.005)	(0.011)	(0.206)
Observations	332,612	332,612	332,612	332,612	332,612	332,612	332,612
R-squared	0.008	0.013	0.096	0.008	0.012	0.095	0.095
demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Local characteristics	NO	NO	NO	NO	NO	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES
F-statistics for “URmsa × Native”	—	—	—	.	247.16	246.50	279.48
F-statistics for “URmsa × Immigrant”	—	—	—	.	66.44	63.94	62.20

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The “URmsa” refers to the UR at the MSA level, which is a measure of local labor market condition.

Table 5. The Effect of UR on Household FI: Analysis by Immigrant Citizenship Status.

	OLS			2SLS-Bartik instrument			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. URmsa × Native	0.008***	0.005***	0.006***	0.009***	0.009***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
b. URmsa × Immigrant noncitizen	0.018***	0.016***	0.014***	0.022***	0.022***	0.020***	0.020***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
c. URmsa × Immigrant citizen	0.010***	0.008***	0.008***	0.014***	0.014***	0.013***	0.013***
	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Diff:							
b-a.	0.011***	0.011***	0.009***	0.013***	0.013***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
c-a.	0.003***	0.002***	0.002**	0.006	0.006	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)	(0.004)
Immigrant citizenship:							
Immigrant noncitizen	0.021***	0.023***	-0.003	0.004	0.007	-0.023	-0.023
	(0.006)	(0.006)	(0.007)	(0.021)	(0.021)	(0.018)	(0.018)
Immigrant citizen	-0.003	0.004	0.025***	-0.022	-0.015	0.014	0.014
	(0.005)	(0.004)	(0.005)	(0.033)	(0.033)	(0.029)	(0.029)
Constant	0.069***	0.089***	0.156***	0.063***	0.073***	0.154***	0.402*
	(0.006)	(0.008)	(0.015)	(0.005)	(0.005)	(0.011)	(0.230)
Observations	332,612	332,612	332,612	332,612	332,612	332,612	332,612
R-squared	0.011	0.016	0.096	0.011	0.015	0.095	0.095
demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Local characteristics	NO	NO	NO	NO	NO	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES
F-statistics for "URmsa × Native"	—	—	—	.	173.20	181.62	181.62
F-statistics for "URmsa × Immigrant-noncitizen"	—	—	—	.	166.35	111.21	111.21
F-statistics for "URmsa × 1960-1969"	—	—	—	.	71.74	86.39	86.39

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The "URmsa" refers to the UR at the MSA level, which is a measure of local labor market condition.

Table 6. The Effect of UR on Household FI: Analysis by Immigrant Cohorts of Arrival.

	Immigrant noncitizen	Immigrant citizen
VARIABLES	(1)	(2)
URmsa × Native	0.008***	0.008***
	(0.001)	(0.001)
URmsa ×1959 or earlier	0.136***	0.007
	(0.012)	(0.039)
URmsa ×1960-1969	0.039*	-0.019
	(0.024)	(0.014)
URmsa ×1970-1979	0.018	0.021***
	(0.016)	(0.003)
URmsa × 1980-1989	0.023***	0.019**
	(0.004)	(0.008)
URmsa × 1990-1999	0.017	0.010***
	(0.010)	(0.003)
URmsa × 2000-2009	0.023***	0.005
	(0.004)	(0.011)
URmsa × 2010-2019	-0.002	0.043
	(0.025)	(0.044)
Diff:		
URmsa × 1959 or earlier - URmsa × Native	0.128***	-0.001
	(0.012)	(0.038)
URmsa × 1960-1969 - URmsa × Native	0.031	-0.028**
	(0.024)	(0.014)
URmsa × 1970-1979 - URmsa × Native	0.009	0.012***
	(0.015)	(0.003)
URmsa × 1980-1989 - URmsa × Native	0.015***	0.010
	(0.004)	(0.007)
URmsa × 1990-1999 - URmsa × Native	0.009	0.002
	(0.011)	(0.003)
URmsa × 2000-2009 - URmsa × Native	0.015***	-0.004
	(0.004)	(0.010)
URmsa × 2010-2019 - URmsa × Native	-0.011	0.034
	(0.025)	(0.045)
Constant	-0.892***	-0.462
	(0.180)	(0.328)

Observations	308,050	308,864
R-squared	0.101	0.090
demographic characteristics	YES	YES
Local characteristics	YES	YES
2003 Population weighted	YES	YES
MSA FE	YES	YES
Year FE	YES	YES
MSA Cluster	YES	YES
F-statistics for interaction terms (range)	41.16-334.43	42.62-243.94

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The "URmsa" refers to the UR at the MSA level, which is a measure of local labor market condition. The estimations use 2SLS.

Table 7. Heterogeneous Effects of UR on Household FI Across Education Levels by Immigrant Statuses.

VARIABLES	Below high school		High school		Associate or less than bachelor		Bachelor		Graduate or professional	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
a. URmsa × Native	0.021***	0.021***	0.012***	0.012***	0.010***	0.010***	0.004***	0.004***	0.002**	0.002**
	(0.005)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
b. URmsa × Immigrant	0.011**		0.023***		0.019***		0.017***		0.010***	
	(0.005)		(0.005)		(0.004)		(0.006)		(0.002)	
b1.Imm noncitizen		0.017***		0.029***		0.019***		0.023***		0.004
		(0.007)		(0.006)		(0.006)		(0.008)		(0.005)
b2. Imm citizen		-0.000		0.017		0.018***		0.013**		0.015***
		(0.010)		(0.012)		(0.004)		(0.006)		(0.003)
Diff:										
b-a:	-0.010		0.011***		0.008**		0.012**		0.008***	
	(0.008)		(0.004)		(0.004)		(0.005)		(0.002)	
b1-a		-0.003		0.017**		0.009		0.019**		0.001
		(0.008)		(0.007)		(0.006)		(0.007)		(0.005)
b2-a		-0.021		0.005		0.007**		0.009*		0.012***
		(0.014)		(0.010)		(0.003)		(0.005)		(0.003)
Constant	1.285**	5.675***	-0.217*	-0.239**	-3.516***	-3.504***	-1.457***	-1.326***	-2.463***	-2.664***
	(0.596)	(0.758)	(0.126)	(0.105)	(0.297)	(0.291)	(0.310)	(0.307)	(0.152)	(0.208)
Observations	28,644	28,644	80,463	80,463	96,835	96,835	80,797	80,797	45,873	45,873
R-squared	0.051	0.052	0.056	0.057	0.052	0.052	0.027	0.026	0.018	0.016
demographic characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Local characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Methods	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. We first compare household FI between immigrant and native populations across varying levels of education (odd columns of Table 7). We further split our immigrant households by citizenship status and conduct a subsequent estimation of the model (even columns of Table 7). Specifically, "b1.Imm noncitizen" and "b2. Imm citizen" represent the "URmsa × Immigrant noncitizens" and "URmsa × Immigrant citizens" respectively.

Table 8. Heterogeneous Effects of UR on Household FI Across Poverty Levels or SNAP Receipt by Citizenship Statuses.

	Below 185% poverty		Above 185% poverty		Not received SNAP		Received SNAP	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
a. URmsa × Native	0.016***	0.016***	0.004***	0.005***	0.008***	0.008***	0.008**	0.008**
	(0.003)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)	(0.004)	(0.003)
b. URmsa × Immigrant noncitizen	0.024***	0.023***	0.010***	0.010***	0.022***	0.020***	0.008	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.011)	(0.011)
c. URmsa × Immigrant citizen	0.017***	0.017***	0.011***	0.010***	0.015**	0.013**	0.007	0.008
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.007)	(0.021)	(0.025)
Diff:								
b-a	0.008	0.008	0.006*	0.006	0.014***	0.013***	-0.000	-0.001
	(0.005)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.010)	(0.010)
c-a	0.002	0.001	0.006	0.005	0.007	0.006	-0.001	0.000
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.006)	(0.021)	(0.025)
Immigrant citizenship:								
Immigrant noncitizen	-0.088**	-0.041	-0.001	-0.018	-0.004	-0.024	-0.052	0.032
	(0.038)	(0.040)	(0.021)	(0.023)	(0.020)	(0.016)	(0.081)	(0.082)
Immigrant citizen	-0.077*	0.006	-0.035	-0.032	-0.024	-0.002	-0.059	0.018
	(0.044)	(0.040)	(0.027)	(0.028)	(0.042)	(0.041)	(0.150)	(0.165)
Constant	0.249***	-5.180***	0.035***	1.054***	0.035***	0.000	0.500***	0.151
	(0.026)	(0.180)	(0.003)	(0.102)	(0.005)	(0.168)	(0.028)	(0.441)
Observations	85,070	85,070	247,542	247,542	304,169	304,169	28,443	28,443
R-squared	0.005	0.049	0.003	0.043	0.010	0.062	0.003	0.020
demographic characteristics	NO	YES	NO	YES	NO	YES	NO	YES
Local characteristics	NO	YES	NO	YES	NO	YES	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO
MSA Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Methods	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The "URmsa" refers to the UR at the MSA level, which is a measure of local labor market condition.

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Online Appendix (Not for Print)

A. 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 decomposition process:

$$UR_{lt} = \lambda B_{lt} + \mu_{lt} \tag{9}$$

$$y_{lt} = \beta \widehat{UR}_{lt} + \epsilon_{lt} \tag{10}$$

Equation (1) represents the first stage, while Equation (2) 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 food security. 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 (2). 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 food insecurity using Bartik instrument is:

$$\hat{\beta}^{bartik} = \frac{B'Y}{B'X} = \frac{G'Z'Y}{G'Z'X} \tag{11}$$

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:

$$\hat{\beta}_k^{bartik} = \frac{{Z_k}'Y}{{Z_k}'X} \tag{12}$$

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:

$$\hat{\alpha}_k = \frac{g_{kt}{Z_k}'X}{\sum_{k=1}^{K} g_{kt}{Z_k}'X} = \frac{\hat{\lambda} g_{kt}{Z_k}'X}{\hat{\lambda}B'X} = \frac{{X_k^{bartik}}'X}{{X_k^{bartik}}'X} \tag{13}$$

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 summarize the decomposition of the Bartik instrument in Table A.1. Panels A and B report the variation in Bartik instruments among industries and years. Panel C summarizes the distribution of Rotemberg weights[21]. Panel D shows the correlation between the Rotemberg weights ($\widehat{\alpha_k}$), industry national employment growth rate ($\widehat{g_k}$), the just identified coefficient

[21] 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.

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 the Rotemberg weights and industry employment national growth rates are negatively correlated, which suggests that observations of declining employment growth are given more weight, as they are during the economic recession. Similarly, Rotemberg weights are also weakly related to the variation in the industry shares across locations. This may reveal that more weight is placed on observations in which the national growth rate of employment and industry share of employment are declining, as they are during a downward fluctuation in the economy. In addition, the variance of the MSA-level industry shares almost has no relationship (or very weakly correlation) with the national growth rate. This reveals that the identifying variation in the Bartik instrument contained in the industry shares is not tied to both the potentially endogenous time-series variation produced by the industry national growth rate.

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

Panel A: Top 5 Rotemberge weight industries					
	$\widehat{\alpha_k}$	g_k	$\widehat{\beta_k}$	95% CI	Ind Share
Construction	1.153	-6.240	0.010	N/A	7.423
Manufacturing	0.431	-3.777	0.007	N/A	13.228
Utilities; Transportation and Warehousing	0.287	1.021	0.006	(.,.)	5.260
Finance, Insurance, Real Estate and Rental and Leasing	0.181	-0.627	0.012	(.,.)	8.284
Information	0.168	-10.291	0.014	(.,.)	3.092
Panel B: Variation across years in α_k					
	Sum	Mean			
2004	0.018	0.001			
2005	-0.174	-0.013			
2006	0.042	0.003			
2007	-0.215	-0.017			
2008	0.060	0.005			
2009	-0.660	-0.051			
2010	0.189	0.015			
2011	0.347	0.027			
2012	0.584	0.045			
2013	0.457	0.035			
2014	0.099	0.008			
2015	0.029	0.002			
2016	0.103	0.008			
2017	0.198	0.015			
2018	0.035	0.003			
2019	-0.113	-0.009			
Panel C: Negative and positive weights					
	Sum	Mean	Share		
Negative	-1.311	-0.187	0.362		
Positive	2.311	0.385	0.638		
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	-0.170	1			
$\widehat{\beta_k}$	-0.055	0.636	1		
$\widehat{F_k}$	0.328	-0.307	-0.019	1	
Var(z_k)	-0.097	-0.284	-0.314	-0.214	1

Note: This table reported the summary statistics about the Rotemberg weights. The g_k is the national industry growth rate, $\widehat{\beta_k}$ is the coefficient from the just identified regression which is $\hat{\beta}_k^{bartik}$ estimated from Equation (12). Following the suggestion from 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.

B. Robustness Check of Bartik Instrument

Table B.2. The Effect of UR on Household FI Using Alternative Bartik Instruments

	Household FI							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	*Baseline*	*Baseline*	*Simple demeaning growth rate*	*Simple demeaning growth rate*	*Top five industries Only*	*Top five industries Only*	*Share-Year Dummy Interaction Instrument*	*Share-Year Dummy Interaction Instrument*
URmsa	**0.011*** **	**0.010*** **	**0.047*** **	**0.027*** **	**0.014*** **	**0.011*** **	**0.008*** **	**0.009*** **
	(0.001)	**(0.001)**	**(0.011)**	**(0.009)**	**(0.001)**	**(0.001)**	**(0.002)**	**(0.002)**
Immigrant	0.053***	0.048***	0.052***	0.049***	0.053***	0.048***	0.053***	0.047***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Constant	0.057***	0.481*	-0.189**	-3.237*	0.033***	0.271	0.070***	0.608
	(0.008)	(0.247)	(0.077)	(1.686)	(0.009)	(0.223)	(0.012)	(0.383)
Observations	332,612	332,612	332,612	332,612	332,612	332,612	332,612	332,612
R-squared	0.012	0.095	-0.042	0.082	0.095	0.095	0.013	0.096
Household characteristics	NO	YES	NO	YES	NO	YES	NO	YES
Local characteristics	NO	YES	NO	YES	NO	YES	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	YES	YES
MSA Cluster	YES	YES	YES	YES	YES	YES	YES	YES
F-statistics	263.83	263.34	23.65	23.54	409.81	404.56	9478.14	9528.12

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. Columns (5) and (6) use a restricted version of the Bartik instrument that only exploits the top five industries. Column (7) and (8) uses a version of the Bartik instrument that use the interaction of industry shares with year dummy. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.