

DISSERTATION

THREE ESSAYS ON THE INEQUALITY OF HOUSEHOLD FOOD SECURITY

Submitted by

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## ABSTRACT

### THREE ESSAYS ON THE INEQUALITY OF HOUSEHOLD FOOD SECURITY

This dissertation contains three essays on the inequality of household food security in the United States. In particular, the second chapter examines the effect of economic cycle, particularly unemployment, on the likelihood of food insecurity for different immigrant households in the United States relative to native US households. As unemployment is not randomly determined for households, we create a Bartik instrument by exploiting exogenous variation in industry shares across locations interacted with national industry growth rates to identify the disproportional effect of unemployment rate on food insecurity for immigrant households. The third chapter examines how immigrant households use time and money to manage their household food security relative to natives. To overcome the potential measurement errors and endogeneity of household level time-use and expenditures, aggregated cell-level means of food production time and expenditures are employed as instruments separately to identify the causal effects of time and money inputs on household food insecurity and how these effects vary across immigrant and native households. The fourth chapter seeks to elucidate the long-term structural nature of food security dynamics through household financial asset holdings in United States. By adopting an econometric strategy, this chapter uses a 19-years panel dataset from the Panel Study of Income Dynamics (2001-2019) to establish the new the Structural Probability of Food Security (SPFS) measure for long-run study of food security dynamics.

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## DEDICATION

*To those who have lived in the shadows of inequality, whose voices often go unheard.*

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# Chapter 1 Introduction

Food insecurity (FI)<sup>1</sup> has remained a significant concern for many US households, with approximately one in every ten affected annually since 1995, when the United States Department of Agriculture (USDA) began nationally measuring FI through the CPS Food Security Supplement. The prevalence of FI peaked at 14.9% in 2011 and gradually declined to 10.5% by 2019, taking nearly eight years to revert to pre-recession (2007) levels. Further, FI disproportionately impacts minority and underrepresented communities. Research indicates that immigrant families, despite their substantial contributions to the US economy, are more vulnerable to economic cycle and more likely to experience FI compared to native households (Chaudry & Fortuny, 2010; P. M. Orrenius & Zavodny, 2009; Potochnick & Arteaga, 2018). Moreover, while the majority of US households never face FI, a small segment endures persistent insecurity, particularly those led by individuals who are low-skilled, female, or non-white (Lee et al., 2023). Understanding the intricate causes and solutions to FI disparities is crucial to achieving the USDA's goal of universal food and nutrition security. Chapter 2 examines how economic cycle disproportionately increase the likelihood of FI among diverse immigrant groups compared to native populations in short run. Chapter 3 investigates the strategies immigrant households employ using time and financial resources to manage their food security (FS). With limited research focused on the dynamics of FS in the US, Chapter 4 explores the long-term structural nature and severity of FI through an analysis of household financial asset holdings.

Particularly, Chapter 2 examines the effect of economic cycle via unemployment on the likelihood of FI among diverse immigrant households in the United States relative to native US

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<sup>1</sup> Household FI defined as a household-level economic and social condition of limited or uncertain access to adequate food by the USDA.

households. Since unemployment is not randomly determined for households, we create a Bartik instrument by exploiting exogenous variation in industry shares across locations interacted with national industry growth rates. Overall, we find a procyclical effect of unemployment on household FI. Notably, the effect for immigrants is pronounced, approximately twice as large in percentage terms compared to natives. Non-citizen immigrants, 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 cycle. It further underscores the pressing need to identify and support those at-risk immigrant cohorts that are most vulnerable to short-term economic disruptions.

Since both time and money are essential constraints in food production, immigrant households who face the challenge of insufficient time for food production may have a higher likelihood of experiencing FI, similar to those who are financially disadvantaged. Chapter 3 uses a merged dataset covering 16 years (2003-2018) of both FS and time-use survey to examine how immigrant households use time and money to manage their household FS relative to natives. To overcome the potential measurement errors and endogeneity of household level time-use and expenditures, aggregated cell-level means of food production time and expenditures are employed as instruments to identify the causal effects of time and money inputs on household FI. Our findings suggest that the marginal returns on time and money inputs vary across different types of households, indicating that household structure matters in managing FI. For single households,

more food expenditure is important, while for married households, more time commitment is crucial. Interestingly, more time input significantly improves FS of natives but does not work for immigrants who already spend more time maintaining cultural food preferences and producing food in either single or married households. Meanwhile, more food expenditures help reduce the probability of FI for both natives and immigrants in single households but not in married households. Our findings show an overall message that less time input and more money is required for immigrants in household food production to remain food secure.

Chapter 4 seeks to explore the long-term structural nature of FS dynamics through household financial asset holdings in United States. We use a 19-year panel dataset from the Panel Study of Income Dynamics (2001-2019) to estimate the Structural Probability of Food Security (SPFS) measure. This metric is estimated by the likelihood that a household's assets will meet or exceed a basic adequacy threshold for at least three months. The SPFS metric enables a nuanced distinction between structural and stochastic dynamics in FS over a long period. Our findings indicate a prevalent stability of FS among U.S. households but highlight that 84% of those facing FI do so due to structural inadequacies in asset holdings, rather than due to unpredictable stochastic events. Notably, households headed by non-white females without a high school diploma suffer most and are caught in structural FI with a pronounced and persistent risk of severe FI.

## **Chapter 2 Economic Cycle and Food Insecurity Amongst**

### **Immigrants in the United States**

#### **2.1 Introduction**

Immigrant-led households significantly contribute to the U.S. economy, evidenced by the \$525 billion they paid in federal taxes in 2021 and their representation of 22.6 percent of all self-employed U.S. residents in 2022 (American Immigration Council, 2023). Additionally, the labor force participation rate of immigrants was almost 11 percent higher than that of native citizens in 2023 (U.S. Bureau of Labor Statistics, 2023). Despite these contributions, immigrants are often more likely to work in riskier jobs and are more vulnerable to labor market fluctuations compared to their U.S.-born counterparts (Bartik, 1991, 1993, 1994, 1996; Charles & DeCicca, 2008; Hoynes, 2000; Kochhar et al., 2010; Liu & Edwards, 2015; P. M. Orrenius & Zavodny, 2009). Moreover, their earnings are approximately 20 percent less than those of U.S.-born workers, and they experience significantly higher poverty rates (P. M. Orrenius & Zavodny, 2009).

Despite their active economic contributions, immigrants often face numerous economic challenges and receive insufficient public assistance. Immigrants are ineligible to apply for public assistance programs (i.e., SNAP, WIC, etc.) until they have established residency for five years<sup>2</sup>. Even after becoming eligible, many immigrants either do not apply for these benefits or use fewer

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<sup>2</sup> The 1996 federal welfare and immigration laws includes important exceptions for certain types of services for immigrants. For example, they are eligible for emergency Medicaid, public health programs that provide immunizations, and/or treatment of communicable disease symptoms and school breakfast and lunch programs regardless of their immigrant status.

benefits than natives (Nowrasteh & Orr, 2018). Altogether, this may put immigrant households at greater likelihood of becoming food insecure when confronted with economic hardships.<sup>3</sup>

While prevailing research has established that immigrant families are more vulnerable to economic cycle, resulting in a higher likelihood of experiencing FI compared to native households (Chaudry & Fortuny, 2010; P. M. Orrenius & Zavodny, 2009), much of this literature lacks a robust causal identification strategy. For instance, Flores-Lagunes et al. (2018) 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 & 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 non-citizens 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 economic cycle (e.g., unemployment rate) 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 unemployment rates.

In this study, we measure the differential impact of economic cycle on FI between immigrant and native households<sup>4</sup> in the United States. We combine annual MSA-level

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<sup>3</sup> FI occurs when households have a lack of consistent access to enough food for a healthy life (FS in the US).

<sup>4</sup> 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.

unemployment rate 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. Additionally, we explore the impact of GR on the differential likelihood of FI between immigrants and natives.

To address endogeneity concerns, our identification approach builds upon the theoretical foundation of shift-share or Bartik instruments (Bartik, 1991; Goldsmith-Pinkham et al., 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 unemployment rate. 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 FS status are determined in our sample. They are therefore unlikely to be correlated with unobserved shocks that

simultaneously affect the unemployment rate, household food consumption, or FI during the research period (2004 - 2019). 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 migrants. 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 et al. (2014) find a 1% increase in the highest national monthly unemployment rate 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 tend to exhibit greater vulnerability within the labor market compared to natives, subsequently leading to a heightened likelihood of economic adversity (Chaudry & Fortuny, 2010; P. M. Orrenius & Zavodny, 2009). Furthermore, we also find immigrants face greater likelihood of FI than those with U.S.-born natives once the MSA unemployment rate rises above the threshold of 2.6%.<sup>5</sup>

Disaggregating our immigrant sample further, we find that both non-citizen immigrants and citizen immigrants experience greater likelihoods of FI than natives, but non-citizens struggle the most. The magnitude of the cyclicalities of FI for non-citizen households is significantly higher than that of natives at 1.2%, while there is no statistical difference between immigrant citizens and natives. This indicates that non-citizen immigrants who typically lack access to benefits from many government safety net programs are more likely to experience economic hardship and are more

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<sup>5</sup> A healthy economy usually maintains an unemployment rate between 3% and 5%.

sensitive to labor market fluctuations than natives (P. M. 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 economic cycle (unemployment rate: 3.4%-22.8%). In contrast, there is evidence of slightly higher likelihoods of FI for immigrant citizens than natives when unemployment rates 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 economic cycle than natives (P. M. Orrenius & Zavodny, 2009).

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. Immigrant cohorts with citizenship arriving from 1970-1999 are negatively affected by economic cycle, which may be due to the large number of Mexican immigrants during that time that possessed low skills and illegal status (Passel & Suro, 2005; Van Hook et al., 2013). The 1980-1989 non-citizen 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<sup>6</sup>. 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

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<sup>6</sup> 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.

in the face of great economic downturns, a situation likely exacerbated by their direct exposure to the challenges of the Great Recession at their time of arrival.

We further explore whether educational attainment, income level and participation in food assistance programs like SNAP play a mitigating role in the negative effects of economic cycle on household FI. Our 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 non-citizens than for immigrant citizens when compared to natives. This pattern underscores the pervasive challenges that immigrants face, irrespective of their educational attainment. It may confirm the argument that both low-skilled and high-skilled immigrants, regardless of their origins, tend to have more cyclical economic outcomes than their native counterparts (Liu & Edwards, 2015; P. M. Orrenius & Zavodny, 2009).

Within poorer household (below 185% of the poverty line), we find no difference in the effects of economic cycle on FI between immigrants and natives. This reveals the central role that poverty levels play in influencing the cyclical patterns of FI (Loopstra & Tarasuk, 2013). Additionally, our results also suggest that access to food assistance programs can potentially mitigate the negative impacts of economic recessions on FI. This is especially pertinent for vulnerable immigrant non-citizens, who often are ineligible for benefits from many government safety net programs.

In our final exploration, we assess the impact of the Great Recession (GR) on household FI using the average unemployment rates across the pre-GR, GR and post-GR periods. A discernible trend emerges as disparities in the probability of FI between immigrants and natives amplify during the GR and this divergence persists, even intensifying, in the aftermath of the GR.

The results of our analysis highlight the potential benefit of expanding work-based public assistance programs like SNAP and unemployment insurance. This is especially pertinent for vulnerable immigrant noncitizens who often are ineligible for benefits from many government safety net programs<sup>78</sup>.

The remainder of this chapter 2 proceeds as follows. The following section discusses our data. The next section presents our empirical methods and discusses the identification strategy and details of construction of Bartik instruments. Then, we report the results of estimation, the robustness check and decompose the Bartik instrument. Following this, we discuss our results and potential policy implications.

## **2.2 Data and Descriptive Statistics**

We create an integrated repeated cross-sectional dataset compiled from the U.S. Bureau of labor statistics (BLS) and Current Population Survey (CPS). We take household-level data from 2004 to 2019 from the CPS's Food Security Supplement (FSS) (S. Flood et al., 2022). We take seasonally unadjusted yearly unemployment rates (UR) for metropolitan statistical areas (MSA) from 2004 to 2019 from the U.S. Bureau of Labor Statistics to measure economic cycles and local labor market activities. MSA-level unemployment rates data are matched with the household information by the MSA of residence and year of interview. Therefore, our dataset only includes households in metropolitan areas but omits much of the agricultural and rural households.

The CPS is the largest monthly national household survey conducted by the U.S. Bureau of Labor Statistics and the U.S. Census Bureau. As the primary source of labor force statistics for

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<sup>7</sup> Non-citizens 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.

<sup>8</sup> Recently, several states have begun to provide unemployment benefits to unauthorized workers: Colorado, California, and New York (Wilson, 2023; Visram, 2023).

the population of the United States, the CPS data provide nationally representative households and individual characteristics like demographic characteristics, immigration information, and labor market conditions. A subsample of about 46 thousand households respond to household FS questions each December in the FSS. In the FSS, the household unit is asked a series of questions about food conditions and behaviors during the previous 12 months. There are 10 questions about adult FS and an additional eight questions for children. The number of affirmative responses is used to determine each household's FS status as: food secure, low food secure, very low food secure. For our analysis, we define the household FS scale variable to be discrete: 0 for food secure, 1 for food insecure, which includes low food secure and very low food secure.

Our sample consists of 332,612 total households from 2004 to 2019. We limited our sample to households headed by people aged 18 to 65, representing the working-age demographic, which is susceptible to the impacts of economic cycle<sup>9</sup>. Of those, 14.5% (n = 48,310) were immigrant households. We define married immigrant households as those where neither the head of the household nor the spouse/partner was born in the U.S. and both members came from the same country. This ensures the immigrant married/partnered households have a similar diet culture and acculturation experience. Similarly, households where both head and spouse/partner are native households are treated as such. This means we exclude households with one native and one immigrant and households with immigrants from different countries. As a stronger predictor of FI (Kalil & Chen, 2008), citizen status of immigrants is considered to help us assign immigrant households to two subgroups: immigrant non-citizen (both non-citizens for married households; n = 23,748; 49% of immigrants) and immigrant citizen (at least one individual is a citizen for married households; n = 24,562; 51% of immigrants).

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<sup>9</sup> 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.

Immigrant cohorts have similar characteristics and face different political and economic conditions (Abramitzky et al., 2021; Borjas, 1995). We use immigrants' arrival year information to split immigrant households into seven arrival cohorts: 1959 or earlier, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2009 to 2010-2019. By limiting our sample to households with heads aged 18 to 65, the immigrant cohorts that arrived before 1969 have a relatively smaller sample size. Similarly, since immigrants who arrived in the U.S. between 2010 and 2019 were not available for interviews before 2010, this cohort also has a reduced sample size. The limited sample size of these groups may mean that they cannot establish a common ground of support, rendering the findings unrepresentative of the broader population.

We provide summary statistics for different immigrant groups and natives in Table 2.1. Immigrants, who may have limited proficiency in English, are less likely to do the interview by phone. This is especially the case for immigrant noncitizens and the cohorts after 1990. In contrast, immigrant citizens and earlier arriving cohorts are similar to natives who prefer to take the interview by phone. Immigrants tend to have a slightly higher share of married households, especially immigrant citizens and late arriving cohorts. Additionally, immigrant households have higher rates of children under 18 years old, particularly for immigrants without citizenship and late arriving immigrants after 1970. More than half of immigrant households have a male household head except for the earliest two cohorts. Immigrants are in general younger and show a higher proportion of advanced degree holders than natives. However, in every arrival cohort, immigrants have a higher proportion of heads' education below high school level, compared to natives. Immigrant noncitizens are most likely (35%) to have low educational attainment, while immigrants with citizenship have a higher share of advanced degrees. This could reflect demands for highly skilled jobs and for jobs that require manual labor (Bandyopadhyay & Grittayaphong, 2020).

Immigrant households with citizenship have a longer residency in the U.S. compared to immigrant noncitizens. On average, immigrants earn lower incomes than natives, and are more likely to fall below 185% of the poverty line. Notably, immigrant citizens have on average higher income than noncitizens and tend to be above the 185% poverty threshold. Immigrants belonging to earlier arrival cohorts generally experience lower poverty rates. Those who arrived after 1970 are more susceptible to poverty. Additionally, a higher proportion of immigrant noncitizens participate in the Supplemental Nutrition Assistance Program (SNAP) compared to both natives and immigrant citizens.<sup>10</sup>

We initially explore the relationship of economic cycle and FI over our entire study period from 2004-2019 in Figure 2.1. In panel A we plot the national level unemployment rate and FI prevalence of native households, immigrant households and immigrants by their citizen status. At the beginning of the research period, the unemployment rate was relatively stable at around 5%. During the Great Recession (GR) from 2007-2009, the unemployment rate rapidly rose from 5% to about 9%, then gradually recovered to below 5% from 2010 to 2015. During this same time, the rate of FI for all households followed the same pattern. During pre-recession (2004-2007), FI for all households was also relatively stable at about 11%. During the Great Recession, the incidence of FI jumped quickly to its highest level at around 15%. National level FI remained high even during the post-recession periods (2010-2011) and started to slowly decrease from 2012 when the economy finally returned to the pre-GR levels around 2017. Altogether, this suggests household FI is sensitive to poor economic conditions and takes time to recover after economic improvements (Lee et al., 2023).

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<sup>10</sup> Immigrant non-citizens can apply for SNAP benefits after a waiting period and meeting certain criteria.

Separating the immigrant households into different citizen status in Panel A, it appears that FI of native households is the lowest and experiences the least volatility. Rates of FI for immigrant households are higher and fluctuate more than natives' in all periods. Non-citizen immigrants appear the most vulnerable since they have the highest FI over time, especially during poor economic conditions. Immigrants with citizenship have similar rates of FI as natives in good economic conditions and have higher rates of FI in bad economic conditions. Interestingly, regardless of citizenship status, the decline of FI after the GR began earlier and more sharply for immigrant households than natives.

In panel B, we separate immigrant households into their respective cohorts. Overall, the incidence of FI varies across cohorts of arrival, which may reflect changes in immigrant flows from different countries of origins (Borjas, 1995; Zong et al., 2018). The earliest two cohorts (1959 or earlier and 1960-1969) on average have lower rates of FI than natives in all periods. Other cohorts seem to experience higher rates of FI than native households, especially in the GR period and for cohorts 2000-2009, 1990-1999 and 1980-1989.

## **2.3 Empirical Methods**

Our goal is to quantify the effect of unemployment rate 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.

### **2.3.1 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:

$$y_{imt} = \alpha + \beta UR_{mt} + \gamma Imm_{imt} + \delta X_{imt} + \pi L_{imt} + \omega_m + \theta_t + \epsilon_{imt} \quad (2.1)$$

where  $y$  is the binary FI status of household  $i$ , in metropolitan statistical area (MSA)  $m$  in year  $t$ . The vector  $UR_{mt}$  is the unemployment rate in MSA  $m$  in year  $t$ .  $Imm_{imt}$  is household  $i$  immigrant status which takes a value of zero for natives. We control for household and household head characteristics  $X$  from Current Population Survey (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, residual wage, years since immigration and the square of years since immigration. Following Gould & Moav (2016), the residual wage representing unobserved skills is calculated as an individual's residual error resulting from a standard Mincer-like regression of wage on education, age, age squared, marital status and immigration status with state and year fixed effects. This is included to control for potential omitted variables bias regarding the unobserved skills that may lead to the FI dispersion across groups. As suggested by Goldsmith-Pinkham et al. (2020), we also control for location characteristics at the initial research period that are correlated with unobserved shocks, denoted as  $L_{imt}$ . These characteristics are from the 2003 CPS monthly data and include the share of white individuals, native households, people with a bachelor's degree or above, the percentage identifying as male, the percentage married, mean household size, mean number of children and median age at the MSA level. Finally, we add MSA- and Year-level fixed-effects ( $\omega_m, \theta_t$ ) to control for time-invariant but spatial-variant omitted variables that are correlated with both household FI and economic cycle. Year fixed-effects capture variation in FI and average UR over time that are not captured by the other time-varying covariates in the model.

We use a linear probability model (LPM) to estimate Equation (2.1). 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<sup>11</sup> have the advantage to be 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:

$$y_{imt} = \alpha^{imm} + \beta_0^{imm} UR_{mt} * (1 - Imm_{ist}) + \beta_1^{imm} UR_{mt} * Imm_{imt} + \gamma^{imm} Imm_{imt} + \delta^{imm} X_{imt} + \pi^{imm} L_{imt} + \omega_m^{imm} + \theta_t^{imm} + \epsilon_{imt}^{imm} \quad (2.2)$$

The estimate of  $\hat{\beta}_0^{imm}$  and  $\hat{\beta}_1^{imm}$  measure the effect of  $UR$  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  $UR$  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 different unemployment rate values. The superscript “*imm*” indicates parameters and coefficients in Equation (2.2) 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  $UR$  on FI to differ across natives, immigrant citizens, and noncitizen households:

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<sup>11</sup> 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.

$$\begin{aligned}
y_{imt} = & \alpha^{cit} + \beta_0^{cit} UR_{mt} * (1 - Imm_{imt}^{noncit}) + \beta_1^{cit} UR_{mt} * Imm_{imt}^{noncit} + \beta_2^{cit} UR_{mt} * Imm_{imt}^{cit} \\
& + \gamma_1^{cit} Imm_{imt}^{noncit} + \gamma_2^{cit} Imm_{imt}^{cit} \\
& + \delta^{cit} X_{imt} + \pi^{cit} L_{imt} + \zeta_m^{cit} MSA_m + \eta_m^{cit} year_t + \epsilon_{imt}^{cit}
\end{aligned} \tag{2.3}$$

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 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  $(\hat{\beta}_1^{cit} - \hat{\beta}_0^{cit}) \cdot UR_{mt} + \hat{\gamma}_1^{cit}$ , 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 (2.3) 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):

$$\begin{aligned}
y_{imt} = & \alpha^{coh} + \beta_0^{coh} UR_{mt} * (1 - Imm_{imt}^{coh1}) + \sum_{j=1}^7 (\beta_j^{coh} * UR_{mt} * Imm_{imt}^{cohj} + \gamma_j^{coh} Imm_{imt}^{cohj}) \\
& + \delta^{coh} X_{imt} + \pi^{coh} L_{imt} + \omega_m^{coh} + \theta_t^{coh} + \epsilon_{imt}^{coh}
\end{aligned} \tag{2.4}$$

$Imm_{imt}^{cohj}$  is an indicator variable capturing whether the household head immigration year falls into one of seven ( $j = [1, \dots, 7]$ ) arrival cohorts from 1960 to 2019. After estimating the Equation 2.4,  $\hat{\beta}_0^{coh}$  represents the estimated impact of  $UR$  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 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  $(\hat{\beta}_1^{coh} - \hat{\beta}_0^{coh})UR_{mt} + \hat{\gamma}_1^{coh}$ . 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 have conducted separate estimations of Equation (2.4) for each citizenship category.

### 2.3.2 Empirical Strategy, Identification, and Inference

Even though our model includes household-level, individual level (household head) characteristics, local controls and fixed effects, the unemployment rate may be endogenous, which would bias our estimates of the effect of UR on household FI. First, unobserved local economic shocks may simultaneously affect the unemployment rate, food consumption and FI, which will lead to biased estimates of the unemployment effect. Second, households experiencing FI might seek to augment their income, which could, in turn, affect labor supply and reduce UR, a form of reverse causality posited by (Krogh & Smith, 2019). This will result in downward bias. Conversely, since FI has been consistently linked to adverse health outcomes, it could restrict affected households from engaging in paid employment due to poor health, as suggested by Gundersen & Ziliak (2015) and Stronks et al. (1997). In this case, it will cause upward bias. Third, households may sort themselves based on industry-specific employment opportunities, which may create correlation between the household FS status in industry-specific locations and unobserved shocks affecting households with 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 et al., 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 unemployment rate) leads to differential changes in the outcomes. Following Goldsmith-Pinkham et al. (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 across industries at the national level ( $g_{k,t}$ ) from 2004 to 2019 using CPS monthly data. 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. 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 unemployment rate in MSA  $m$  and year  $t$  is given as:

$$B_{m,t} = \sum_j^{13} s_{m,k,2003} * g_{k,t} \quad (2.5)$$

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 MSA-level unemployment rate 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 (NAICS), industries in the monthly CPS data are disaggregated into 13 categories<sup>12</sup>.

We use  $B_{m,t}$  as an instrument to separately estimate equations (2.1) - (2.4) via two-stage least-squares (2SLS). To explain the identification process, we consider the simple equation (2.1). So, the complete identification model comprises the first-stage regression (as shown in Equation 2.6), the second-stage regression (originally presented in Equation 2.1, and now shown in Equation 2.7), and the exclusion restrictions specified in Equation 2.8. The details of these components are as follows:

$$UR_{mt} = \lambda_0 B_{m,t} + \lambda_1 Imm_{imt} + \lambda_2 X_{imt} + \delta_m + \delta_t + \mu_{imt} \quad (2.6)$$

$$y_{imt} = \alpha + \beta \widehat{UR}_{mt} + \gamma Imm_{imt} + \delta X_{imt} + \theta_m + \theta_t + \epsilon_{imt} \quad (2.7)$$

$$0 = \text{cov}(B_{m,t}, \epsilon_{imt} | Imm_{imt}, X_{imt}, \theta_m, \theta_t) \quad (2.8)$$

There are two main requirements for our instrument to be valid. First, the relevance assumption implies the Bartik instrument causes variation in MSA level unemployment rate, which means  $\lambda_0$  in Equation (2.6) is statistically different from zero. Second, the exclusion restrictions (main identifying assumption) in Equation (2.8) requires that conditional on controls,  $B_{m,t}$  does

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<sup>12</sup> 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.

not affect household-level FI ( $y_{imt}$ ) directly, but only through  $UR_{mt}$ . In other words, the Bartik instrument doesn't correlate with the error term  $\epsilon_{imt}$  in Equation (2.7).

Building on Goldsmith-Pinkham et al. (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 unemployment rate. 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<sup>13</sup>. This means that unobserved shocks ( $\epsilon_{imt}$ ) 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 composition of local industries using data collected in 2003 prior to the beginning of research period (2004 - 2019). As such, our instrument is unlikely to be correlated with unobserved shocks that simultaneously affect unemployment rate, household food consumption and FI. Even though the increase in the probability of household-level FI could affect the unemployment rate to keep income and food consumption smooth, it is unlikely to be correlated with the pre-determined composition (or shares) of local industries.

However, 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

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<sup>13</sup> Alternatively, Borusyak et al. (2022) assumes the aggregated shocks are exogenous, while the cross-sectional shares may be endogenous.

industries, like manufacturing, retail, and service industries. When there are unobserved shocks that disproportionately affect these lower skilled households, both household-level FI and unemployment rate in these locations will be sensitive to these shocks. So, 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 et al. (2020) and Graham & 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. And if we find there are correlations between the shares of industries and the local characteristics which is the potential confounding factors, it may imply that there are omitted variables influencing estimation like households sorting behavior.

Table 2.2 reports these correlation estimates for the shares of top five industries fixed in the initial period (2003) and initial period MSA-level characteristics<sup>14</sup>. 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 implies that the variation in demographic characteristics by MSA explains a reasonable amount of the cross-sectional variation in the Bartik instrument. Further, we find that construction, manufacturing and utilities, transportation, and warehousing and 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.

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<sup>14</sup> Goldsmith-Pinkham et al. (2020) suggest that looking at industries with the largest Rotemberg weights (top five industries with more weight in the overall estimate of Bartik instrument) focuses attention on the instruments where confounding variables are most problematic. We explain more about the Rotemberg weights in the results.

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 2.2 imply that household sorting may occur, where households select industries based on specific characteristics, and that unobserved shocks to particular demographic groups may influence our estimations.

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

### **2.3.3 Strength of the 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 residualized UR (Figure 2.2). 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 2.2 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 economic cycle appears valid.

## 2.4 Results

### 2.4.1 The Effect of Economic Cycle on Household FI

#### A. Analysis for All households

We first examine the response of household FI to economic cycle (MSA unemployment rate), without distinguishing between the different effects on native and immigrant households. We use a binary control variable (0=ative; 1=immigrant) to identify household immigrant status. Table 2.3, 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 unemployment rate 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 unemployment rate 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 et al. (2014) and Potochnick & 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 et al., 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 et al. (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 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., unemployment rate) in a way that drives both FI and economic cycle. Nevertheless, we find little changes in the estimated marginal effect of 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 MSA-level UR would increase the probability of household-level FI increase by 1.0%. The 2SLS results also suggest immigrant households are 4.8% more likely to be food insecure than natives.

### **B. Analysis by Immigrant Status**

We next examine whether economic cycle affect FI of US immigrants differently than natives in the United States by estimating Equation (2.2). We first report the OLS estimations in Table 2.4, columns (1) - (3) under different sets of controls. Overall, 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 unemployment rate 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 unemployment rate 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 unemployment

rate. Overall, the OLS estimation results reveal that when the unemployment rate 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 UR, we test and confirm immigrants are always more likely to be food insecure than natives at various unemployment rates.

Columns (4) - (7) report our 2SLS estimations using our Bartik instrument. Column (4) does not include controls, and columns (5) - (6) include household-level demographic controls as well as location fixed effects. Column (7) adds the MSA level local demographic characteristics. The result after controlling all covariates indicates that the impact of the unemployment rate 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 unemployment rate (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 Figure 2.3. We see that the differences in the incidence of household-level FI are increasing from 1.5% to 17.9% with the greater unemployment rate. 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 UR, the results indicate that immigrant households are statistically more likely to be food insecure than native households when the unemployment rate exceeds 2.6%<sup>15</sup>.

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<sup>15</sup> However, it is important to note that only 1% of the MSA-level unemployment rates in our sample fall below this threshold.

### **C. 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 economic cycle have different effects on natives relative to immigrant citizens and non-citizens (Table 2.5). Columns (1) - (3) of Table 2.5 are OLS estimations, and the columns (4) - (7) report the 2SLS results using our Bartik instrument.

Our OLS estimates show a higher unemployment rate is significantly associated with a higher likelihood of FI among immigrant non-citizens, citizens and natives. Specifically, a 1% increase in the UR is associated with a 1.4% - 1.8% increase of the risk of household FI for immigrant non-citizens, 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 FI for non-citizen immigrants relative to natives, and 0.2% - 0.3% greater FI for citizen immigrants relative to natives.

The 2SLS estimates further support that immigrant non-citizen households are more susceptible to the unemployment rate compared to natives. In contrast, the effect of unemployment on immigrant citizen households is statistically indistinguishable from that of natives. For native households, with all covariates considered, a 1% increase in the unemployment rate raises the probability of household FI by 0.8% - 0.9%. Simultaneously, a 1% increase in the unemployment rate (UR) heightens the likelihood of FI for immigrant non-citizens by 2% and immigrant citizens by 1.3% - 1.4%. Comparing these impacts, we observe that the effect of the unemployment rate (UR) on FI of non-citizen immigrants is 1.2% higher than for natives. Immigrant citizens are 0.4% - 0.6% more likely to experience FI than natives, though this difference is not statistically significant.

We employ our 2SLS estimates to illustrate and contrast the predicted probabilities of FI between immigrant and native households across varying unemployment rates (see Figure 2.4). The “Immigrant Noncitizen vs Native” line has a steeper positive slope than the “Citizen vs Native” line. This is driven by the differences in marginal effect of UR on FI between immigrants (non-citizens or citizens) and natives. 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 economic conditions, with notable statistical significance observed when the unemployment rate is within the range of 6% to 10.8%. Overall, Figure 2.4 demonstrate 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. These results indicate that immigrants face a heightened likelihood of FI in comparison to natives, with noncitizens experiencing more vulnerability.

#### **D. Analysis by Immigrants’ Cohorts of Arrival**

We then evaluate heterogenous responses of household FI between immigrant cohorts of arrival and natives, distinguishing among various immigrant citizenship statuses. Table 2.6 presents the 2SLS estimation results incorporating the full set of control variables. Specifically, the analysis detailed in column (1) is confined to a sample comprising both immigrant noncitizens and native-born individuals. Conversely, the analysis shown in column (2) is restricted to a sample that includes immigrant citizens and native-born individuals.

We observe that a 1% increase in unemployment causes a 0.8% greater likelihood of FI for native households. Within the immigrant noncitizen group, earlier cohorts are more sensitive to URs in terms of their FI, whereas later cohorts are less affected. Notably, the cohort from 1959 or

earlier, having the longest U.S. residence, stands out as being most impacted by the UR with a 13.6% increase in FI. This unexpected result may come from the limited sample size for this group. Following closely are the cohorts from 1980-1989 and 2000-2009, each showing a 2.3% increase. For immigrant citizens, the 1970-1979 cohort is the most vulnerable to adverse economic conditions, with a 2.1% increase in FI. The cohorts from 1980-1989 and 1990-1999 follow with a 1.9% and 1.0% increase in 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 be that immigrants who fail to become citizens after a long period in the US also face other challenges. This might also stem from the inadequate sample size within the 1959 cohort of immigrants lacking citizenship<sup>16</sup>. The 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 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 Great Recession. 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

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<sup>16</sup> After limiting the sample age between 18-65 years old, there are 45 nonimmigrant citizen households in the 1959 cohort.

of immigrants with citizenship display similar or even less vulnerability to unemployment than natives (cohort 1960-1969).

In Figure 2.5 we illustrate the predicted gap in FI between various cohorts and natives across different immigrant citizenship categories, spanning a range of unemployment rates that all cohorts could potentially encounter. Setting aside the implications of citizenship, the results underscore the diverse resilience and vulnerabilities of FI across different immigrant cohorts when confronted with economic challenges. Across the majority of immigrant noncitizen cohorts (panel a), a notable trend emerges where the gap in FI intensifies as the UR escalates. An exception lies with the 2010-2019 cohort, which exhibits a significantly reduced likelihood of FI compared to natives when the UR surpasses 6.3%. Those positively affected groups (with positive slopes) also exhibit varying degrees of vulnerability. Notably, the cohort that arrived in 1959 or earlier, which appears to be the most sensitive to changes in the unemployment rate, shows a significantly greater likelihood of FI compared to native populations when their local unemployment rate exceeds 8%. But this finding may not be representative due to its limited sample size. In contrast, the 1960-1969 cohort, despite its apparent vulnerability, does not demonstrate significant disparities in FI likelihood across the range of unemployment rates. The immigrant cohort from 1980-1989 exhibits the second highest level of vulnerability to FI compared to natives. Their susceptibility is especially significant within the unemployment rate range of 3.9% to 18.7%. The 2000-2009 cohort, similarly, reveals a more pronounced likelihood of FI than natives when the UR exceeds 4.1%. The 1990-1999 cohort have a statistically 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 unemployment rate, 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 unemployment rate climbs above 10%. The 2000-2009 cohort also exhibits a significantly reduced propensity for FI in comparison to natives within the unemployment rate 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.

#### **2.4.2 Heterogeneous Effects Across Different Subsamples by Household Characteristics**

Economic cycles are expected to have a larger effect on low-skilled workers and low-income households. To examine this, we estimate Equations (2.2) and (2.3) across subsamples defined by education groups, poverty levels, and SNAP participation status. Education groups are defined by the educational attainment of household heads. For poverty groups, we identify households with income above or below 185% of the poverty line, which is the eligibility threshold for WIC. We use a binary indicator for households that report using SNAP in the past year or not. For our results across these subsamples, odd-numbered columns report specifications in the absence of any control variables, and even-numbered columns include our full set of household, local characteristics, and fixed effect controls.

We first compare household FI between immigrant and native populations across varying levels of education (Table 2.7). First, across all levels of educational attainment, both native-born and immigrant populations are more likely to experience FI as unemployment rates rise. Second, the influence of unemployment wanes as educational attainment rises. For native-born individuals,

the effect diminishes from 2.3% to 0.2% as we move from below high school education to graduate education. For immigrants, the effect of unemployment, with all controls in place, 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 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 (Table 2.8). 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 unemployment rates on immigrant noncitizens to native-born individuals, significant disparities emerge, particularly among those with high school and bachelor's degrees. For immigrant citizens, the data indicates that those with a high school education or less remain unaffected by unemployment rates, 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 2.8 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 2.9, columns 1 - 4) and split the immigrant sample by citizenship status. For those residing below 185% of the poverty line, an increase in the unemployment rate significantly affects the likelihood of

experiencing FI: 1.6% for native-born individuals, 2.3% for immigrant noncitizens, and 1.7% for immigrant citizens. Conversely, for individuals above the 185% poverty threshold, the increase in the unemployment rate still impacts 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 unemployment rates affect 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 2.9, 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<sup>17</sup>. Among the group that has not received SNAP benefits, elevated unemployment rates 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 unemployment rate 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. Conversely, in the face of unemployment, 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.

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<sup>17</sup> 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.

We further disaggregate our samples to examine whether there is a heterogeneous effect of the unemployment rate on FI for immigrants versus natives across different poverty levels and SNAP participation (Table 2.10). Overall, we do not find significantly different effects between immigrant and natives across all these subgroups. Interestingly, for poor households whose income is below 185% of the poverty line, the unemployment rate has a positive effect on FI of both immigrant non-citizens (2.6%) and natives (1.9%) without SNAP benefits but has no effect on these households with SNAP benefits (columns 1 - 4). When we refer to the households whose income is above 185% of the poverty line (columns 5 - 8), we again find that higher unemployment rates lead to a greater probability of FI for these households not receiving SNAP including both immigrants and natives. But it does not affect FI of these households receiving SNAP. Data reporting specific income values and information on SNAP eligibility is unavailable and prevents us from more precisely assessing the impact of SNAP in these scenarios. However, our findings may preliminarily indicate that both income levels and SNAP participation appear to act as equalizing forces. This suggests that these economic factors might overshadow other socio-cultural or legal distinctions traditionally separating immigrants from native-born individuals.

### **2.4.3 The effect of Great Recession on FI**

We evaluate the influence of the Great Recession (GR) on FI among immigrants and native-born households (Table 2.11). We use average unemployment rates from the pre-GR, GR, and post-GR periods, which are 4.85%, 6.46%, and 8.94%, respectively. Using these values, we forecast the disparities in FI between each immigrant subgroup and their native counterparts before, during, and after the GR. Additionally, we assess the variation in the relative probability of FI between immigrant subgroups and native-born individuals.

The disparities in FI between immigrant and their native counterparts increased gradually before, during and after the Great Recession from 3.8% to 7% (columns 1 - 3). Immigrant non-citizens consistently show a higher likelihood of FI compared to natives in the periods before, during, and following the Great Recession. Specifically, the disparity in the probabilities of FI between immigrant non-citizens and natives expands from 3.5% pre-GR to 5.4% during the GR and further increasing to 8.3% post-GR.

Examining specific cohorts without citizenship, most demonstrate a greater likelihood of FI than natives throughout the pre-GR, GR, and post-GR phases, except for the cohorts from 1960-1969, 1970-1979, and 2010-2019. Additionally, the 1959 cohort shows a large increase in FI in the post-G period. Most cohorts with citizenship show greater likelihood of FI than natives during and post-GR as well, except for the 1960-1969 cohort.

We next compare the changes in the differences in FI incidence across the periods i.e., before and after the GR (columns 4 - 5). The gap in the likelihoods of FI between immigrants and natives is 1.3 percent larger going from pre-GR to GR and 1.9 percent larger going from GR to post-GR. Among immigrant non-citizens, nearly all cohorts exhibit a heightened likelihood of FI compared to natives throughout the pre-GR, GR, and post-GR periods, except for the 2010-2019 cohort. The 1950 or earlier cohort without citizenship faced the most substantial adverse impact from the GR, with an escalation of 20.6%. This upward trend persisted post-recession, surging by an additional 31.8%. As previously noted, while the cohort from 1950 or earlier without citizenship experienced the most substantial adverse impact from the Great Recession, with a surge of 20.6%, this result may be implausible due to the extremely limited sample size. Notably, the cohorts from 1980-1989 and 2000-2009 experienced significant increases in the likelihood of FI from the pre-GR to the GR period, and from the GR to the post-GR phase. In contrast, the likelihood of FI for

citizen immigrants as a whole relative to natives across the pre-GR, GR, and post-GR periods is not statistically significant. However, the disparities in FI between the 1970-1979 cohort and their native counterparts significantly escalates by 2% during the GR and by an additional 3.1% in the post-GR phase. Notably, the 1960-1969 cohort shows a reduced likelihood of FI across various stages of the Great Recession.

#### **2.4.4 Robustness Check**

We use three alternative Bartik instruments suggested by Goldsmith-Pinkham et al. (2020) to further test the robustness of our Bartik instrument results. Columns (1) and (2) of Appendix Table A report our benchmark results using interacted industry shares and leave-one-out industry national growth rates as Bartik instrument with and without the full set of controls. Columns (3) and (4) report the effect of economic cycle on household FI with a version of the Bartik instrument where we normalize the growth rate by demeaning. Specifically, on the base of the leave-one-out approach, we subtract the simple mean 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 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<sup>18</sup>. 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

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<sup>18</sup> We discuss about how to decide these five industries in the next section.

instrument produces almost the same time-series variation in economic cycle 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 economic cycle on their own.

#### **2.4.5 Decomposition of the Variations in Bartik Instrument**

We measure the relative importance of each industry share in determining parameter estimates by decomposing the identifying variation in our Bartik instrument. Goldsmith-Pinkham et al. (2020) argue that just-identified two-stage least squares approach using Bartik instruments can be numerically treated as a generalized methods of moments (GMM) estimator with the local industry shares as instruments and a weight matrix constructed from the national industry growth rates. Building on Rotemberg (1983), we further decompose the Bartik estimator into a weighted combination of the just-identified instrument variable estimators using each industry share as a separate instrument. The weights depend on the covariance between the  $k^{\text{th}}$  instrument's fitted value of the endogenous variable and the endogenous variable itself. The computed weights are referred to as the Rotemberg weights, which sum to 1 and can be negative. This decomposition increases the transparency of the estimator by highlighting the contribution of different industries that reflect variation in the data driving the estimate. The high-weight instruments are more sensitive to misspecification<sup>19</sup> and hence make it clear which instruments from different industries are most defensible. We compute the Rotemberg weights (details of the calculation are in Appendix Table B) on the Bartik estimates with controls, aggregated across time periods and locations and report the detailed summary of Rotemberg weights in Table B.

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<sup>19</sup> Andrews et al. (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.

We find the identifying variation of our instrument is concentrated in only a small number of industries. The top five instruments account for 96% ( $= 2.2 / 2.311$ ) of positive weight in the estimator, which is shown in Panel A of Table B. The top five instruments are “Construction”, “Manufacturing”, “Utilities, Transportation and Warehousing”, “Finance, Insurance, Real Estate, and Rental and Leasing” and “Information”. The basic intuition is that if any particular instrument is misspecified, then the bias in these top five instruments will greatly affect the overall bias in the estimator. We could also say our estimate is very sensitive to deviations from the identifying assumption related to geographic variation in employment shares in the top five industries, especially for Construction. It is unsurprising that much of the variation is driven by the employment fluctuations occurring in the “Construction” industry given that immigrants play a much greater role in some particularly labor-intensive fields. Our analysis also confirms the manufacturing industry which includes the automobile industry plays a large role in our Bartik instrument, which is consistent with the fate of the automobile industry in Bartik instrument discussions (e.g., Bound & Holzer (2000)).

If we sum the Rotemberg weights across years, identifying variation in our instrument is concentrated in employment movement during the Great Recession (2009) and economic recovery years of 2012 to 2013. This is precisely when the unemployment rate is most likely to affect household balance sheets and thus influence household food consumption decisions and FI status.

## **2.5 Discussion**

Our study estimates how economic cycle (as proxied by MSA unemployment rates) affect household FI of immigrants relative to natives in the United States. A shift-share instrumental variable approach, also called Bartik instruments, is used to address potential endogeneity of unemployment rates that could bias estimates of their effect on household FI. After identifying the

differential effect of the economic cycle 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, income level, and food assistant program participation helps us explore potential mediating pathways.

Overall, the Bartik instrument performs well. Comparing the results with the literature, our 2SLS estimates are consistent and confirm that weaker economic conditions worsen household FI which is also called the cyclicity of FI (Cho et al., 2022). However, our estimated effects are on the higher end of the relevant literature since we address potential downward bias via a Bartik instrument and control for unobserved sub-state level shocks through MSA fixed effects. Our estimate of 2SLS regression with a full set of controls and MSA fixed effects indicate that an increase of 1 percentage point in the MSA unemployment rate 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. For example, Nord et al. (2014) predicted a 1% increase in the highest monthly unemployment rate in national level is associated with a 0.5% increase in the prevalence of household FI.

Comparing between natives and immigrants we find the effect of the unemployment rate on FI is approximately twice as strong for immigrants as for natives (1.6% vs 0.8%). Moreover, when the MSA unemployment rate exceeds a 2.6% threshold, our findings suggest that immigrant households exhibit heightened vulnerability to FI compared to U.S.-born households. This pattern may also imply that immigrants, facing more pronounced job losses and diminished incomes during economic downturns than natives, are more sensitive to the fluctuation in business cycles (Chilton et al., 2009; Kochhar et al., 2010; Liu & Edwards, 2015; P. M. Orrenius & Zavodny, 2009).

When examining the varied capacities of immigrant populations to manage FI, the impact of unemployment is markedly higher for immigrant non-citizens compared to natives. In contrast, the effect of unemployment on immigrant citizens is not distinguishable from natives. This observation is congruent with the hypothesis that citizenship is correlated with FI (Kalil & Chen, 2008). Similar to Potochnick & Arteaga (2018), our estimation indicates that immigrant non-citizens grapple with elevated likelihoods of encountering FI relative to natives. Moreover, the susceptibility to FI for immigrant non-citizens rises more precipitously with increasing unemployment rates (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 unemployment rate ranges between 3.5% and 16.3%. This pattern underscores the pivotal role of citizenship status, and by extension eligibility for governmental assistance programs, in mitigating the detrimental effects of economic cycle.

We also observe varying impacts of the unemployment rate on FI across different cohorts. All non-citizen cohort groups have a heightened susceptibility to FI in comparison to natives, particularly when compared to immigrants holding citizenship. Strikingly, among all non-citizen cohorts, the earliest immigrant group (1959 or earlier) without citizenship experiences the most pronounced increase in the likelihood of FI during economic downturns. However, this may largely be ascribed to the inadequate sample size represented in the 1959 cohort of immigrants without citizenship. In contrast, the earliest cohorts with citizenship, especially the 1960-1969 group, seem to be the least impacted. These insights accentuate the pronounced vulnerability of immigrant households.

We also find different effects of unemployment on FI across cohort groups. First, cohorts from 1970-2000, regardless of their citizenship status, display heightened sensitivity to the unemployment rate in terms of FI. Several factors, such as selection effects of lower skilled worker, strict migration policies at their time of arrival, and the adverse economic conditions they encountered upon arrival, may contribute to these patterns. Post-1970, a significant influx of low-skilled immigrants primarily from Mexico, who were notably disadvantaged, arrived in the U.S. (Van Hook et al., 2013). The 1980-1989 cohort immigrants, predominantly from impoverished nations in Latin America and Asia, entered amidst stricter migration policies (Abramitzky et al., 2021). Many in the 1990-1999 cohort, largely unauthorized and lower-skilled, hence became vulnerable to economic upheavals (Passel & Suro, 2005). The 2000-2009 cohort immigrants, on the other hand, faced the brunt of the Great Recession.

Selection effects might account for the observed resilience to FI in the earliest cohorts (pre-1970) and the 2010-2019 cohort (Berning, Norris, et al., 2023). Immigrants from the pre-1970 cohorts predominantly hailed from wealthier countries like Italy, Germany, and Canada, often bringing along higher human capital (Zong et al., 2018). In contrast, those arriving between 2010-2019 mainly came from India and China, characterized by higher education levels and skills, making them less vulnerable to economic shocks.

Models examining subsamples across household characteristics highlight that the complex relationship between educational attainment, unemployment, and FI among native-born and immigrant populations in the United States. 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 economic fluctuations 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 et al., 2008; Kochhar et al., 2010; Liu & Edwards, 2015; P. M. Orrenius & Zavodny, 2009). The 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 increased the likelihoods 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.

The heterogeneous effects of UR on FI for immigrants versus non-immigrants across poverty levels and SNAP participation indicate that the unemployment rate does not differentially impact the FI of immigrants relative to natives. This may indicate that poverty is one of the strongest contributors to FI disparities even across immigrant status (Loopstra & Tarasuk, 2013; Chen et al., 2023). The lack of specific data about specific household income and SNAP receipt precludes us from a more precise assessment of the contribution of SNAP. Nevertheless, our findings underscore that augmenting access to food assistance programs could be a strategic lever to temper the detrimental impacts of economic downturns on FI, especially for more vulnerable immigrant non-citizens.

Finally, we examine the different incidence of FI between immigrants and natives during the Great Recession (GR). Flores-Lagunes et al. (2018) find that immigrants relative to non-immigrants have a 1.86 percentage point increase in differential FI during the GR and a decrease of 0.99% in the post-GR period. Our results also show the likelihood of FI for immigrant non-

citizens increased by 1.9% from pre-GR to GR period. However, we find the differential in FI increased by 2.9% in the post-GR period. Although the likelihood of FI also increases for immigrant citizens, the rate of increase is slower and is not significantly different across the different periods. These findings differ from the estimated associations from Potochnick & Arteaga (2018) who show that the GR increased the likelihood of FI for immigrants with citizenship status by 7% compared to natives but did not increase the likelihood of FI between non-citizens immigrants and natives.

Additionally, we find the GR intensifies the disparities in FI between specific immigrant cohorts and natives. This divergence persisted and even amplified in the post-recession period. These findings highlight the heightened vulnerability of specific subgroups emphasizing the need for targeted support and interventions.

## **2.6 Conclusion**

Our primary contribution to the literature is to identify a causal effect of economic cycle (via unemployment) on household FI to explore whether immigrants are more vulnerable than natives. Economic cycle 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 unemployment 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 unemployment rate on FI for immigrants is notably twice as significant compared to natives (1.6% vs 0.8%).

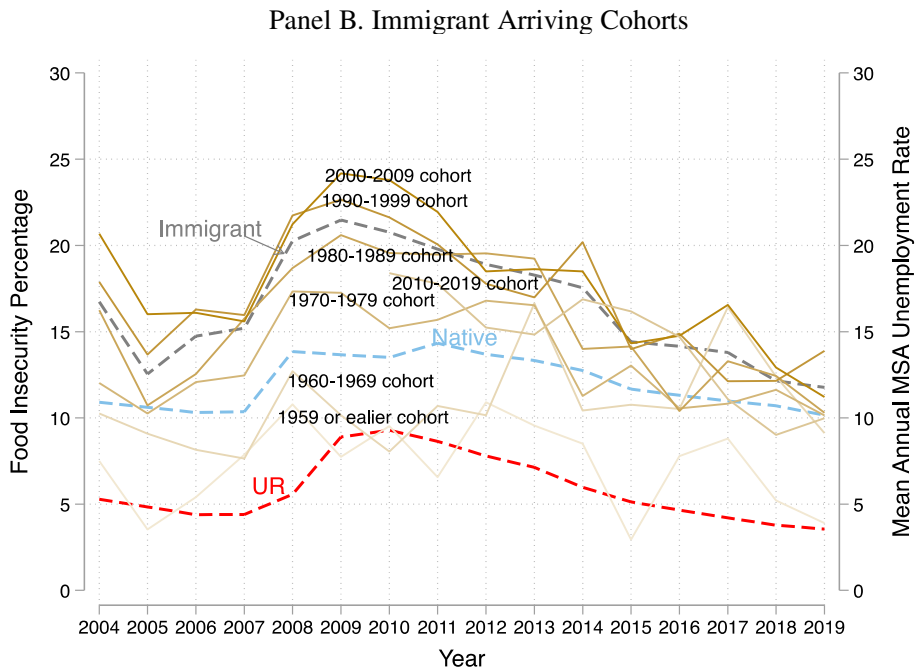
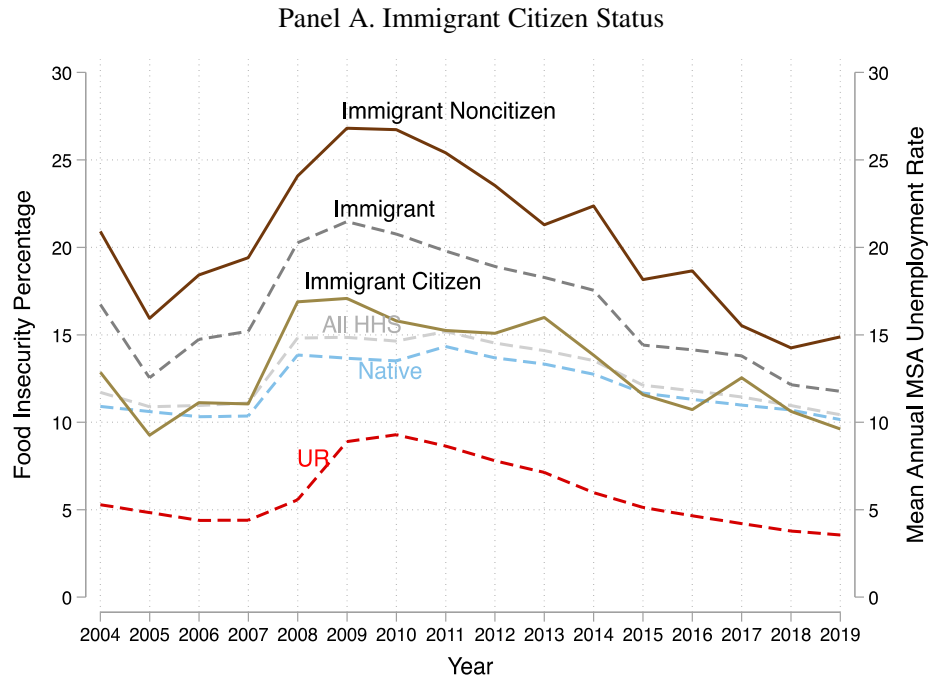
Looking more closely at our sample, we find outcomes vary considerably among immigrant subgroups. FI in immigrant noncitizen households is more affected by unemployment than in native households, while immigrant citizens face the same likelihood as natives. Within each citizenship category (immigrant citizen or noncitizen), the effect of the economic cycle on FI varies distinctly across different immigrant arrival cohorts. These findings 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 natives (Abramitzky et al., 2021; Borjas, 1995; Van Hook et al., 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 income may be one of the strongest contributors to the cyclical nature of 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 non-citizens.

In summary, our study offers significant insights into the disparate impacts of economic cycles on immigrant populations in comparison to native-born individuals. 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 are already being made by Colorado, California, and New York (Visram, 2023; Wilson, 2023). Research, notably by (Browning & Crossley, 2001) and (Fu et al., 2023), confirms that enhanced unemployment insurance (UI) can help stabilize household food consumption and reduce FI. It is

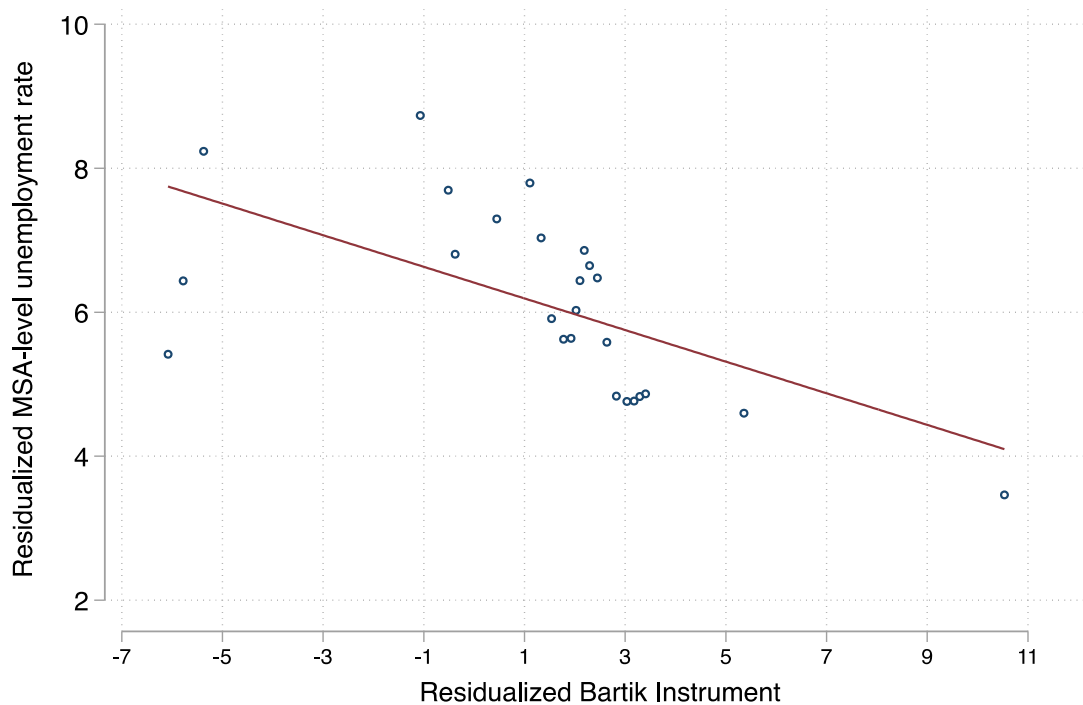
important to note that our findings using this MSA-level dataset are more relevant for households in metropolitan areas than for those in agricultural and rural regions.

UI 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 necessity for a comprehensive reform that extends traditional UI to all residents, regardless of immigration status for both states and the nation (Kallick et al., 2022). Colorado is the first state to create a UI expansion program for undocumented workers serving as an exemplar for other states (Wilson, 2023). 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**



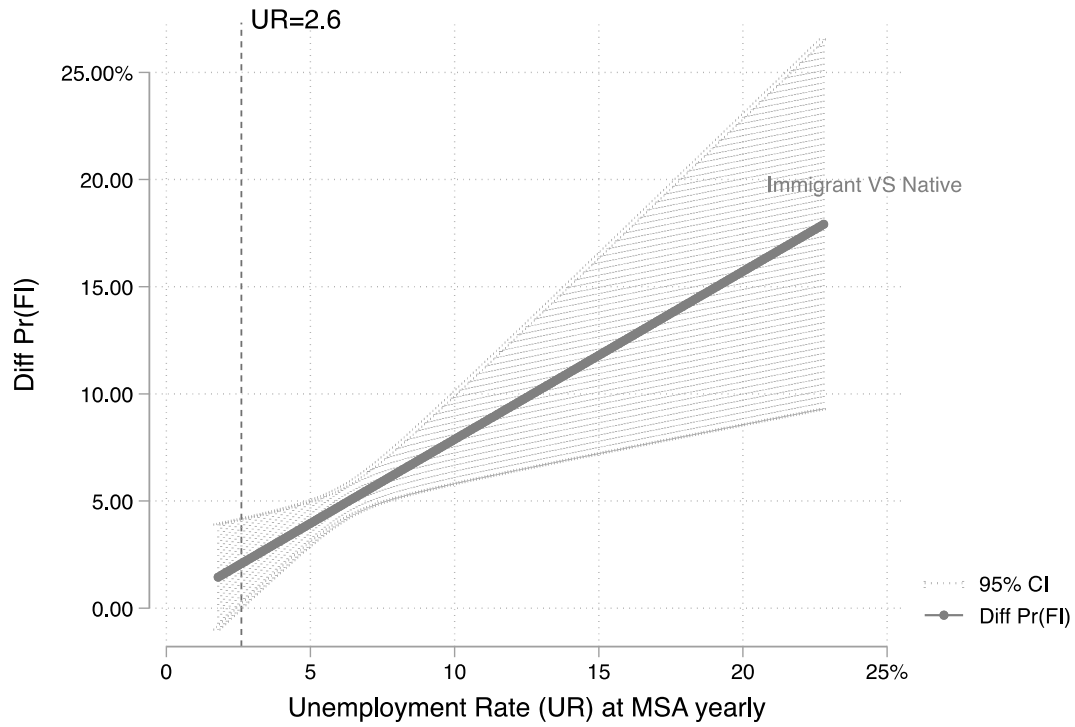
**Figure 2.1. Economic cycle and FI Trends over Time by Groups.**



**Figure 2.2. First Stage Effect of Bartik Instrument on Unemployment Rate.**

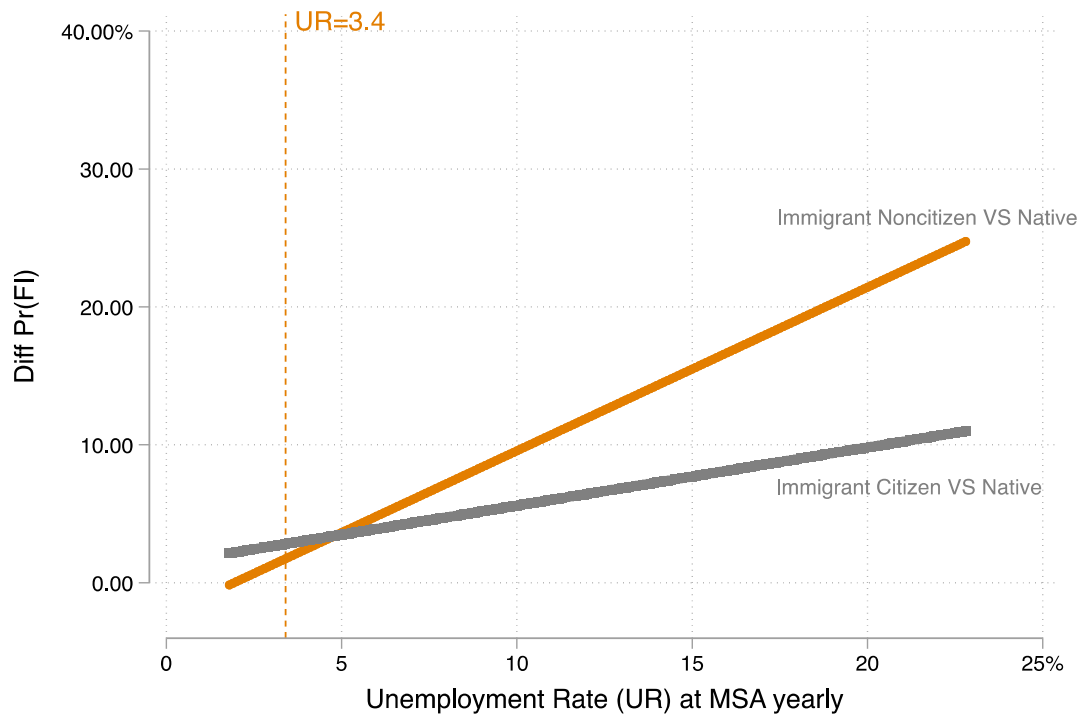
*Note:* The residualized variables on the y- and x-axis are generated by the regression of MSA unemployment rate on Bartik instrument with full set of the same control variables, as in the IV estimations of the effect of unemployment rate on household FI. We then group the value of residualized Bartik 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 ordinary least squares (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



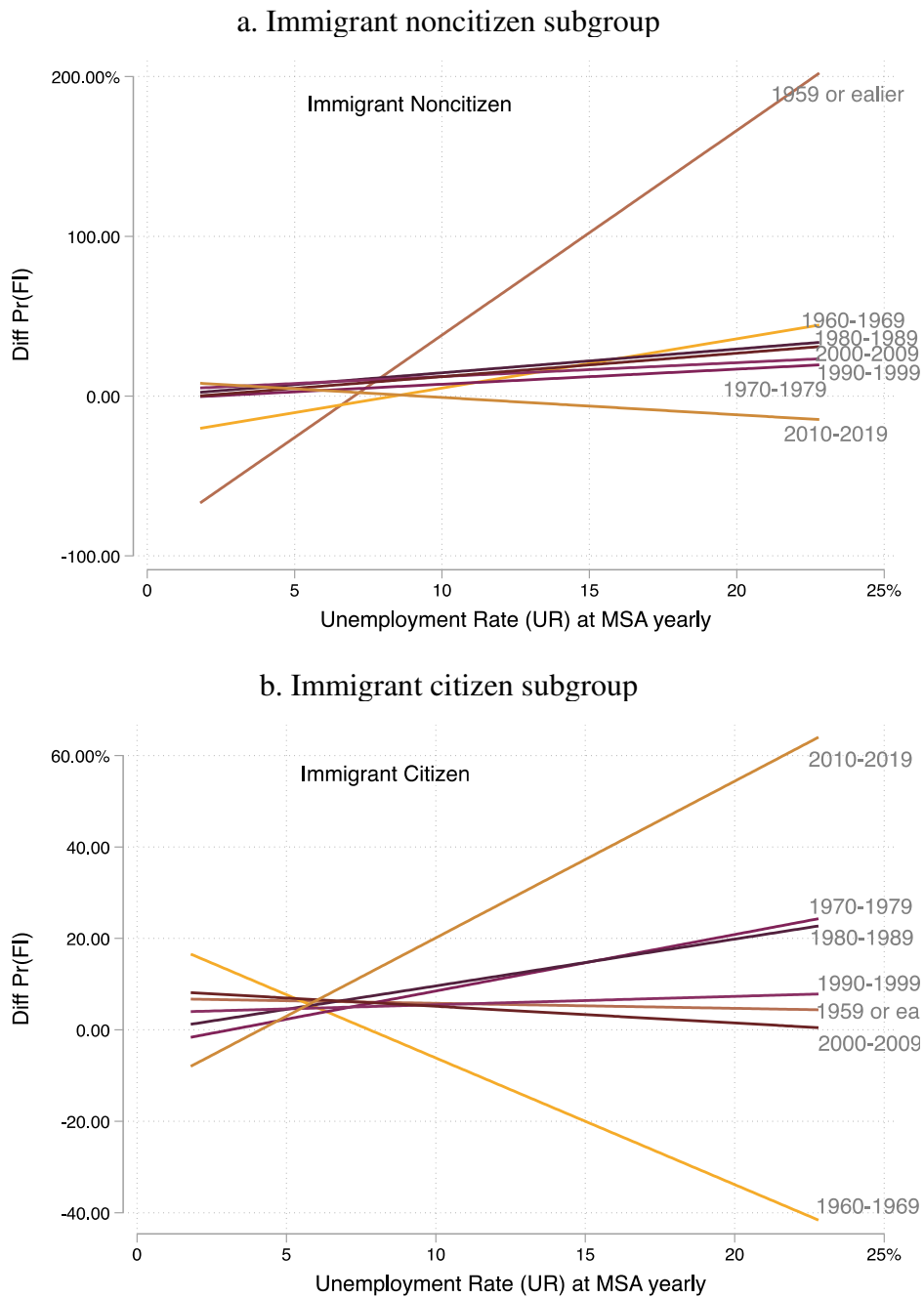
**Figure 2.3. Difference in Probability of FI Between Immigrant and Natives.**

*Note:* The y-axis variable is the difference in the predicted probabilities of being food insecure between immigrant and native households. The calculation is  $(\hat{\beta}_1 - \hat{\beta}_0) UR_{mt} + \hat{\gamma}$  from equation (2.2). 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 2.4.



**Figure 2.4. Difference in Probability of FI Between Immigrant Citizens, Non-Citizens, 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. Specifically, the orange line is calculated as  $(\hat{\beta}_1 - \hat{\beta}_0) UR_{mt} + \hat{\gamma}_1$  from Equation (2.3). 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  $\hat{\gamma}_1$  represents the predicted difference in the incidence of FI between immigrant noncitizens and natives when UR is 0. The grey line is calculated as  $\hat{\beta}_2 * UR_{mt} + \hat{\gamma}_2$  from equation (2.3) where  $\hat{\beta}_2$  is the predicted difference in the effect of UR on the FI of immigrant citizens versus native households and  $\hat{\gamma}_2$  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 2.5.



**Figure 2.5. Difference in Probability of FI Between Immigrant Cohorts and Natives across different immigrant citizenship statuses**

*Note:* The range of unemployment rate (UR) values from 1.8 to 22.9 percentage points. Lines are calculated as the sum of the predicted differences in marginal effect of UR between each cohort and natives and the predicted different probability of FI when UR = 0. The predicted values used to do the calculations are reported in Table 2.6.

**Table 2.1. Summary Statistics by Immigration Status.**

	Native	Imm	Immigrant citizen status		Immigrant Cohorts						
			Non-citizen	Citizen	1959 or earlier	1960-1969	1970-1979	1980-1989	1990-1999	2000-2009	2010-2019
<i>Interview type (share)</i>											
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
<i>Education Level</i>											
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
<b>Observations</b>	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 Current Population Survey FS Supplement. 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 2.2. 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** (0.231)	2.525*** (0.681)	-0.667** (0.335)	0.539 (0.450)	-0.014 (0.222)	-19.303*** (5.673)
Share of Native Born	0.108 (0.209)	1.368** (0.655)	0.131 (0.217)	-0.172 (0.278)	-0.228 (0.219)	-3.885 (4.675)
Share of bachelor's degree or above	-0.332 (0.277)	-1.311* (0.787)	-0.237 (0.310)	0.512 (0.364)	0.423* (0.219)	8.876* (5.313)
Share of Male	1.347*** (0.361)	-0.728 (0.936)	0.418 (0.341)	-0.383 (0.518)	-0.165 (0.324)	6.337 (9.454)
Share of Married	0.169 (0.409)	-2.583* (1.445)	-0.168 (0.556)	0.110 (0.612)	0.537 (0.345)	11.157 (7.830)
Mean Household Size	-2.517*** (0.665)	3.724 (2.357)	-0.217 (0.687)	0.363 (0.950)	1.212* (0.646)	-45.233*** (17.205)
Number of Children	1.794** (0.750)	-0.431 (2.487)	1.036 (0.876)	0.244 (0.913)	-1.535*** (0.576)	32.367** (16.208)
Median Age	0.052 (0.263)	-2.312** (0.950)	0.809* (0.465)	1.330* (0.720)	-0.572** (0.255)	20.108*** (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 2.3. The Effect of Economic Cycle on Household FI.**

VARIABLES	OLS			2SLS-Bartik instrument			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
URmsa	0.009*** (0.001)	0.007*** (0.002)	0.008*** (0.002)	0.011*** (0.001)	0.011*** (0.001)	0.010*** (0.001)	0.010*** (0.001)
HH Immigrant (0=ative)	0.048*** (0.006)	0.053*** (0.006)	0.047*** (0.005)	0.048*** (0.006)	0.053*** (0.006)	0.048*** (0.005)	0.048*** (0.005)
Constant	0.059*** (0.007)	0.076*** (0.010)	0.145*** (0.017)	0.048*** (0.007)	0.057*** (0.008)	0.142*** (0.012)	0.481* (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 2.4. The Effect of Economic Cycle on Household FI: Analysis by Immigrant Status.**

VARIABLES	OLS			2SLS-Bartik instrument			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. URmsa × Native	0.008*** (0.001)	0.005*** (0.001)	0.006*** (0.001)	0.009*** (0.001)	0.009*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
b. URmsa × Immigrant	0.014*** (0.001)	0.011*** (0.002)	0.011*** (0.002)	0.018*** (0.003)	0.018*** (0.003)	0.016*** (0.003)	0.016*** (0.003)
<i>Diff:</i>							
b-a	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.009*** (0.003)	0.009*** (0.003)	0.008*** (0.003)	0.008*** (0.003)
Immigrant	0.009* (0.005)	0.014*** (0.004)	0.016*** (0.004)	-0.010 (0.018)	-0.005 (0.018)	0.000 (0.017)	0.000 (0.017)
Constant	0.069*** (0.006)	0.090*** (0.008)	0.157*** (0.015)	0.063*** (0.005)	0.073*** (0.005)	0.155*** (0.011)	0.463** (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 unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle.

**Table 2.5. The Effect of Economic Cycle on Household FI: Analysis by Immigrant Citizenship Status.**

VARIABLES	OLS			2SLS-Bartik instrument			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. URmsa × Native	0.008*** (0.001)	0.005*** (0.001)	0.006*** (0.001)	0.009*** (0.001)	0.009*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
b. URmsa × Immigrant noncitizen	0.018*** (0.002)	0.016*** (0.002)	0.014*** (0.002)	0.022*** (0.003)	0.022*** (0.003)	0.020*** (0.003)	0.020*** (0.003)
c. URmsa × Immigrant citizen	0.010*** (0.001)	0.008*** (0.002)	0.008*** (0.002)	0.014*** (0.005)	0.014*** (0.005)	0.013*** (0.005)	0.013*** (0.005)
<i>Diff:</i>							
b-a.	0.011*** (0.001)	0.011*** (0.001)	0.009*** (0.001)	0.013*** (0.003)	0.013*** (0.003)	0.012*** (0.003)	0.012*** (0.003)
c-a.	0.003*** (0.001)	0.002*** (0.001)	0.002** (0.001)	0.006 (0.005)	0.006 (0.005)	0.004 (0.004)	0.004 (0.004)
<i>Immigrant citizenship:</i>							
Immigrant noncitizen	0.021*** (0.006)	0.023*** (0.006)	-0.003 (0.007)	0.004 (0.021)	0.007 (0.021)	-0.023 (0.018)	-0.023 (0.018)
Immigrant citizen	-0.003 (0.005)	0.004 (0.004)	0.025*** (0.005)	-0.022 (0.033)	-0.015 (0.033)	0.014 (0.029)	0.014 (0.029)
Constant	0.069*** (0.006)	0.089*** (0.008)	0.156*** (0.015)	0.063*** (0.005)	0.073*** (0.005)	0.154*** (0.011)	0.402* (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 unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle.

**Table 2.6. The Effect of Economic Cycle on Household FI: Analysis by Immigrant Cohorts of Arrival.**

VARIABLES	Immigrant non-citizen	Immigrant citizen
	(1)	(2)
URmsa × Native	0.008*** (0.001)	0.008*** (0.001)
URmsa × 1959 or earlier	0.136*** (0.012)	0.007 (0.039)
URmsa × 1960-1969	0.039* (0.024)	-0.019 (0.014)
URmsa × 1970-1979	0.018 (0.016)	0.021*** (0.003)
URmsa × 1980-1989	0.023*** (0.004)	0.019** (0.008)
URmsa × 1990-1999	0.017 (0.010)	0.010*** (0.003)
URmsa × 2000-2009	0.023*** (0.004)	0.005 (0.011)
URmsa × 2010-2019	-0.002 (0.025)	0.043 (0.044)
<i>Diff:</i>		
URmsa × 1959 or earlier - URmsa × Native	0.128*** (0.012)	-0.001 (0.038)
URmsa × 1960-1969 - URmsa × Native	0.031 (0.024)	-0.028** (0.014)
URmsa × 1970-1979 - URmsa × Native	0.009 (0.015)	0.012*** (0.003)
URmsa × 1980-1989 - URmsa × Native	0.015*** (0.004)	0.010 (0.007)
URmsa × 1990-1999 - URmsa × Native	0.009 (0.011)	0.002 (0.003)
URmsa × 2000-2009 - URmsa × Native	0.015*** (0.004)	-0.004 (0.010)
URmsa × 2010-2019 - URmsa × Native	-0.011 (0.025)	0.034 (0.045)
Constant	-0.892*** (0.180)	-0.462 (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 unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle. The estimations use 2SLS.

**Table 2.7. Heterogeneous Effects of Economic Cycle on Household FI Across Education Levels by Immigrant Status.**

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	0.023*** (0.005)	0.021*** (0.005)	0.010*** (0.002)	0.012*** (0.002)	0.009*** (0.001)	0.010*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.002** (0.001)	0.002** (0.001)
b. URmsa × Immigrant	0.012** (0.005)	0.011** (0.005)	0.027*** (0.005)	0.023*** (0.005)	0.020*** (0.004)	0.019*** (0.004)	0.017*** (0.006)	0.017*** (0.006)	0.010*** (0.002)	0.010*** (0.002)
<i>Diff:</i>										
b-a	-0.011 (0.008)	-0.010 (0.008)	0.016*** (0.003)	0.011*** (0.004)	0.011*** (0.003)	0.008** (0.004)	0.013** (0.005)	0.012** (0.005)	0.008*** (0.002)	0.008*** (0.002)
Immigrant	0.024 (0.057)	0.086* (0.049)	-0.085*** (0.021)	-0.005 (0.020)	-0.043** (0.021)	-0.010 (0.023)	-0.042 (0.039)	-0.015 (0.043)	-0.039*** (0.013)	-0.020* (0.011)
Constant	0.186*** (0.034)	1.285** (0.596)	0.110*** (0.010)	-0.217* (0.126)	0.088*** (0.009)	-3.516*** (0.297)	0.025*** (0.009)	-1.457*** (0.310)	0.016** (0.006)	-2.463*** (0.152)
Observations	28,644	28,644	80,463	80,463	96,835	96,835	80,797	80,797	45,873	45,873
R-squared	0.009	0.051	0.002	0.056	0.003	0.052	0.005	0.027	0.002	0.018
demographic characteristics	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Local characteristics	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	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. The “URmsa” refers to the unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle.

**Table 2.8. Heterogeneous Effects of Economic Cycle on Household FI Across Education Levels by Citizenship Status.**

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	0.023*** (0.005)	0.021*** (0.005)	0.010*** (0.002)	0.012*** (0.002)	0.009*** (0.001)	0.010*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.002** (0.001)	0.002** (0.001)
b. URmsa × Immigrant noncitizen	0.019*** (0.005)	0.017*** (0.007)	0.031*** (0.006)	0.029*** (0.006)	0.021*** (0.005)	0.019*** (0.006)	0.025*** (0.008)	0.023*** (0.008)	0.004 (0.005)	0.004 (0.005)
c. URmsa × Immigrant citizen	0.000 (0.010)	-0.000 (0.010)	0.022** (0.010)	0.017 (0.012)	0.018*** (0.003)	0.018*** (0.004)	0.014** (0.006)	0.013** (0.006)	0.015*** (0.002)	0.015*** (0.003)
<b>Diff:</b>										
b-a	-0.004 (0.007)	-0.003 (0.008)	0.020*** (0.007)	0.017** (0.007)	0.012** (0.005)	0.009 (0.006)	0.020*** (0.007)	0.019** (0.007)	0.002 (0.005)	0.001 (0.005)
c-a	-0.022 (0.014)	-0.021 (0.014)	0.011 (0.008)	0.005 (0.010)	0.009*** (0.003)	0.007** (0.003)	0.009* (0.005)	0.009* (0.005)	0.013*** (0.003)	0.012*** (0.003)
<b>Immigrant citizenship:</b>										
Immigrant noncitizen	0.003 (0.048)	0.047 (0.051)	-0.072 (0.045)	-0.041 (0.049)	-0.026 (0.030)	-0.013 (0.031)	-0.074 (0.052)	-0.055 (0.056)	-0.001 (0.028)	0.018 (0.028)
Immigrant citizen	0.051 (0.098)	0.132 (0.086)	-0.088* (0.052)	0.011 (0.060)	-0.045** (0.019)	-0.015 (0.027)	-0.027 (0.036)	-0.002 (0.043)	-0.067*** (0.017)	-0.041 (0.028)
Constant	0.186*** (0.034)	5.675*** (0.758)	0.110*** (0.010)	-0.239** (0.105)	0.088*** (0.009)	-3.504*** (0.291)	0.025*** (0.009)	-1.326*** (0.307)	0.016** (0.006)	-2.664*** (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	0.013	0.052	0.005	0.057	0.003	0.052	0.004	0.026	-0.000	0.016
demographic characteristics	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Local characteristics	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
2003 Population weighted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
MSA FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	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.

**Table 2.9. Heterogeneous Effects of Economic Cycle on Household FI Across Poverty Levels or SNAP Receipt by Citizenship Status.**

VARIABLES	Below 185% poverty		Above 185% poverty		Not received SNAP		Received SNAP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
a. URmsa × Native	0.016*** (0.003)	0.016*** (0.003)	0.004*** (0.001)	0.005*** (0.000)	0.008*** (0.001)	0.008*** (0.001)	0.008** (0.004)	0.008** (0.003)
b. URmsa × Immigrant noncitizen	0.024*** (0.004)	0.023*** (0.004)	0.010*** (0.004)	0.010*** (0.004)	0.022*** (0.003)	0.020*** (0.003)	0.008 (0.011)	0.006 (0.011)
c. URmsa × Immigrant citizen	0.017*** (0.006)	0.017*** (0.006)	0.011*** (0.004)	0.010*** (0.004)	0.015** (0.007)	0.013** (0.007)	0.007 (0.021)	0.008 (0.025)
<b>Diff:</b>								
b-a	0.008 (0.005)	0.008 (0.006)	0.006* (0.003)	0.006 (0.004)	0.014*** (0.003)	0.013*** (0.003)	-0.000 (0.010)	-0.001 (0.010)
c-a	0.002 (0.006)	0.001 (0.006)	0.006 (0.004)	0.005 (0.004)	0.007 (0.007)	0.006 (0.006)	-0.001 (0.021)	0.000 (0.025)
<b>Immigrant citizenship:</b>								
Immigrant noncitizen	-0.088** (0.038)	-0.041 (0.040)	-0.001 (0.021)	-0.018 (0.023)	-0.004 (0.020)	-0.024 (0.016)	-0.052 (0.081)	0.032 (0.082)
Immigrant citizen	-0.077* (0.044)	0.006 (0.040)	-0.035 (0.027)	-0.032 (0.028)	-0.024 (0.042)	-0.002 (0.041)	-0.059 (0.150)	0.018 (0.165)
Constant	0.249*** (0.026)	-5.180*** (0.180)	0.035*** (0.003)	1.054*** (0.102)	0.035*** (0.005)	0.000 (0.168)	0.500*** (0.028)	0.151 (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 unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle

**Table 2.10. Heterogeneous Effects of Economic Cycle on Household FI Across Combined Poverty Levels and SNAP Receipt by Citizenship Status.**

VARIABLES	Income below 185% poverty line & Not received SNAP		Income below 185% poverty line & Received SNAP		Income above 185% poverty line & not Received SNAP		Income above 185% poverty line & Received SNAP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
a. URmsa × Native	0.018*** (0.004)	0.019*** (0.004)	0.010* (0.005)	0.008* (0.005)	0.005*** (0.000)	0.005*** (0.000)	0.004 (0.013)	0.005 (0.013)
b. URmsa × Immigrant noncitizen	0.026*** (0.004)	0.026*** (0.005)	0.010 (0.011)	0.007 (0.010)	0.011*** (0.003)	0.010*** (0.004)	0.025 (0.030)	0.027 (0.028)
c. URmsa × Immigrant citizen	0.021** (0.009)	0.019* (0.010)	0.008 (0.019)	0.009 (0.021)	0.010** (0.004)	0.010** (0.004)	-0.048 (0.096)	-0.044 (0.094)
<b>Diff:</b>								
b-a	0.008 (0.007)	0.007 (0.007)	0.000 (0.010)	-0.001 (0.010)	0.006* (0.003)	0.006* (0.003)	0.021 (0.026)	0.022 (0.025)
c-a	0.003 (0.006)	0.001 (0.008)	-0.002 (0.020)	0.000 (0.023)	0.005 (0.004)	0.005 (0.004)	-0.052 (0.089)	-0.049 (0.087)
<b>Immigrant citizenship:</b>								
Immigrant noncitizen	-0.041 (0.045)	-0.010 (0.043)	-0.071 (0.076)	0.005 (0.068)	-0.008 (0.018)	-0.021 (0.019)	-0.005 (0.197)	0.077 (0.187)
Immigrant citizen	-0.044 (0.050)	0.030 (0.056)	-0.060 (0.142)	0.001 (0.155)	-0.030 (0.029)	-0.032 (0.030)	0.360 (0.617)	0.466 (0.587)
Constant	0.146*** (0.028)	-14.052*** (0.560)	0.479*** (0.033)	5.618*** (0.516)	0.026*** (0.003)	1.007*** (0.098)	0.585*** (0.079)	-0.052 (1.471)
Observations	60,535	60,535	24,535	24,535	243,634	243,634	3,908	3,908
R-squared	0.002	0.035	0.004	0.024	0.002	0.032	-0.007	0.026
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 unemployment rate at the Metropolitan Statistical Area (MSA) level, which is a measure of economic cycle.

**Table 2.11. The Effect of the Great Recession on Household FI by Immigrant Citizenship Status and Cohort vs Natives.**

Immigrant groups vs natives	FI			Differences	
	PreGR (2003-2006)	GR (2007-2009)	PostGR (2010-2011)	GR-PreGR	PostGR-GR
	(1)	(2)	(3)	(4)	(5)
<b>Immigrants</b>	0.038*** (0.005)	0.051*** (0.004)	0.070*** (0.008)	0.013*** (0.004)	0.019*** (0.007)
<i>Citizenship &amp; Cohorts</i>					
<i>Immigrant non-citizen</i>	0.035*** (0.005)	0.054*** (0.004)	0.083*** (0.010)	0.019*** (0.005)	0.029*** (0.007)
1959 or earlier	-0.288*** (0.050)	-0.072 (0.070)	0.246*** (0.070)	0.206*** (0.019)	0.318*** (0.030)
1960-1969	-0.108 (0.074)	-0.058 (0.039)	0.018 (0.035)	0.050 (0.039)	0.076 (0.059)
1970-1979	0.026 (0.043)	0.041 (0.028)	0.064* (0.038)	0.015 (0.025)	0.023 (0.038)
1980-1989	0.069** (0.028)	0.093*** (0.029)	0.130*** (0.034)	0.024*** (0.0067)	0.037*** (0.011)
1990-1999	0.078*** (0.008)	0.092*** (0.019)	0.113** (0.044)	0.014 (0.017)	0.022 (0.026)
2000-2009	0.047*** (0.015)	0.070*** (0.013)	0.107*** (0.014)	0.024*** (0.007)	0.036*** (0.010)
2010-2019	0.048* (0.025)	0.030 (0.020)	0.003 (0.080)	-0.018 (0.040)	-0.027 (0.062)
<i>Immigrant citizen</i>	0.034*** (0.009)	0.041*** (0.004)	0.051*** (0.010)	0.007 (0.007)	0.010 (0.011)
1959 or earlier	0.064 (0.079)	0.062** (0.031)	0.059 (0.088)	-0.002 (0.062)	-0.003 (0.095)
1960-1969	0.081 (0.052)	0.037 (0.032)	-0.032 (0.022)	-0.045** (0.023)	-0.069** (0.035)
1970-1979	0.021 (0.019)	0.041** (0.021)	0.072*** (0.026)	0.020*** (0.005)	0.031*** (0.008)
1980-1989	0.043* (0.025)	0.060*** (0.022)	0.085*** (0.029)	0.017 (0.012)	0.025 (0.019)
1990-1999	0.046** (0.022)	0.049** (0.020)	0.053*** (0.019)	0.003 (0.005)	0.005 (0.008)
2000-2009	0.070** (0.029)	0.064*** (0.017)	0.055** (0.023)	-0.006 (0.017)	-0.009 (0.026)
2010-2019	0.025 (0.030)	0.080* (0.044)	0.165 (0.154)	0.056 (0.072)	0.085 (0.110)

*Note:* we use the average unemployment rate (at 4.85%, 6.46% and 8.94% separately) during preGR, GR and postGR to predict the FI probability of each immigrant subgroups.

## **Chapter 3 How Immigrants Use Time and Money to Manage**

### **Household Food Security**

#### **3.1 Introduction**

In the United States, households with immigrants are at a greater risk of FI (Chilton et al., 2009; Potochnick & Arteaga, 2018; Walker et al., 2021). FI occurs when households lack consistent access to enough food for an active and healthy life. Household FI is associated with an increased risk for various adverse health outcomes and health disparities (Hromi-Fiedler et al., 2011; Seligman et al., 2010). Although immigrants play a significant role in the US economy, having higher employment rates than natives since 2001, they face more economic challenges, earn about 20 percent less than US-born workers, and experience much higher poverty rates (Orrenius & Zavodny, 2009). Additionally, conditional on their immigration status, immigrants are often ineligible for public assistance programs, and those who are eligible use fewer benefits than natives (Nowrasteh & Orr, 2018). Meanwhile, immigration policy combined with other aspects of identity and structural constraints create barriers for immigrant to have adequate access to culturally appropriate foods which contributes to FI (Alonso et al., 2018; Wright et al., 2021). Consequently, immigrant households may lack the resources necessary to maintain adequate FS. By identifying limitations of resources to immigrants maintaining adequate FS, effective policies and procedures can be explored to mitigate FI and support the long-term health of immigrant households. This paper aims to examine how immigrant households use time and expenditures to produce food and manage their household FS.

In household food production, both time and money are essential inputs for FS. Becker (1965) explains that household production is a function of both market inputs and time. Vickery (1977) further notes that any income-support that only accounts for money differences but not for time differences across households may be biased against time-poor households and discriminates against households with one adult. Davis & You (2011) apply similar logic to explain the inadequacy of food-assistance programs for achieving minimum nutritional standards, specifically the Thrifty Food Plan. Accounting for time, they find the mean poverty rate estimate increases from 38% to 87%. Thus, failing to account for the time required to produce food can severely distort estimates of the actual need of households. Building on this concept, Davis & You (2013) develop a household food production framework where time and money are inputs. They indicate that time and money are poor substitutes in household food production suggesting that time may be an essential constraint for food production faced by low-income and immigrant households. To our knowledge, nobody has considered how inputs of time and money simultaneously affect household FS, an important output of food production.

Immigrant households that are time-poor may be at risk of experiencing FI just as if they were money poor, particularly if money and time do not act as quality substitutes for FI. Given that many immigrants do not have access to food assistance or are hesitant to acquire it, immigrants are expected to be more reliant on their own money and time. However, immigrants are often more money poor with higher poverty rates than US-born workers (P. M. Orrenius & Zavodny, 2009; Vahabi & Damba, 2013). Immigrants may also be more time poor than US-born households. Dramski (2017) shows that immigrants are more likely to work unusual hours, such as nights and weekends, taking jobs natives do not want to do. Further, immigrants have jobs that are characterized as being more physically arduous than jobs held by natives (P. Orrenius & Zavodny,

2015) and riskier (P. M. Orrenius & Zavodny, 2009). More intense work activities could allow for less time/energy to manage food production activities or make such food production more difficult, ultimately leading to household FI. Given the differences between natives and immigrants, and the long-term negative health implications of FI, it is essential to better understand the household food production challenges faced by immigrants relative to natives.

In this study, we compare how immigrant households use time and expenditures to produce food and thus manage their household FS in comparison with natives. To do this, we examine households from 2003-2018 that completed both the Current Population Survey (CPS) Food Security Supplement (FSS) and the American Time Use Survey (ATUS). The CPS dataset provides food expenditure, household FS information from FSS and households' demographic characteristics. The ATUS provides measures of the amount of time people spend doing various activities over a 24-hour period, including food production related activities. To account for the effect of different household structures on food production, we analyze the FS status of single and married headed households separately as a function of time and expenditures for natives and immigrants. Overall, our study makes the following three contributions.

First, we advance the literature on the determinants of household FI by considering both time and money invested in food production, separately for single and married headed households. Numerous studies have examined factors that determine FI, such as job loss and low income (Loopstra & Tarasuk, 2013); socio-demographics (Tarasuk et al., 2019); food assistance and other welfare program participation (Borjas, 2004; Gundersen & Kreider, 2008; Mykerezzi & Mills, 2010). Meanwhile, a few studies have explored the association between FI and food expenditure, or time spent on food related activities separately (Beatty et al., 2014; Berning, Cleary, et al., 2023; Gundersen & Ribar, 2011). Nevertheless, we are the first paper to including both time and money

in our FS function and explore the effects of time and money on FI simultaneously for all households, and households with different structures. Consistent with the literature, we find that more time and expenditures inputs in food production are both associated with a decrease in the likelihoods of FI across all households, single and married headed households. Specifically, there is a 2% to 3.3% decrease in the probability of FI for every additional 10 hours spent on food production. Likewise, we find a 2.5% to 4% decrease in the probability of FI for every additional \$100 spent on food production.

However, one concern about the estimations is that variation in time use and weekly food expenditures suffer from measurement error, may be subject to reverse causality, or may be correlated to unobserved shocks on households with particular demographic profiles which would bias our estimates. Based on the suggestions of Hanushek et al. (1996) and Frazis & Stewart (2012), we aggregate our data into different cell levels based on particular household characteristics and then instrument for household-level time and expenditure inputs with cell-level mean values. Using the matched dataset and instrumental variable approach, we make the second contribution to solve the bias in OLS estimates and identify the causal effects of time and money inputs on household FI with two-stage least squares (2SLS) regression analysis.

With well performing instrumental variables, the different results from 2SLS relative to OLS estimations emphasize the importance of adjusting for endogeneity and measurement error. For all households, on average, we find that both time (in units of 10 hours) and expenditures (in units of 100 dollars) statistically decrease the probability of financial instability by 3.6% and 22.6%, respectively, after correcting for potential measurement error and endogeneity using IV. However, for single households, we find that each additional \$100 spent on food decreases the probability of financial instability by 26.5%, while time spent on food production has no

significant effect. For married households, every additional 10 hours spent on food production decreases the probability of financial instability by 10.5%, but food expenditures have no statistical effect. Our results highlight the varying effects across different household structures, which may suggest different strategies employed by these households to deal with financial instability.

The last and most important contribution is our exploration of how time and money inputs in food production help mitigate the disparity in the likelihoods of FI between immigrants and natives. We compare the effects of time spent on food production and financial investments on financial instability among immigrants relative to natives, separately by marital status. Since citizenship is a strong predictor of FI (Kalil & Chen, 2008), we identify immigrants as non-citizens and citizens. Our benchmark regression models suggest there is no statistical difference in the likelihood of FI between single immigrants, with or without citizenship, and single natives. With married households, both noncitizen and citizen immigrants are statistically more likely to be food insecure than natives.

When we consider the effects of time and expenditure, we find that time spent on food production significantly reduce the likelihood of FI for natives but does not improve the likelihood of FI for both immigrant non-citizens and citizens in either single households or married households. The differences in FI between immigrants and natives further confirms that spending more time on food production does not help immigrants, no matter with or without citizenship, narrow the FI gap with natives. These results are contrary to the immigrant time-poor hypothesis that suggests immigrants may not have enough time to maintain household FS. Our descriptive results show that immigrant citizens and noncitizens have already spend more time in food production than natives. Thus, the impact of time investment on reducing the likelihood of FI is not significant for non-citizen and citizen immigrants. This may be because immigrants face

barriers to access to culture already and therefore spend a lot of time trying to achieve cultural FS (Vahabi & Damba, 2013).

In comparison, more food expenditures help decrease the probability of FI for both natives and immigrants in single households but not in married households. This may reveal that marriage may provide other benefits like higher household level income and joint food consumption with lower food due to household scale or scope economics. Meanwhile, there is no different effects of food expenditure on FI between single natives and single immigrant. This may indicate that food expenditure plays the same important role in the FS of both natives and immigrants. Finally, more food expenditures significantly narrow the FI gap between married immigrant citizens and married natives (Pilossoph & Wee, 2021). This is consistent with the descriptive findings that married immigrants with citizenship who have higher education levels and spend more money on food tend to be more food secure.

The remainder of the chapter is structured as follows. Section 3.2 describes the matched data we use and summary statistics. Section 3.3 introduces the empirical approach and identification strategy with IV. Section 3.4 reports the empirical results for all households, single and married headed households. Section 3.5 and 3.6 discuss the results and make the conclusion.

## **3.2 Data and Summary Statistics**

### *CPS-FSS Data and ATUS Data*

We create an integrated dataset pairing households that completed the CPS FSS in 2003 to 2018 and the ATUS in 2004 to 2019 (S. M. Flood et al., 2023). The universe for FSS are households eligible for the basic CPS in December. Households that have completed their final month of the CPS are selected randomly to participate in the ATUS, with one individual over the age of 15

being selected from each household. As a result, we analyze CPS data from FS Supplement in year  $t$  in conjunction with ATUS data in year  $t+1$  using IPUMS-created individual identifier.

As the largest monthly national household survey conducted by the U.S. Bureau of Labor Statistics and the U.S. Census Bureau, the CPS provides national representative households and individual characteristics like demographic characteristics, place of birth, and year of immigrant, etc. Additionally, the FSS data in December also has information about household FS, food expenditures, and ways to cope with FI. Household level FS is assessed using an 18-item scale developed by the Food and Nutrition Service of the US Department of Agriculture (USDA) to measure limited or uncertain access to food due to insufficient resources. Finally, household's FS status is then defined as food secure, low food secure, very low food secure. In our analysis, we define household food secure status with a discrete variable: 0 for food secure, and 1 for food insecure (including both low food secure, very low food secure).

The data used for assessing a household's time allocation is the ATUS with approximately 11,000 individuals per year. This data measures the amount of time people spend doing various activities, such as paid work, household production, food acquisition and meal production. In each ATUS sample household unit, one individual who is selected to be the "designated person" reports sequentially the length of time spent on activities from top-level categories into sub-categories for their single designated diary day (24 hours). To reduce variability in response rates across the week, the preassigned survey day of the week is randomly assigned to each designated person with 50% of the sample reporting about the weekdays and 50% reporting about weekend. Our study focuses on six activities related to food production: meal preparation, grocery shopping, purchasing food (not groceries), eating time, travel related food preparation and travel related eating or drinking.

There are three limitations with using ATUS data to conduct time analysis (Berning, Cleary, et al., 2023; Davis & You, 2010). First, the ATUS data only collect time use for one day of the week. In this case, time spent of food production activities on the other six days of the week is unavailable. As such, certain activities such as shopping may not be observed resulting in undercounting of that activity. Second, only one individual in the household survey reports time spent on activities so the time spent by other household members such as spouses cannot be directly observed. This may be less of an issue with single households but may cause significant bias for married households. And the direction of the bias which is determined by whether spousal time is a substitute or complement Leeds & Allmen (2004) is not clear a priori. Third, the “designated person” in the ATUS sample household may not be the person who is primarily in charge of household food production. In this case, we will expect that the reported food production time is underestimated.

Following the time imputation strategies proposed by You & Davis (2019) and Berning, Cleary, et al. (2023), we solve the first two challenges in ATUS data. We impute time use for non-survey days separately for married and single households. For single households, the only problem is that its respondents only report time use for one day of the week. So, we employ a two-part model to solve this issue by using the observed time use of household respondents across different food production activities on their “designated diary day” to predict the time use on specific activities for the unobserved six days in the week since the ATUS sample is randomized by day over the week. Specifically, using data from respondents  $r$ , the first part is the estimate the probability of a survey respondent  $i$  engaging in food production activity  $j$  on day  $d$  from a probit model, such that  $Pr^r(FP_{ijd} > 0 | X^r, D = d; \hat{\theta}^r)$ , where  $FP_{ijd}$  is the time spent on food production activity  $j$  on day  $d$ ;  $X^r$  is a set of covariates;  $\hat{\theta}^r$  is the predicted values from the

respondents. Then the expected time of day-specific imputed food production activity  $j$  on day  $d$  for a household  $i$  will be written as:  $E^r(FP_{ijd}|X^r, D = d; \hat{\theta}^r) = Pr^r(FP_{ijd} > 0|X^r, D = d; \hat{\theta}^r) * E^r(FP_{ijd}|FP_{ijd} > 0, X^r, D = d; \hat{\theta}^r)$ , where  $E^r(FP_{ijd}|FP_{ijd} > 0, X^r, D = d; \hat{\theta}^r)$ , the second part, is the conditional expected value of time in food production for household  $i$  on day  $d$  based on a conditional exponential model. Now we will get six predicted daily time use and one actual reported daily time use for food production activity  $j$  in one week for household  $i$ . Finally, we get the weekly estimated time use of food production activity  $j$  for single household  $i$  by summing six predicted values and one observed value.

For married households, we not only predict the time use on specific activities for the unobserved six days in the week but also predict their non-respondent spousal time use. Like the time use imputation for single household, we first employ the two-part methods to predict day-specific values for respondent  $r$ , the  $Pr^r(FP_{ijd} > 0|X^r, D = d; \theta^r)$  and  $E^r(FP_{ijd}|FP_{ijd} > 0, X^r, D = d; \theta^r)$ . But these two parts  $Pr^r$  and  $E^r$  are gender specific for married household. Now by multiplying the  $Pr^r$  and  $E^r$ , we could get the expected time of day-specific imputed food production activity  $j$  on day  $d$  for the respondent of a married household  $i$ ,  $E^r(FP_{ijd}|X^r, D = d; \hat{\theta}^r)$ . Second, the expected day-specific non-respondent spousal time use for food production activity  $j$  is predicted based on their covariates ( $X^s$ ) and predicted values from our respondents ( $\hat{\theta}^r$ ),  $E^s(FP_{ijd}|X^s, D = d; \hat{\theta}^r) = Pr^s(FP_{ijd} > 0|X^s, D = d; \hat{\theta}^r) * E^s(FP_{ijd}|FP_{ijd} > 0, X^s, D = d; \hat{\theta}^r)$ . Third, we get the weekly estimated time use of food production activity  $j$  for the respondent and non-respondent spouse of married household  $i$  by summing their six predicted daily values and one observed daily value separately. Finally, we impute total household food production time for married households by summing up the weekly time use of respondent and non-respondent spouse.

### *Summary Statistics of the Matched Dataset*

Our dataset linking CPS-FSS data with ATUS data has 47,486 matched households. Berning, Cleary, et al. (2023) compared the ATUS, CPS-FSS and matched samples and found that the composition of the three datasets appeared to be relatively similar, implying that the statistical analysis using matched data will be not biased. Since the matched dataset does not have prescribed weights to make the data representative, summary statistics do not use population weights. The demographic information is taken from the FSS reporting.

Table 3.1 shows the descriptive statistics of the matched households across immigration status (native/immigrant non-citizen and immigrant citizen) separately for single and married households. Of the matched households, 24,526 (52%) are household head with spouse—married households, and 22,960 (48%) are single head households. Immigrant households are defined as the households whose both head and spouse are not born in the US for married households and only head is not born in US for single households. Native households with spouses are treated similarly. We exclude households with mixed nativity marriages—one native and one immigrant spouse—as they may encounter unique production challenges compared to households where both partners are immigrants. Such households potentially access a broader array of resources and networks from both native and immigrant communities, which could influence their FS differently. Since previous literature finds citizen status of immigrants as a strong predictor of FI (Kalil & Chen, 2008), we further assign the immigrant households to two citizenship subgroups: immigrant without citizenship (both no for married households; head no for single households) and immigrant with citizenship (at least one individual yes for married households ; head yes for single households). For single households, there are 20,265 (88.3%) native households, 1,216 (5.3%) immigrant noncitizens and 1,479 (6.4%) immigrant citizens. Married households consist of 21,065

(85.9%) native households, 1,657 (6.7%) immigrant noncitizens and 1,804 (7.4%) immigrant citizens. Overall, there are more immigrant noncitizens in single households than married households. Immigrant citizens have longer time since immigration, around 13 years, than immigrant noncitizens. Single immigrant citizens have longer time since immigration than married households. And for married or single households, there are larger proportion of white across different immigrant groups.

Immigrant households tend to have a higher number of children under 18 years old and usually have larger household size, particularly for immigrants without citizenship. Immigrant households especially immigrants with citizenship are more likely to live in metropolitan cities than natives. Single immigrant households tend to live in metropolitan cities more than married immigrant households. More than half of single households are female headed households for native and immigrant groups. Married households are more likely to have a male as the head. The household head in single households are older than the head in married households. And no matter in married or single households, immigrants without citizenship are the youngest. Immigrant households tend to have a bimodal distribution in education achievement, similar to existing literature (Budiman, 2020). Specifically, for both married and single households, immigrant noncitizens and citizens have both higher rates of “below high school degree” (low-skilled) and “master’s degree and above” (high-skilled) than natives. It also shows that immigrants with citizenship have higher rates of earning higher level degrees than immigrant noncitizens, except for “below high school degree”. Both immigrant households with citizenship and without citizenship have larger proportions of unemployed and employed but lower proportions in “Not in labor force” and “Armed forces”. And relative to married households, single households are more likely to be employed.

In examining weekly expenditures and time use in food production, it is observed that single immigrant households, regardless of citizenship status, incur higher weekly food expenditures and greater food production times compared to their native counterparts. In contrast, among married households, the expenditures of native and noncitizen immigrant households are similar, while those of citizen immigrant households are higher. Furthermore, immigrant households, both noncitizens and citizens, allocate more time to food production than native households, with married households displaying a more significant overall time commitment.

Furthermore, over our entire study period from 2003-2019, US immigrant non-citizens persistently have the highest rate of FI over time, followed by immigrant citizens and natives (Figure 3.1). FI of native households is also more relatively stable across time than immigrant households. Immigrant households with no citizenship who have less access to government support programs such as SNAP have the biggest proportion of FI, especially during the recession from 2007-2009. But they recover sooner than the other groups perhaps because they are more likely to engage in various forms of contingent and flexible employment (Liu & Kolenda, 2012). Meanwhile, immigrant citizens experience slightly higher FI relative to natives but with larger fluctuations.

In Table 3.2, we additionally analyze weekly food expenditures across various groups, taking into account their FS status and marital situation, distinguishing between immigrants and natives. Food secure households on average spend more on weekly food expenditures than food insecure household no matter single or married households, which is consistent with existing literature (Gundersen & Ribar, 2011). Notably, both non-citizen and citizen immigrant households generally have higher costs for food production compared to native households. The exception to this trend occurs within the subset of married and food-secure households, where natives' spending

surpasses that of immigrant non-citizens, yet remains below the expenditure of immigrant citizens. Additionally, within the food-secure category, both single and married non-citizen immigrants tend to spend less on food than their citizen counterparts. Conversely, in the context of FI, non-citizen immigrants' food expenditures are higher than those of citizen immigrants. An intriguing trend is observed when assessing the variance in food expenditures between food-insecure and food-secure households: immigrant non-citizens demonstrate the smallest disparity, whereas immigrant citizens show the greatest. This suggests that food expenditures among immigrant non-citizens remain relatively stable regardless of their FS status. This was unexpected since immigrant noncitizens usually have higher rate of FI and are more likely to experience economic hardship than immigrant citizens (U.S. Census Bureau, 2023; Van Hook & Balistreri, 2006).

Among these different groups categorized by immigrant status, marital status, and FS status, we continue to compare the differences in mean imputed weekly food production time in Table 3.3. Similar to food expenditures, food secure households spend more time on household food production than food insecure households, no matter single or married, except for single, non-citizen households. And there are slight differences (less than a half hour) in the weekly food time between food insecure and food secure immigrant households. Immigrant households, both citizens and noncitizens, usually spend more time in food production than natives, especially in food insecure households. Meanwhile, food secure and married, immigrant noncitizen households spend almost the same food time as immigrant citizens. Married households spend almost twice as much time on food production as single households.

We further decompose the distribution of imputed food production time use across different food production activities. Food secure households spend more time on every category of food production, except for food preparation. This may be explained that food insecure

households with economic hardship may choose to use less money to buy cheaper unprepared food, which results in spending more time on preparing food. Immigrant households spend more time on every category of food production, mainly in food preparation and secondly in grocery/nongrocery shopping, which may be explained by their efforts to maintain their cultural food preferences and traditional eating habits (Cantarero et al., 2013). Surprisingly, immigrant citizens who have more years of immigration also have similar but slightly lower food preparation time than immigrant noncitizens.

Altogether, these unconditional means show that immigrant households invest more time and money in food production than natives, yet they still face more probability of being FI. We next estimate how immigrant households use time and expenditures to produce food and manage their household FS relative to natives separately for married and single households with a set of control variables.

### 3.3 Empirical Methods

#### 3.3.1 Empirical Models

To estimate the effect of intrahousehold food time and expenditure (or money) allocation on FI among immigrants relative to natives, we begin by examining how time spent on food production and food expenditures is associated with household FI through the specification of a general household food production model (Becker, 1965; Davis & You, 2013). Our benchmark regression model takes the form:

$$y_{hst} = \alpha + \beta T_{hst} + \gamma M_{hst} + \delta_{imm}^{noncit} Imm_{hst}^{noncit} + \delta_{imm}^{cit} Imm_{hst}^{cit} + \delta_x X_{hst} + \theta_s + \eta_t + \epsilon_{hst}, \quad (3.1)$$

where the dependent variable  $y$  is a binary FI status variable for household  $h$ , in state  $s$  and year  $t$  that takes a value of 1 if the household is food insecure and 0 if the household is food secure.  $T$  is weekly total food production time in hours.  $M$  is weekly total food expenditures in dollars<sup>20</sup>. Because of the role of citizenship as a symbol of eligibility for to receive food assistance (Kalil & Chen, 2008),  $Imm_{hst}^{noncit}$  and  $Imm_{hst}^{cit}$  are dummy variables for immigrant non-citizen and immigrant citizen. Both dummy variables use native as the base group.  $X$  is a vector of household and individual demographic characteristics including household head gender, age, race, education level, employment status, metro status, children under 18, household size and years since immigration. State and year fixed effects ( $\theta_s$  and  $\eta_t$ ) are included to absorb time and spatially invariant unobservable variations in the outcome variable  $y$ . The scalar  $\alpha$  and vectors  $\beta$ ,  $\gamma$ ,  $\delta_{imm}$ , and  $\delta_x$  are the estimated parameters with the error term of  $\epsilon_{hst}$ . We are primarily interested in  $\hat{\beta}$  and  $\hat{\gamma}$  which respectively represent the associations of time and money with FI.

Similar to the estimations of Chapter 1 models, we estimate the LPM for Equation (3.1) using the matched ATUS + CPS-FSS sample, as LPM estimates have the advantage of being easy to interpret, representing the ceteris paribus marginal effects of each covariate on the probability of FI. Since there is no weight available for the matched sample, we do not use weight for the benchmark analysis. To account for the effects of different household structures on food production, we separately estimate models for all households, single headed households, and married households.

Next, our primary concern is the different FI challenges faced by immigrants and natives by comparing the associations of their food time and expenditure investments with FI. To

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<sup>20</sup> To enhance the interpretability of the coefficients, we change the unit of food production time to 10 hours and food expenditure to 100 dollars in our tables of results.

comparing these different associations across immigrant and US native households, we further add interaction terms between time or expenditure allocations and immigrant citizenship status to Equation (3.1), such that:

$$\begin{aligned}
y_{hst} = & \alpha + \beta_1 T_{hst} * (1 - Imm_{hst}^{noncit}) + \beta_2 T_{hst} * Imm_{hst}^{noncit} + \beta_3 T_{hst} * Imm_{hst}^{cit} \\
& + \gamma_1 M_{hst} * (1 - Imm_{hst}^{noncit}) + \gamma_2 M_{hst} * Imm_{hst}^{noncit} + \gamma_3 M_{hst} * Imm_{hst}^{cit} \\
& + \delta_x X_{hst} + \theta_s + \eta_t + \epsilon_{hst}, \quad (3.2)
\end{aligned}$$

Where  $Imm_{hst}^{noncit}$  and  $Imm_{hst}^{cit}$  are still dummy variables for immigrant non-citizen and immigrant citizen. Now  $\widehat{\beta}_1, \widehat{\beta}_2$  and  $(\widehat{\beta}_1 + \widehat{\beta}_3)$  estimate the marginal products of food production time on FI for natives, immigrant non-citizens and immigrant citizens. The difference in the associations of time with FI between immigrant non-citizens (immigrant citizens) and natives is given by  $\widehat{\beta}_2 - \widehat{\beta}_1$  and  $(\widehat{\beta}_3)$ . The estimated  $\widehat{\gamma}_1, \widehat{\gamma}_2$  and  $(\widehat{\gamma}_1 + \widehat{\gamma}_3)$  represent the associations of food expenditure on FI for natives, immigrant non-citizens and immigrant citizens. And  $\widehat{\gamma}_2 - \widehat{\gamma}_1$  captures the difference in the different association of food expenditure with FI between immigrant non-citizens and natives.  $\widehat{\gamma}_3$  is the difference between immigrant citizens and natives. Consistent with Equation (3.5), this Equation (3.6) also will be estimated separately for all households, single headed households, and married households.

### 3.3.2 Identification Strategy

After controlling for household-level, individual level controls and fixed effects in our empirical specification, there may still be factors that bias the estimates of the effect of food production time and food expenditure on household FI. First is the potential measurement error issue of time and expenditures in food production. Food production time taken from the ATUS 24-hour diary may be a poor indicator of a household's actual long-run time use which is the true time variable of

interest for our analysis of household FI (Frazis & Stewart, 2012). Even though we impute other six days' time use and spousal's time use to get the weekly household time use, the predicted weekly time use also remain measure error with the short reference period relative to the year survey period for household FI. Therefore, as suggested by Frazis & Stewart (2012), a concern is that our measure of weekly food production time in the short run may have little effect on household FI for 12-month periods so that there will be downward bias. Similarly, our weekly food expenditures may be measured with some error.

Additionally, there are potential endogeneity concerns. First, time and expenditures vary with household demographic composition. For example, elderly households spend more time in meal preparation and eating time than younger households (Berning, Cleary, et al., 2023). Households with higher educational attainment (diet-health knowledge) spend more money on food expenditure (Blisard et al., 2003). So, unobserved shocks on households with particular demographic profiles could also affect these particular households' food time and expenditure inputs. Second, unobserved state-specific economic shocks may simultaneously affect both household time, expenditures, and FS. For example, a trade war leading to higher food prices may affect both FI status and time or expenditures. Third, FS status may also affect a household's allocation of time and expenditures, resulting in reverse causality. For instance, food insecure households may spend more time on work and decrease food production time and even food expenditure to get through economic hardship.

To address these estimation concerns, we aggregate households' food production time and money at the cell level based on observed characteristics (for example, by age and marriage status) and then use cell-level mean values as instruments (IV) for time and expenditures (Hanushek et al., 1996). We illustrate the details in constructing these cell-level aggregations below. Using

aggregated cell-level values to predict household values can help reduce measurement error resulting from the deviation between short-period values and long-run true values (Frazis & Stewart, 2012). Furthermore, cells can be treated as a sensible measure of the labor market the same demographic characteristics belong to, so we also include cell-level fixed effects to serve the purpose of controlling for any unobservable factors that may exist between these different labor markets (Farré et al., 2018). We make full use of intra-cell variation, allowing the average probability of FI to vary across cells. Finally, the IV approach has the added advantage to mitigate the reverse causality problems.

To construct the aggregated time and money as IVs for food time, we first divide each household into 13 age-cohort groups with 5-years interval from 20-85 years old as the cells for food time. This is because previous literature suggests that there are strong life-cycle variations in food production time by age (Faberman, 2015). Then we calculate three year moving average values of other time use (total time spent except for food production time) across each age cohort cell at a national level by marriage status (married or single) on a sample-weighted basis. We use total other time because other time affects FI only through the food time. We separately calculate the aggregated values by marriage status due to the strong correlation between household composition and time use, which is also true for food expenditures (Berning, Cleary, et al., 2023). Altogether, cells are defined by marital status (married or single head) and age-cohort resulting in  $2 \times 13 = 26$  cells. Figure 3.2 illustrates that there are significant cross-age and cross-marriage status variations in the use of predicted weekly time for food production and total other activities. For both single and married households, the time spent on food production steadily increases across age cohorts, while the corresponding total other time steadily decreases across age cohorts. Notably, married households significantly spend more time on food production than single

households but spend less total other time than single households. Constructing values at national level, not at state level, avoids potential unobserved correlation with state-trend factors that could bias our household estimates. The instrument ( $IV\_FT_{cst}$ ) for food production of households at cell level  $c$  in state  $s$  and year  $t$  is given as:

$$IV\_FT_{cst} = \text{Mean\_other time}_{c,t=3} \quad (3.3)$$

For our expenditure instruments, we create cells based on household characteristics that capture variation in food expenditures—marriage status (household composition), age, education attainment and race (Blisard et al., 2003). Figure 3.3 shows the distribution of food expenditure for these different characteristics used to construct the cells. We find a clear variation in household food expenditure across age groups, showing an inverted U-shape. Moreover, even within the same age group, there are variations in food expenditure across different demographic characteristics, particularly for married households, households with higher education degrees and white households who have higher household expenditure. Cells  $c$  for household food expenditures are divided by marital status, age-cohort group, educational attainment (below high school, high school, associates, bachelors, advanced degree) and race (white or non-white) resulting in  $2 \times 13 \times 5 \times 2 = 260$  cells. We create the instrument for food expenditures using a three-year moving average by cell at the national level on a sample-weighted basis. The aggregate food expenditures at the cell level are not driven by cell-specific characteristics and their change over time does not vary by demographic characteristics like marriage status, age, education, race.

The instrument for food production  $IV\_FE_{hcst}$  of households at cell level  $c$  in state  $s$  and year  $t$  is given as:

$$IV\_FM_{cst} = \text{Mean\_FoodExpenditures}_{c,t=3} \quad (3.4)$$

We use  $IV\_FT_{cst}$  and  $IV\_FM_{cst}$  as instruments for household level food time and expenditures to separately estimate Equations (3.1)-(3.2) via two stage least square (2SLS). To clearly explain the identification process, we use Equation (3.1) as the main model. Then the first-stage regressions for time and money include both the two IVs in each model with other controls identical to those in Equation (3.1), as follows:

$$T_{hst} = \lambda_0 IV\_FT_{cst} + \lambda_1 IV\_FM_{cst} + \lambda_{imm}^{noncit} Imm_{hst}^{noncit} + \lambda_{imm}^{cit} Imm_{hst}^{cit} + \lambda_x X_{hst} + \theta_s^T + \eta_t^T + \zeta_c + \mu_{hst}^T \quad (3.5)$$

$$M_{hst} = \omega_0 IV\_FM_{cst} + \omega_1 IV\_FT_{cst} + \omega_{imm}^{noncit} Imm_{hst}^{noncit} + \omega_{imm}^{cit} Imm_{hst}^{cit} + \omega_x X_{hst} + \theta_s^M + \eta_t^M + \zeta_c + \mu_{hst}^M \quad (3.6)$$

The relevance assumption suggests the cell-level food time and expenditures cause the variations in individual values, which means  $\widehat{\lambda}_0$  and  $\widehat{\omega}_0$  are statistically different from zero in Equation (3.5) and (3.6). Exclusion restrictions require conditional on controls, the instruments  $IV\_FT_{cst}$  and  $IV\_FM_{cst}$  only affect household FI status through their individual food time and expenditure but not through other factors. In other words, these instruments should not correlate with the error term in main Equations (3.1 & 3.2).

The relevance assumption of the cell-level instruments is credible because the cell mean values as instruments (IV) for time and expenditure are calculated as the aggregated values at the cell-level based on the household demographics. Intuitively, our instruments capture household variation in time and expenditures across the household characteristics.

The exclusion restrictions are also plausible. On one hand, the new cell level IVs for time and expenditures accounts for within-cell variation, which addresses the concern that both FS and food time and expenditures vary with household demographic composition. On the other hand, using the mean cell level for other time as an instrumental variable for food production time will

intuitively only affect FS through food production time. Additionally, aggregated cell-levels IVs based on characteristics at the national level also reduce the omitted variable bias introduced by the cell-level and state-trend unobserved factors that will affect both household FI and food time and expenditures. Moreover, adding cell-fixed effects  $\zeta_c$  (marriage-age-education-race cells) will help control for the unobservable difference that may exist between these different labor markets or different cells with the same demographic characteristics (Farré et al., 2018).

### **3.3.3 Strength of the Cell-level Instruments for Time and Money**

Once we construct the cell-level mean values as instruments (IV) for household-level time and expenditures using Equations (3.3) and (3.4), the relevance of our cell-level instruments could be examined by reporting the first-stage regression results from Equations (3.5) and (3.6). The binned scatter plot of residualized instruments against residualized time or money input in Figure 3.4 respectively represents the first stage effect of the cell-level instruments on food production time or food expenditure for all households in our sample. The residualization is generated by running full multivariate regressions on a full set of controls including household and individual demographic characteristics as well as year and state fixed effects. It shows that there are tight relationships between food production time or expenditure and its corresponding instruments, even when control variables are included. We further plot these first stage effects for single and married households separately in appendix Figure C. The dispersion of the binned scatter around the red regression line in Figure C suggests that there are still statistically significant relationships between cell-level instruments and time or expenditure on food production, regardless of whether the household is single or married. Therefore, the relevance assumption of cell-level mean values as instruments (IV) in predicting time and expenditures is valid.

## 3.4 Results

We first regress household FI on time and expenditures to get the marginal products of time and expenditures on FS across all households, single and married households. Then we introduce interaction terms between time and expenditures and immigrant status in the models to estimate the differential effects of food production time and food expenditures on FI between immigrants and natives.

### 3.4.1 Estimates of the Effects of Food Time and Expenditure on FI

#### *All Households*

We examine the effects of food time and expenditures on household FI by estimating Equation (3.1) for all households (Table 3.4). Column (1)-(3) report the results of linear probability model (OLS) with standard errors clustered at state level using different sets of controls. To make the coefficients interpretable, we adjust the unit of food production time to 10 hours and the unit of food expenditure to 100 dollars in our results. When there are not any controls, we find 10 hours increase in weekly time spent on food production are associated with an 6.2% decrease in the probability of FI. Alternatively, 100 dollars increases in weekly food expenditure are associated with a 2.2% decrease in the probability of FI. We also find that noncitizen immigrants are about 11% more likely to be food insecure than natives and citizen immigrants are about 2% more likely to be food insecure than natives. When adding state and year fixed effects, the estimated results do not change meaningfully. This suggests that unobserved state and year factors may not affect the association between food production time and expenditures and FI.

With all controls including the household demographics, the association between food production time and FI decreases to 2%. But the association between food expenditures and FI increases slightly to 3.3%. This is consistent with Tables 3.2 and 3.3 which show food secure

households on average spend more time and money on food production. In this same specification, immigrant noncitizens are still 3% more likely to be food insecure than natives, while immigrant citizens and natives are not statistically different in FI. This is consistent with Figure 3.1 showing that immigrant non-citizens have the highest rate of FI and immigrant citizens almost have similar food insecure rate with natives.

The 2SLS estimates for all households using cell-level aggregated time and expenditure as instruments are reported in columns (4)-(7). Columns (4)-(6) have the same sets of controls as the OLS estimates. Column 7 adds cell fixed effects (constructed as marriage-age-education-race) to control for the unobserved shocks for households with those particular demographics. After using IVs to control for endogeneity and correct for measurement error, the effects of food time and expenditure on FS increase relative to the OLS estimates. Models without controls in column (4) and with only state- and year- fixed effects in column (5) have almost the same estimates, showing that each additional 10 hours spent on food production reduces the likelihood of household FI by 9.2%, compared to a reduction of 6.2% as estimated by the OLS model. But the corresponding 2SLS estimates of the effect of food expenditures is not statistically significant. At the same time, the inequalities in the likelihoods of FI between immigrant noncitizens and native, and between immigrant citizens and natives are similar to the OLS estimates, at about 11% and 2% respectively.

After adding household demographic characteristics in column (6), our estimates suggest that an additional 10 hours and \$100 spent on food production will respectively decrease the likelihood of household FI by 5.1% and 15.9%, which are larger than the OLS estimates with the same controls. Further, we find only immigrant noncitizens are statistically more likely to be food insecure than natives. Finally, estimates including additional cell fixed effects in column (7) do not change much and suggest that every 10 hours spent on food production statistically decreases

the likelihood of household FI by 3.6%, and every \$100 spent on food production decreases the likelihood of household FI by 22.6%. But there is no statistical difference in FI likelihood between immigrants and natives after adding cell fixed effects.

### *Single Households*

Next we report the effects of food time and expenditures on household FI by estimating Equation (3.1) for single households (Table 3.5). We report the OLS estimates in columns (1) to (3). Time and expenditures are correlated with a decrease in the likelihood of FI. And the associations between time or expenditure and FI for single households are higher than those for all households in Table 3.4. Specifically, when there are no controls or only state and year fixed effects, spending 10 hours or \$100 on food production is correlated with an 8.7%-9.7% decrease in the probability of FI. The likelihood of FI for non-citizen immigrants is 6% higher than natives, but not significantly different for citizens. After adding household demographic characteristics, the association between food production time and FI decreases to 3.3%, while the association between food expenditures and FI increases to 4%. Our findings indicate that for single households, there are no statistical differences in the likelihood of FI between immigrants (both citizens and noncitizens) and natives.

Columns (4)-(7) report the 2SLS results for single households. When there are no demographic controls in columns (4) and (5), spending 10 hours on food production decreases the single households' FI probability by 18.5%, but food expenditures do not have a statistically significant effect. In these models, only immigrants without citizenship are at higher likelihood of FI than natives but not for immigrant without citizenship. After controlling for household demographics and cell-level fixed effects in columns (6) and (7), the time spent on food production does not statistically affect the likelihood of FI. However, spending \$100 on food statistically

decreases the probability of FI for single households by 18.6%-26.5%. Consistent with the OLS results, there are no statistical differences between immigrants (both citizens and non-citizens) and natives in terms of FI probability after including covariates.

### *Married Households*

Table 3.6 reports the OLS and 2SLS results for married households. Consistent with the OLS estimates for all households and single households, we find that both more food production time and food expenditure inputs are statistically associated with a decrease in the probability of FI. Adding household demographics as controls, the association between time and FI decreases from 6.8% to 3%, and the association between food expenditures and FI is stable around 2%. In these models, both immigrant non-citizens and immigrant citizens are statistically more likely to be food insecure than natives, especially immigrant non-citizens with almost twice the probability.

The 2SLS estimates report that only more time investment in food production significantly decreases the married households' likelihood of FI. The estimates without households' demographics in column (4) and (5) show that both time and expenditure in food production decrease the likelihood of FI for married households. But when we add household demographic characteristics and cell fixed effects, the effect of food expenditure is not statistically significant. Whereas time still reduces the likelihood of FI by 14.6%-10.5%, which are higher than the estimates in OLS models. In married households, immigrants without citizenship or with citizenship are more vulnerable to be food insecure than natives, even including all the controls in the model. And immigrant non-citizens are at the highest likelihood of FI, 10.4% higher than natives. By contrast, immigrant citizens are 0.7% more likely to be food insecure.

Overall, in all cases across all households, single and married households, our cell-level instrumental variables for food production time and expenditure which attempts to correct for

endogeneity and measurement error perform well with a high F-statistics reported in the last rows in columns 4-7 from Table 3.4 to Table 3.6 (Stock et al., 2002). With the IV approach, time and expenditures inputs have a significant impact on household FI. We also find there are different effects of time and expenditures for all households, single and married households. For all households, more time and expenditures investment have statistically negative marginal effects on FI. For single households, only food expenditure investment has a statistically negative effect on FI, whereas for married households, only food time has a statistically negative effect on FI.

### **3.4.2 Comparing the Effects of Food Time and Expenditure on FI Between Immigrants and Natives.**

We compare the effects of time and expenditure investment in food production on FI between immigrants and natives by estimating Equation (3.2) with the interacted terms of food time/expenditure and immigrant status, separately for all households, single households, and married households in Tables 3.7-3.9. We report both OLS and 2SLS estimates in each case.

#### *All households*

We first compare the effects of time and expenditures on FI between immigrant citizens and natives for all households in Table 3.7. Columns (1)-(3) report the OLS results. When comparing the differences in the association between time and FI among various immigrant groups and natives, we surprisingly find that time spent on food production is statistically associated with a greater reduction in the probability of FI for natives than noncitizen immigrants. Similarly, more time spent on food production is statistically related to a greater reduction in the likelihood of FI for natives than citizen immigrants. Specifically, more time spent on food production is associated with a decrease in the probability of FI for natives from 2.8% to 7.1% with different sets of controls.

But there are positive but non-statistical associations between time input and the likelihood of FI for immigrant non-citizens and citizens.

We then compare the differences in the effects of expenditures between the different immigrant groups and natives. The results indicate that there is no difference in the effect of food expenditure when comparing non-citizen immigrants and native households. But an additional \$100 spent on food production decreases the probability of FI more for immigrant citizens about 2% than natives, which is very stable even with adding different controls. To be specific, an extra \$100 spent on food production is statistically associated with a decrease in the probability of food expenditure at 3.1% for natives, 2.4% for immigrants without citizenship, and 4.8% for immigrants with citizenship after controlling for all covariates. Using different sets of control variables in columns (1) to (3), these correlations between food expenditures and FI are not very different, with a maximum increase of 4.8% after including all covariates.

The 2SLS estimates in column (4)-(7) show similar but slightly larger results. Comparing the different effects of food time across different immigrant groups, it appears that more time spent on food production leads to a greater reduction in the probability of FI for natives than noncitizen immigrants with more controls in the models (9.8%-6.1%). The same is true for the difference between immigrant citizens and natives (8.2%-6.5%). If we look at the effect of time input on household FI separately for these different groups, spending an additional 10 hours on food production time statistically decreases the likelihood of FI for natives by 5% - 10.6% but is not significant for both noncitizen and citizen immigrants under all controls.

Finally, an extra \$100 in food production causes a greater decrease in the likelihood of FI for both immigrant non-citizens (at 7.4% with 10% significant level) and citizens (at 7% with 1% significant level) than natives with all controls. Specifically, an additional \$100 spent on food

production decreases the likelihood of FI by about 26% for both immigrant noncitizens and immigrant citizens and by 19.4% for natives including all controls in the model.

### *Single households*

We compare the effects of time and expenditure between immigrants and natives for single households (Table 3.8). Column (1)-(3) show the OLS estimates on each group. Comparing the associations between immigrant groups and natives in single households shows that more time invested in food production is associated with a 5% (at 10% significant level) greater reduction in the likelihood of FI for natives than for non-citizen after controlling all variates (column 3). There is the same difference between single immigrant citizens and single natives. Specifically, every additional 10 hours invested in food production is associated with a 4.6% statistical decrease in the probability of FI for single natives under all control variables. However, for both immigrant noncitizens and citizens, the associations are positive but not statistically significant at the 5% significance level. Furthermore, the effects of food expenditures on FI are not statistically different between immigrants, including both citizens and non-citizens, and natives. An additional \$100 spent on food production is statistically associated with a 3.9% decrease in the probability of FI for single natives, a 3% decrease for single immigrant noncitizens, and a 5.1% decrease for single immigrant citizens.

Compared to the OLS results, the 2SLS estimations show higher effects of time and money investment in food production for single households. Under different sets of covariates, we find additional 10 hours investment in food production leads to 26%-13.9% greater reduction in the likelihood of FI for single natives than single immigrant non-citizens, and 15.7%-12.1% greater reduction in the likelihood of FI for single natives than single immigrant citizens. When we look at the impact of time input on FI for each group, one hour spent on food production helps native

households statistically decrease the probability of being FI by 22.8-5.4%. But time spent on food production increases the probability of FI for immigrants without citizenship at 10% significant level and for immigrants without citizenship at 5% significant level. These results reveal that time spent in food production does not narrow the FI gap between immigrants and natives but could actually widen the gap. This is probably because immigrants have already invested more time in food production than natives from the very beginning shown in Table 3.3.

However, based on our 2SLS results, more dollar spending will statistically cause the same decrease of the likelihood of FI among immigrants including both citizen and noncitizens and natives around 26.5-31.8%. Nevertheless, an extra \$100 input could lead to 5.3% more decrease the likelihood of FI for single immigrant citizens than single native households but at 10% significant level. This may align with the fact that there is larger gap in food production between food insecure with single immigrant citizens and food secure with single immigrant citizens households in Table 3.2. So, more money input will help immigrant citizens decrease the likelihood of FI and narrow the FI gap with natives.

#### *Married households*

We compare the effects of food time and expenditures on FI between immigrants and natives for married households (Table 3.9). The OLS estimates (column 1 to 3) show that even though more time input in food production is statistically associated with a decrease in the probability of being food insecure by 3% for natives, by 5.8% for immigrant noncitizens and is not significant associated for immigrant citizens with all controls, these effects are not statistically different. For food expenditure, higher expenditures are statistically associated with a decrease in the probability of being food insecure for both natives and immigrants. The decrease is 2.3% for married natives, 2.1% for noncitizen immigrants, and 4.2% for citizen immigrants, with all controls included. By

comparing with natives, more money input is statistically associated with 1.9% greater reduction of the probability of FI for married immigrant citizen.

The effects of time and expenditure for married households estimated by 2SLS are shown in column (4)-(7) of Table 3.9 which there are different results from OLS estimations. For the effect of time estimated including all covariates and fixed effect, additional 10 hours in food production statistically causes a 15.6% greater decrease in the probability of FS for married native households than married immigrant citizens, but not for married immigrant noncitizens relative to natives. For the effects for each group, the married native households have the largest negative and significant effect of food production time on FI at 13.1% but married native households including both noncitizens and citizens do not have statistical effect of money input on FI. These results are consistent with descriptive comparisons in Table 3.3 that married immigrant households have spent more time than their corresponding native households. Unlike the 2SLS results from all households and single households, an additional \$100 input in food production could not statistically decrease the probability of FI for any households including natives and immigrants.

### **3.5 Discussion**

Given the higher likelihood of FI faced by immigrants, this study examines how immigrant households use time and expenditures to produce food and manage their household FS relative to natives. Aggregated cell means of food production time and expenditures are employed as instruments separately to address potential measurement errors and endogeneity of household level time-use and expenditures. Using these instruments, we determine the impact of time and expenditures on household FI, while existing studies mainly focus on correlations and consider only one input. Next, we compare the different effects of food time and expenditure investments

for immigrants and natives to explore whether these different effects contribute to the disparity in FI faced by immigrants and natives.

We examine the effects of time and money inputs for all households, single and married headed households separately and get different results between 2SLS estimates and OLS estimates. The OLS estimates across all households, single and married headed households consistently indicate that more time and expenditures are associated with a decrease in the probability of FI, which is consistent with the literature and our descriptive analysis.

The 2SLS results suggest that adjusting for endogeneity and measurement error is important. For all households, more time and expenditure investment have negative effects on FI. In single households, only food expenditures have a negative effect on FI, whereas only food time has a negative effect on FI of married households. Beatty et al. (2014) explore how FI status is associated with time spent on food-related activities. But their findings differ from ours in that single households' FI are associated with 20% more time in meal preparation and 13% less time eating while married households' FI is associated with 17% less time eating and 14% less time in grocery shopping.

The varying effects of time and money investment in food production across different types of households suggests household structure matters with managing FI. The impact of food expenditure in single households reflects the well-established fact that single headed households make less than their married peers and may not enjoy the marriage benefits of lower food expenditure due to household scale economies (Bütikofer & Gerfin, 2017; Lazear & Michael, 1980). The benefits of time for FS of married households reveal the limited time spent on household food production as married people are torn between the demands of work and child rearing (S. M. Flood & Genadek, 2016) and emphasize the importance of complementarities in

consumption of food production time for married households (Mansour & McKinnish, 2014). These results may also indicate that it is difficult to substitute time for money to manage FI (Davis & You, 2013). Married households with sufficient money may still need more time input to keep food secure. Similarly, single households with sufficient time may require more resources to increase their expenditures on food production.

The comparison of the different effects of food time and expenditures for immigrants and natives under different household structures helps explain whether the different effects contribute to their disparity in likelihoods of FI. Our causal analysis suggests that time spent in food production improves the FS of natives but does not improve the likelihood of FI for immigrants, either single households or married households. This could be that immigrant households regardless of citizens and noncitizen, have already spent more time on food production than natives. It may be that immigrants have to invest more time in food production to maintain cultural food preferences while facing limited access to culturally appropriate foods and resources (Vahabi & Damba, 2013). In contrast, food expenditures are helpful for both natives and immigrants in single households to maintain FS but are less impactful for married households. As we discussed before, marriage may provide other benefits through bargaining and sharing of internal resources such that food expenditures are not a limiting resource.

The differences we find between immigrants and natives further confirms that more time input does not narrow the FI gap between immigrants and natives and may actually exacerbate the gap for both single immigrants with and without citizenship and married immigrants with citizenship who already spend more time than natives on food production. Nevertheless, more food expenditure could be used to significantly narrow the FI gap between immigrant and natives, especially between married immigrant citizens and married natives. Surprisingly, immigrant

citizens found to be less likely to report hardship than the native-born population (Iceland, 2021) were better able to benefit from food expenditure in terms of FI. But this is consistent with the descriptive findings that married immigrants with citizenship who have higher education levels tend to spend more money on food and be more food secure.

The fact that less time is required in food production for immigrants who have already invested more time in food production may reflect high cost of time in food production and its high opportunity cost measured by the market wage rate (Davis & You, 2010). Additionally, more money required in food production not only indicates the fact that immigrants are experiencing economic hardship in maintaining their FS and but also may reveal the situation that immigrants work harder than natives to get more paid. Empirical studies have examined that immigrants are working harder than natives, are more likely to work unusual hours (Dramski, 2017) and their job are riskier and physically more arduous (P. M. Orrenius & Zavodny, 2009; P. Orrenius & Zavodny, 2015).

The findings that less time input and more money required for immigrants also suggest that developing ways to support the acquisition and preparation of culturally relevant foods in food assistant programs or local communities (i.e., food preparation, sharing, and consumption; food-ways), could help create time savings and increase immigrants' FS (Alonso et al., 2018). Allowing to buy prepared food items with an EBT card from SNAP which could help participants reduce food production time could also be a way to improve their FS.

### **3.6 Conclusions**

Our findings elucidate marked disparities in the effects of time and money investments in food production among diverse immigrant cohorts, delineated by household composition. Targeted fiscal support for food expenditures in single-person households could mitigate economic distress

and diminish the prevalence of FI. Conversely, for married households, increased access to ready-made meals via food assistance initiatives may yield time savings in food preparation and a corresponding reduction in FI. Single immigrants, particularly those dedicating additional time to preserve cultural dietary practices, may benefit from increased monetary subsidies and access to culturally appropriate pre-prepared meals. Programs aimed at bolstering immigrant household welfare should consider addressing the barriers to availability, access, and stable utilization of traditional foods—accounting for food preparation, sharing, and consumption norms (food-ways). For instance, enabling cultural-specific grocers to accept Electronic Benefit Transfer (EBT)/Food Stamp payments could be beneficial. Notably, H-MART, the preeminent Asian supermarket chain in the United States, accepts EBT in its California, Georgia, Illinois, Maryland, Michigan, Texas, and Virginia locations. Our insights and subsequent policy recommendations are in concordance with the core objectives of the United States Department of Agriculture (USDA) regarding food and nutrition security, which advocate for the acknowledgment of structural disparities in the allocation of financial and temporal resources for food production between native-born and immigrant households, underscoring the imperative of applying an equity lens to these efforts.

As with all studies, ours has several limitations. First, the limited sample size in our matched dataset, especially for immigrants, doesn't allow us to divide the households into single or married households with different numbers of children and income levels and further explore the effects of time and money inputs for these household subgroups. Second, future studies about food production could consider the different strategies of different household structures to maintain their FI, especially for the married households. For example, how complementary are couples in household food production? Third, future studies could consider the cost of time input in food production measured by wage rates using the opportunity cost approach like Davis & You

(2010), which will help to illustrate the tradeoff between home production and labor market opportunity. Fourth, we now assume there are the linear relationships between time/expenditure and FS. Future studies may try to explore nonlinear analysis.

Tables and Figures

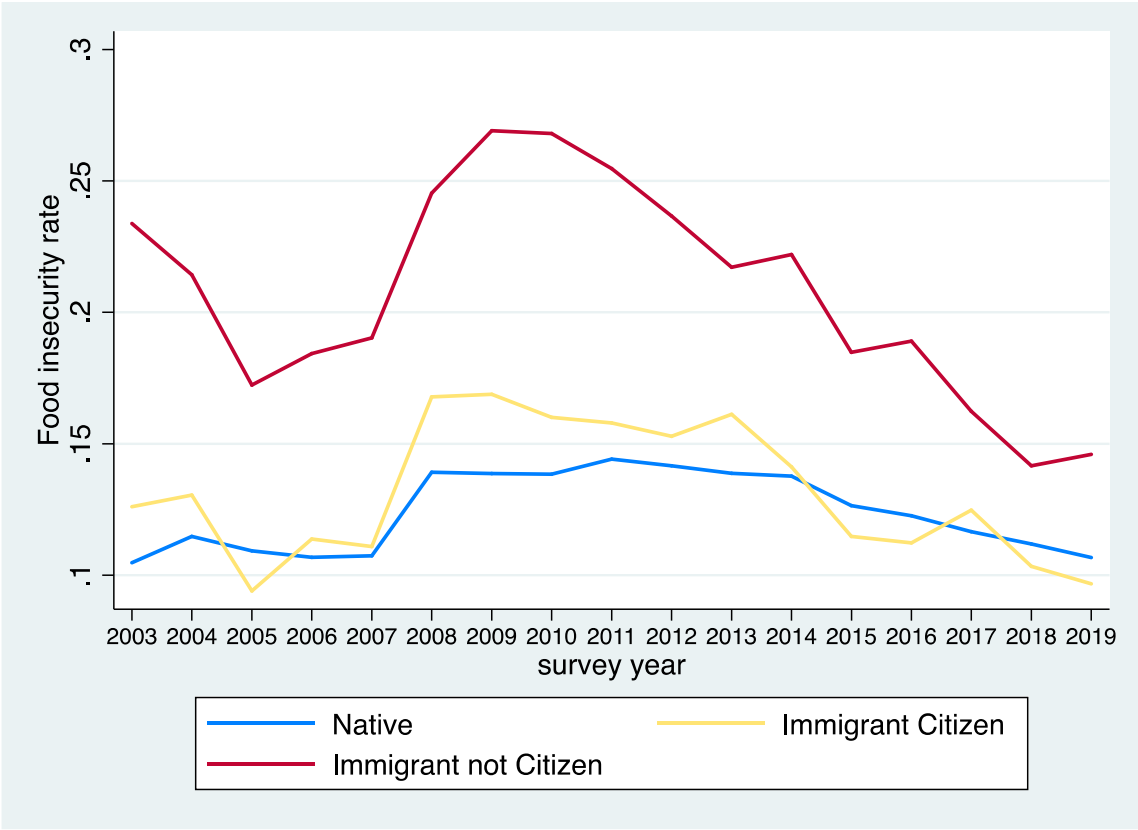
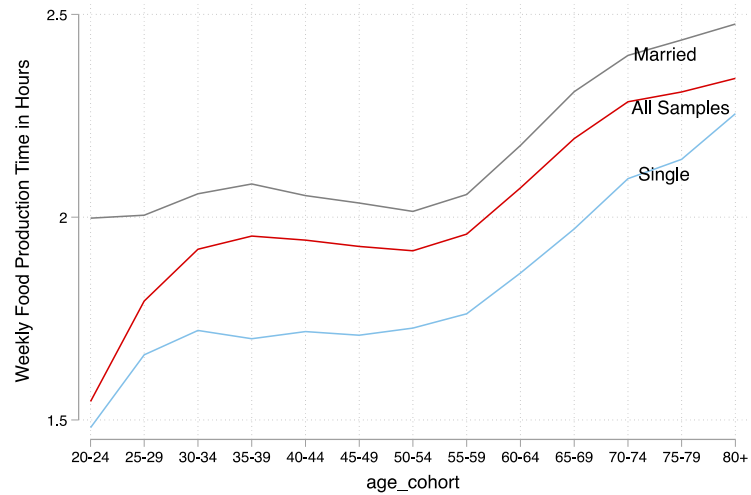
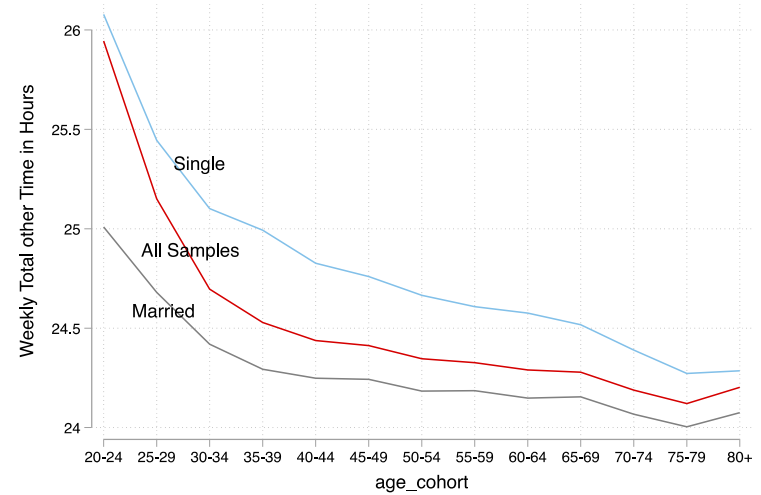


Figure 3.1. FI Rates Change Over Time Across Different Groups.



**a. Average Weekly Food Production Time Changes Across Age Cohorts**

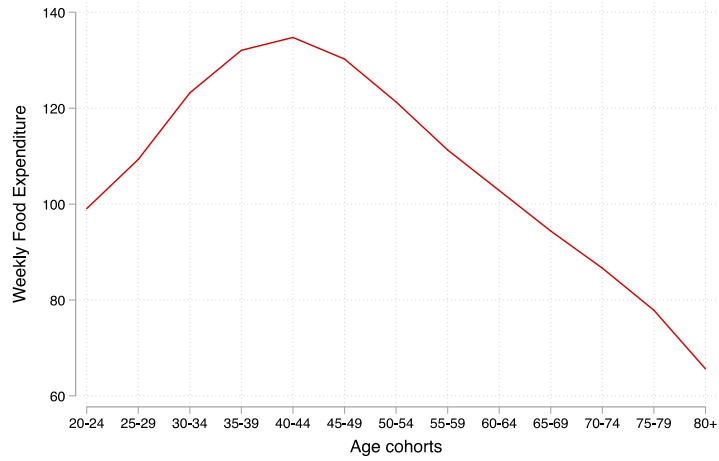


**b. Average Weekly Total Other Time use Changes Across Age Cohorts**

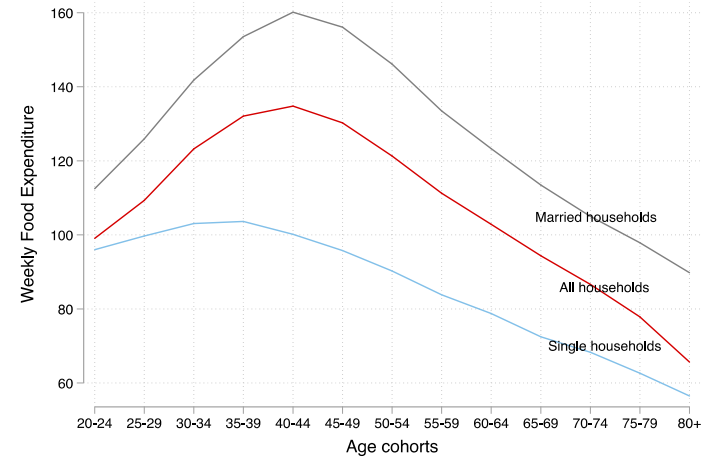
**Figure 3.2. Variation in Time Use across Subgroups**

*Note:* These two figures present two charts illustrating the variations in average weekly time spent on food production and other activities across different age cohorts, categorized by marital status, using the raw data of ATUS without a time imputation strategy.

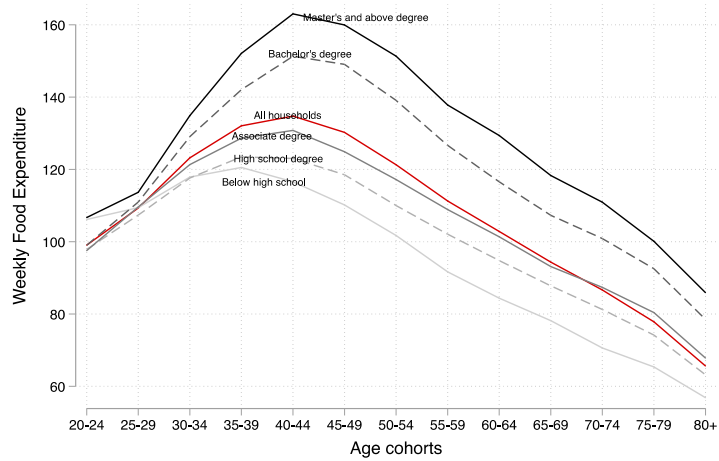
*Source:* Authors' calculations, Current Population Survey, and American Time Use Survey



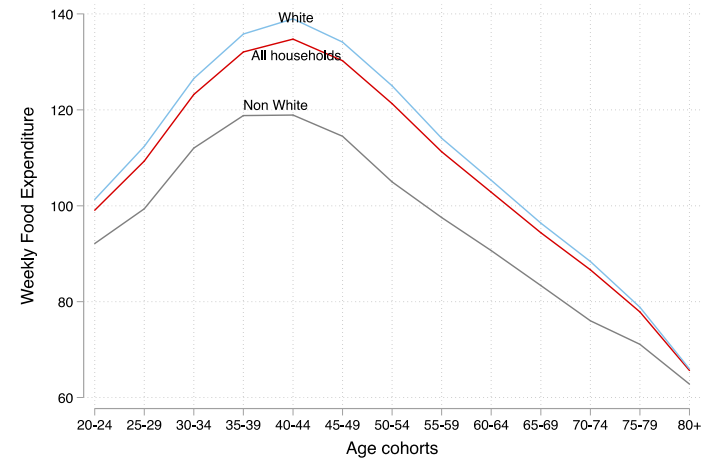
**a. Average Weekly Food Expenditure Across Age Cohorts**



**b. Average Weekly Food Expenditure Across Marriage Status**

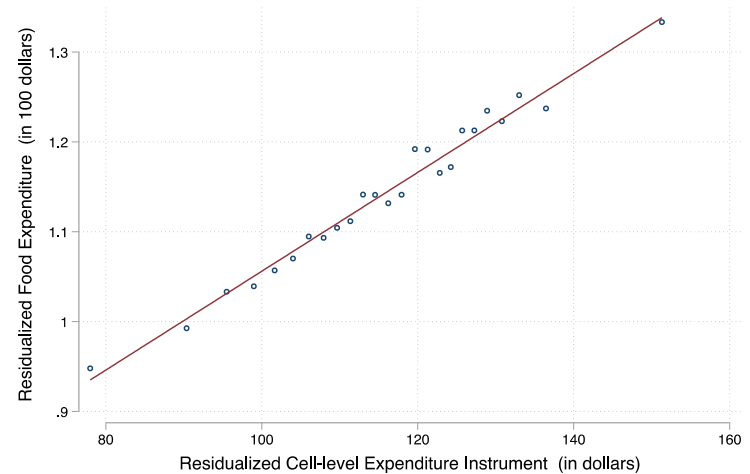
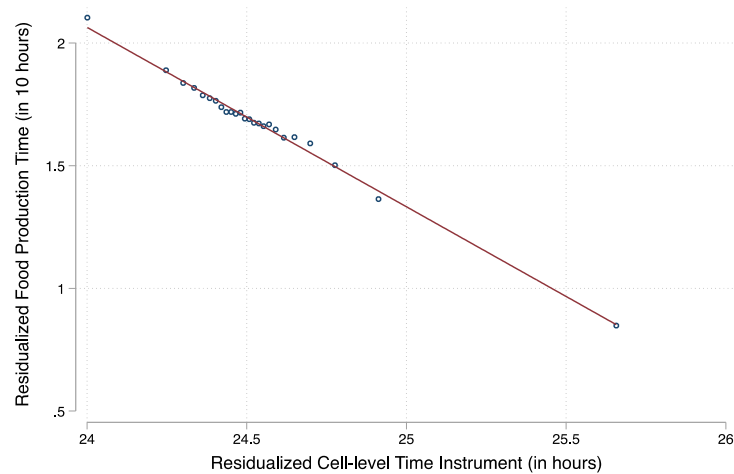


**c. Average Weekly Food Expenditure Across Education Level**



**d. Average Weekly Food Expenditure Across Race**

**Figure 3.3. Variation of Food expenditure Across Subgroups**



**a. First Stage Effect of cell-level Instrument on Food Production time    b. First Stage Effect of cell-level Instrument on Food Expenditure**

**Figure 3.4. First Stage Effects of Cell-level Instruments on Weekly Time and Money use**

*Note:* The figure is a visual representation of the first stage regressions about the residualized cell-level instruments and weekly food production time (Figure 3.4a) and food expenditure (Figure 3.4b) for all households. The residualized y- and x-axis variables are generated by the regression of predicted weekly food production time or food expenditure on its corresponding cell-level instrument for all households with full set of the same control variables as in the IV estimations of the effect of time and money inputs on household FI. We then group the values of residualized cell-level instruments for time and money into equal sized bins, compute the mean of instruments and time (or money) residuals within each bin, and create a scatterplot of these data points. Finally, the red lines are the plotted the best linear fit lines for time and money inputs, constructed from the OLS regressions of the y-residuals on the x-residuals. The slopes of the fit lines match the first-stage regression coefficients on the cell-level instruments.

*Source:* Authors' calculations, Current Population Survey, and American Time Use Survey

**Table 3.1. Descriptive Statistics of Households by Native and Immigrant from Matched Dataset, 2003-2018**

	Single HHS			Married HHS		
	Native	Immigrant Noncitizen	Immigrant Citizen	Native	Immigrant Noncitizen	Immigrant Citizen
Weekly Food Expenditure (in 100 dollars)	0.86 (0.61)	1.04 (0.68)	1.05 (0.75)	1.38 (0.76)	1.34 (0.76)	1.44 (0.81)
Weekly Food Production Time (in 10 hours)	1.00 (0.26)	1.02 (0.37)	1.08 (0.40)	2.29 (0.39)	2.36 (0.41)	2.38 (0.39)
<b>Characteristics</b>						
Children under 18						
Yes	22.36%	40.87%	29.48%	55.49%	80.81%	61.47%
Metro or not						
Metropolitan	81.66%	96.38%	96.01%	79.65%	94.15%	95.18%
Household size	1.83 (1.26)	2.79 (1.80)	2.42 (1.70)	3.24 (1.26)	3.96 (1.36)	3.57 (1.32)
Gender for head						
Male	37.87%	46.71%	40.43%	60.94%	61.07%	64.75%
Age for head	54 (17.57)	43 (14.18)	53 (16.18)	49 (14.83)	40 (10.56)	49 (13.61)
Education for head						
High school degree-Some college	48.88%	33.31%	38.95%	41.88%	26.43%	32.04%
Associate degree	10.40%	4.52%	8.92%	11.05%	3.80%	7.15%
Bachelor's degree	18.87%	12.01%	19.95%	25.82%	17.56%	25.50%
Master's degree	8.15%	8.06%	10.21%	11.33%	12.25%	13.36%
Above Master's degree	2.73%	3.29%	4.60%	4.30%	5.79%	5.99%
Employment status for head						
Employed	56.12%	69.57%	65.31%	67.47%	70.31%	70.40%
Not in labor force	40.40%	25.25%	30.43%	29.57%	25.71%	25.50%
Armed force	0.10%	0.00%	0.14%	0.82%	0.12%	0.39%
Years of immigration for head	--	15.12 (12.05)	29.51 (14.38)	--	12.19 (9.37)	25.73 (13.05)
Race for head						
White	76.80%	74.42%	66.73%	89.73%	72.42%	63.25%
<b>Sample size</b>	<b>20265</b>	<b>1216</b>	<b>1479</b>	<b>21065</b>	<b>1657</b>	<b>1804</b>

*Note:* Standard deviations in parentheses. The food production time represents the estimated weekly time use, determined using the imputation strategy, for both single and married households.

**Table 3.2. Comparisons of Mean Weekly Food Expenditure (in 100 dollars) Among Subgroups.**

	Mean	Std. dev
<b><i>FS/Single</i></b>		
Native	0.871	0.614
Immigrant citizen	1.072	0.766
Immigrant not citizen	1.048	0.688
<b><i>FI/Single</i></b>		
Native	0.792	0.615
Immigrant citizen	0.899	0.622
Immigrant not citizen	1.018	0.661
<b><i>FS/Married</i></b>		
Native	1.396	0.756
Immigrant citizen	1.468	0.822
Immigrant not citizen	1.362	0.773
<b><i>FI/Married</i></b>		
Native	1.183	0.730
Immigrant citizen	1.194	0.632
Immigrant not citizen	1.268	0.675

*Note:* The table presents mean weekly food expenditure in units of 100 dollars, with standard deviations for different subgroups based on their FS status (FS - Food Secure, FI - Food Insecure), marital status (Single, Married), and immigration status (Native, Immigrant citizen, Immigrant not citizen).

**Table 3.3. Comparisons of Mean Weekly Food Production Time (in 10 hours) Among Subgroups.**

	Food preparation	Eating	Grocery shopping	Non-grocery shopping	Travel related food preparation	Travel related eating/drinking	Total
<b><i>FS/Single</i></b>							
Native	0.259 (0.132)	0.618 (0.164)	0.062 (0.038)	0.012 (0.009)	0.003 (0.006)	0.055 (0.044)	1.010 (0.261)
Immigrant citizen	0.300 (0.214)	0.647 (0.200)	0.066 (0.045)	0.013 (0.010)	0.003 (0.006)	0.057 (0.054)	1.085 (0.394)
Immigrant not citizen	0.294 (0.210)	0.595 (0.187)	0.057 (0.042)	0.013 (0.010)	0.003 (0.011)	0.053 (0.038)	1.015 (0.375)
<b><i>FI/Single</i></b>							
Native	0.299 (0.144)	0.530 (0.133)	0.057 (0.038)	0.011 (0.010)	0.002 (0.005)	0.041 (0.048)	0.940 (0.239)
Immigrant citizen	0.348 (0.206)	0.598 (0.254)	0.061 (0.043)	0.011 (0.007)	0.002 (0.004)	0.039 (0.022)	1.059 (0.429)
Immigrant not citizen	0.362 (0.362)	0.558 (0.168)	0.060 (0.051)	0.010 (0.007)	0.002 (0.005)	0.041 (0.033)	1.034 (0.359)
<b><i>FS/Married</i></b>							
Native	0.634 (0.205)	1.385 (0.256)	0.129 (0.048)	0.025 (0.012)	0.009 (0.039)	0.116 (0.060)	2.297 (2.297)
Immigrant citizen	0.748 (0.249)	1.364 (0.239)	0.146 (0.055)	0.025 (0.012)	0.007 (0.028)	0.097 (0.047)	2.387 (0.380)
Immigrant not citizen	0.822 (0.276)	1.294 (0.232)	0.149 (0.057)	0.024 (0.011)	0.008 (0.031)	0.084 (0.039)	2.381 (0.410)
<b><i>FI/Married</i></b>							
Native	0.706 (0.261)	1.177 (0.252)	0.123 (0.048)	0.021 (0.012)	0.008 (0.026)	0.081 (0.053)	2.115 (0.430)
Immigrant citizen	0.870 (0.319)	1.227 (0.212)	0.144 (0.053)	0.019 (0.009)	0.010 (0.041)	0.076 (0.044)	2.346 (0.424)
Immigrant not citizen	0.879 (0.292)	1.177 (0.198)	0.148 (0.066)	0.018 (0.009)	0.013 (0.078)	0.067 (0.028)	2.301 (0.418)

*Note:* This table displays the average weekly hours (in unit of 10 hours) spent on food-related activities among different subgroups categorized by FS status, marital status, and citizenship. Activities include food preparation, eating, grocery shopping, non-grocery shopping, and travel related to food. The last column represents the total time spent on all activities combined.

**Table 3.4. The Effects of Food Time and Expenditure on Household FI for All households.**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Food time in 10 hours	-0.062*** (0.004)	-0.059*** (0.004)	-0.020*** (0.003)	-0.092*** (0.006)	-0.087*** (0.006)	-0.051*** (0.006)	-0.036*** (0.006)
Food expenditure in 100 dollars	-0.022*** (0.002)	-0.023*** (0.002)	-0.033*** (0.002)	0.015* (0.009)	0.008 (0.009)	-0.159*** (0.024)	-0.226*** (0.030)
Immigrant not citizen	0.106*** (0.009)	0.104*** (0.010)	0.031*** (0.009)	0.107*** (0.009)	0.106*** (0.010)	0.018** (0.009)	0.015 (0.010)
Immigrant citizen	0.021** (0.009)	0.022** (0.008)	0.008 (0.015)	0.020** (0.009)	0.023*** (0.009)	0.006 (0.014)	0.010 (0.015)
Constant	0.240*** (0.009)	0.246*** (0.008)	0.353*** (0.021)	0.247*** (0.009)	0.260*** (0.008)	0.313*** (0.026)	0.409*** (0.075)
Observations	45,778	45,778	45,778	45,774	45,774	45,774	45,774
R-squared	0.032	0.039	0.1090	0.024	0.033	0.050	-0.018
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for food time	--	--	--	5153.50	4258.68	2909.65	3644.48
F-statistics for food expenditure	--	--	--	3532.66	3680.67	432.71	381.92

Note: Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 3.5. The Effects of Food Time and Expenditure on Household FI for Single households.**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Food time in 10 hours	-0.097*** (0.013)	-0.087*** (0.013)	-0.033*** (0.008)	-0.185*** (0.027)	-0.183*** (0.028)	-0.006 (0.022)	-0.018 (0.022)
Food expenditure in 100 dollars	-0.022*** (0.004)	-0.023*** (0.003)	-0.040*** (0.004)	0.006 (0.008)	-0.005 (0.010)	-0.186*** (0.034)	-0.265*** (0.038)
Immigrant not citizen	0.062*** (0.016)	0.062*** (0.017)	-0.010 (0.014)	0.058*** (0.015)	0.058*** (0.016)	-0.021 (0.013)	-0.018 (0.014)
Immigrant citizen	-0.012 (0.010)	-0.009 (0.010)	-0.028 (0.018)	-0.010 (0.010)	-0.007 (0.010)	-0.031* (0.016)	-0.018 (0.017)
Constant	0.277*** (0.0151)	0.280*** (0.0177)	0.285*** (0.0336)	0.340*** (0.027)	0.351*** (0.028)	0.276*** (0.035)	0.430*** (0.120)
Observations	22,050	22,050	22,050	22,049	22,049	22,049	22,049
R-squared	0.009	0.019	0.110	0.003	0.013	0.065	0.014
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for food time	--	--	--	835.51	638.49	280.62	295.89
F-statistics for food expenditure	--	--	--	545.52	636.26	86.27	77.68

*Note:* Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 3.6. The Effects of Food Time and Expenditure on Household FI for Married households**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Food time in 10 hours	-0.066*** (0.006)	-0.068*** (0.006)	-0.030*** (0.008)	-0.191*** (0.013)	-0.187*** (0.013)	-0.146*** (0.021)	-0.105*** (0.027)
Food expenditure in 100 dollars	-0.021*** (0.003)	-0.022*** (0.003)	-0.025*** (0.003)	-0.035*** (0.006)	-0.043*** (0.006)	0.023 (0.043)	0.055 (0.103)
Immigrant not citizen	0.139*** (0.009)	0.136*** (0.009)	0.074*** (0.011)	0.149*** (0.010)	0.135*** (0.009)	0.099*** (0.015)	0.104*** (0.024)
Immigrant citizen	0.051*** (0.010)	0.049*** (0.010)	0.046** (0.019)	0.064*** (0.011)	0.051*** (0.010)	0.064*** (0.019)	0.070*** (0.021)
Constant	0.247*** (0.015)	0.253*** (0.014)	0.419*** (0.027)	0.550*** (0.030)	0.533*** (0.028)	0.610*** (0.063)	0.521*** (0.150)
Observations	23,728	23,728	23,728	23,725	23,725	23,725	23,725
R-squared	0.031	0.040	0.100	-0.005	0.009	0.070	0.065
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for food time	--	--	--	1029.69	1055.87	488.65	688.74
F-statistics for food expenditure	--	--	--	1026.38	1211.94	80.20	42.30

*Note:* Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 3.7. Heterogenous Effects of Food Time and Expenditure on FI Between Immigrant and Natives for All households.**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Food time</i> ×Native	-0.071*** (0.003)	-0.068*** (0.003)	-0.028*** (0.005)	-0.106*** (0.006)	-0.102*** (0.006)	-0.064*** (0.005)	-0.050*** (0.006)
<i>Food time</i> ×Immigrant not citizen	-0.013 (0.010)	-0.012 (0.010)	0.003 (0.011)	-0.008 (0.020)	-0.005 (0.020)	-0.006 (0.017)	0.011 (0.017)
<i>Food time</i> × Immigrant citizen	-0.010 (0.010)	-0.010 (0.010)	0.014 (0.009)	-0.024** (0.012)	-0.023* (0.012)	0.005 (0.011)	0.015 (0.010)
<i>Food Expenditure</i> ×Native	-0.020*** (0.002)	-0.020*** (0.002)	-0.031*** (0.002)	0.029*** (0.009)	0.022** (0.009)	-0.130*** (0.024)	-0.194*** (0.031)
<i>Food Expenditure</i> ×Immigrant not citizen	-0.019** (0.009)	-0.020** (0.009)	-0.024** (0.010)	-0.106** (0.044)	-0.116*** (0.044)	-0.208*** (0.038)	-0.268*** (0.039)
<i>Food Expenditure</i> × Immigrant citizen	-0.038*** (0.008)	-0.039*** (0.008)	-0.048*** (0.008)	-0.038* (0.020)	-0.042** (0.020)	-0.212*** (0.029)	-0.264*** (0.029)
Immigrant not citizen	0.003 (0.025)	0.004 (0.026)	-0.032 (0.023)	0.096*** (0.029)	0.103*** (0.030)	0.014 (0.032)	0.002 (0.032)
Immigrant citizen	-0.064*** (0.017)	-0.059*** (0.017)	-0.048** (0.023)	-0.043* (0.024)	-0.036 (0.023)	-0.010 (0.031)	-0.014 (0.031)
Constant	0.251*** (0.009)	0.258*** (0.007)	0.359*** (0.021)	0.255*** (0.010)	0.268*** (0.008)	0.322*** (0.027)	0.418*** (0.075)
<i>Diff:</i>							
Food time×Immigrant not citizen- Food time×Native	0.057*** (0.011)	0.056*** (0.010)	0.031*** (0.009)	0.098*** (0.023)	0.096*** (0.023)	0.058*** (0.019)	0.061*** (0.020)
Food time×Immigrant citizen- Food time×Native	0.061***	0.059***	0.042***	0.082***	0.078***	0.069***	0.065***

Food Expenditure×Immigrant not citizen- Food Expenditure×Native	(0.010) 0.001	(0.010) 0.001	(0.007) 0.007	(0.011) -0.135***	(0.011) -0.139***	(0.011) -0.077**	(0.011) -0.074*
Food Expenditure×Immigrant citizen- Food Expenditure×Native	(0.010) -0.019**	(0.010) -0.018**	(0.0102) -0.016**	(0.048) -0.067***	(0.047) -0.065***	(0.039) -0.081***	(0.038) -0.070***
	(0.008)	(0.008)	(0.008)	(0.018)	(0.018)	(0.021)	(0.021)
Observations	45,778	45,778	45,778	45,774	45,774	45,774	45,774
R-squared	0.0336	0.0407	0.1099	0.020	0.029	0.061	0.006
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for							
“foodtime × Native”	--	--	--	.	3174.94	1709.33	2307.14
“foodtime × Imm noncitizen”	--	--	--	.	1292.08	1181.02	1097.84
“foodtime × Imm citizen”	--	--	--	.	2285.75	2389.04	2479.22
“foodexpenditure × Native”	--	--	--	.	1466.52	573.70	434.26
“foodexpenditure × Imm noncitizen”	--	--	--	.	58.67	102.44	88.00
“foodexpenditure × Imm citizen”	--	--	--	.	257.30	241.63	257.37

*Note:* Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\*  
p<0.01, \*\* p<0.05, \* p<0.1.

**Table 3.8. Heterogenous Effects of Food Time and Expenditure on FI Between Immigrant and Natives for Single households.**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Food time</i> ×Native	-0.130*** (0.012)	-0.118*** (0.012)	-0.046*** (0.008)	-0.228*** (0.031)	-0.227*** (0.032)	-0.029 (0.029)	-0.054** (0.027)
<i>Food time</i> ×Immigrant not citizen	0.040 (0.026)	0.043* (0.026)	0.004 (0.025)	0.032 (0.056)	0.020 (0.053)	0.065 (0.050)	0.086* (0.048)
<i>Food time</i> × Immigrant citizen	-0.003 (0.027)	-0.001 (0.027)	0.004* (0.024)	-0.071* (0.041)	-0.070* (0.041)	0.057* (0.029)	0.067** (0.031)
<i>Food Expenditure</i> ×Native	-0.021*** (0.004)	-0.022*** (0.003)	-0.039*** (0.004)	0.006 (0.009)	-0.006 (0.011)	-0.179*** (0.035)	-0.265*** (0.039)
<i>Food Expenditure</i> ×Immigrant not citizen	-0.014 (0.013)	-0.017 (0.012)	-0.030** (0.015)	-0.018 (0.049)	-0.034 (0.048)	-0.190*** (0.049)	-0.271*** (0.052)
<i>Food Expenditure</i> × Immigrant citizen	-0.036** (0.016)	-0.037** (0.016)	-0.051*** (0.016)	-0.037* (0.023)	-0.044* (0.023)	-0.245*** (0.040)	-0.318*** (0.044)
Immigrant not citizen	-0.118*** (0.030)	-0.108*** (0.030)	-0.068*** (0.026)	-0.180** (0.081)	-0.164** (0.078)	-0.100 (0.070)	-0.150** (0.066)
Immigrant citizen	-0.131*** (0.040)	-0.119*** (0.040)	-0.066 (0.044)	-0.131** (0.057)	-0.134** (0.058)	-0.045 (0.058)	-0.083 (0.058)
Constant	0.308*** (0.014)	0.306*** (0.017)	0.294*** (0.035)	0.383*** (0.032)	0.389*** (0.033)	0.286*** (0.039)	0.468*** (0.125)
Diff:							
Food time×Immigrant not citizen- Food time×Native	0.170*** (0.029)	0.162*** (0.029)	0.050* (0.026)	0.260*** (0.068)	0.246*** (0.007)	0.094* (0.056)	0.139** (0.055)
Food time×Immigrant citizen- Food time×Native	0.126*** (0.030)	0.118*** (0.029)	0.050* (0.026)	0.157*** (0.047)	0.156*** (0.048)	0.086* (0.045)	0.121*** (0.042)

Food Expenditure×Immigrant not citizen- Food Expenditure×Native	0.007 (0.014)	0.0051 (0.014)	0.008 (0.015)	-0.024 (0.052)	-0.028 (0.050)	-0.011 (0.036)	-0.005 (0.039)
Food Expenditure×Immigrant citizen- Food Expenditure×Native	-0.015 (0.016)	-0.015 (0.016)	-0.012 (0.017)	-0.043* (0.023)	-0.038 (0.023)	-0.066*** (0.026)	-0.053* (0.029)
Observations	22,050	22,050	22,050	22,049	22,049	22,049	22,049
R-squared	0.0111	0.0204	0.1106	0.005	0.015	0.065	0.008
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for							
“foodtime × Native”	--	--	--	.	390.39	126.38	190.07
“foodtime × Imm noncitizen”	--	--	--	.	48.26	55.39	43.55
“foodtime × Imm citizen”	--	--	--	.	36.57	46.84	53.29
“foodexpenditure × Native”	--	--	--	.	357.26	110.08	153.67
“foodexpenditure × Imm noncitizen”	--	--	--	.	56.03	83.56	80.54
“foodexpenditure × Imm citizen”	--	--	--	.	43.89	86.32	78.36

*Note:* Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.

**Table 3.9. Heterogenous Effects of Food Time and Expenditure on FI Between Immigrant and Natives for Married households.**

VARIABLES	OLS			2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Food time</i> ×Native	-0.070*** (0.006)	-0.072*** (0.007)	-0.030*** (0.008)	-0.202*** (0.015)	-0.198*** (0.015)	-0.174*** (0.026)	-0.131*** (0.035)
<i>Food time</i> ×Immigrant not citizen	-0.069*** (0.022)	-0.071*** (0.022)	-0.058*** (0.021)	-0.076 (0.071)	-0.071 (0.072)	-0.047 (0.055)	-0.022 (0.058)
<i>Food time</i> × Immigrant citizen	-0.0169 (0.026)	-0.019 (0.026)	0.008 (0.023)	-0.096 ** (0.048)	-0.094** (0.048)	-0.029 (0.588)	0.024 (0.054)
<i>Food Expenditure</i> ×Native	-0.019*** (0.003)	-0.020*** (0.003)	-0.023*** (0.003)	-0.024*** (0.006)	-0.033*** (0.006)	0.049 (0.043)	0.079 (0.108)
<i>Food Expenditure</i> ×Immigrant not citizen	-0.023** (0.010)	-0.022** (0.010)	-0.021** (0.009)	-0.270*** (0.069)	-0.274*** (0.070)	-0.081 (0.078)	-0.009 (0.139)
<i>Food Expenditure</i> × Immigrant citizen	-0.040*** (0.012)	-0.041*** (0.011)	-0.042*** (0.010)	-0.075*** (0.028)	-0.077*** (0.027)	-0.008 (0.051)	0.026 (0.109)
Immigrant not citizen	0.142*** (0.050)	0.138** (0.052)	0.139** (0.054)	0.182 (0.155)	0.159 (0.153)	-0.015 (0.123)	-0.023 (0.129)
Immigrant citizen	-0.045 (0.066)	-0.045 (0.065)	-0.012 (0.053)	-0.115 (0.127)	-0.134 (0.127)	-0.185 (0.126)	-0.208* (0.121)
Constant	0.253*** (0.015)	0.259*** (0.014)	0.417*** (0.028)	0.562*** (0.034)	0.546*** (0.032)	0.662*** (0.077)	0.572*** (0.157)
Diff:							
Food time×Immigrant not citizen- Food time×Native	0.001 (0.023)	0.001 (0.023)	-0.028 (0.022)	0.126 (0.078)	0.128 (0.078)	0.127* (0.065)	0.109 (0.068)
Food time×Immigrant citizen-	0.053** (0.023)	0.053* (0.023)	0.038 (0.022)	0.106** (0.078)	0.104** (0.078)	0.145** (0.065)	0.156*** (0.068)

Food time×Native	(0.0263)	(0.0264)	(0.0227)	(0.0508)	(0.0501)	(0.0590)	(0.0580)
Food Expenditure×Immigrant not citizen- Food Expenditure×Native	-0.004	-0.003	0.002	-0.245 ***	-0.240***	-0.130**	-0.088
Food Expenditure×Immigrant citizen- Food Expenditure×Native	(0.011)	(0.011)	(0.010)	(0.069)	(0.070)	(0.061)	(0.065)
	-0.021*	-0.021**	-0.019**	-0.051*	-0.043*	-0.056**	-0.053**
	(0.011)	(0.010)	(0.009)	(0.026)	(0.026)	(0.023)	(0.021)
Observations	23,728	23,728	23,728	23,725	23,725	23,725	23,725
R-squared	0.0312	0.0408	0.1008	-0.035	-0.021	0.049	0.045
Demographic characteristics	NO	NO	YES	NO	NO	YES	YES
Cell FE	NO	NO	NO	NO	NO	NO	YES
State FE	NO	YES	YES	NO	YES	YES	YES
Year FE	NO	YES	YES	NO	YES	YES	YES
F-statistics for							
“foodtime × Native”	--	--	--	.	507.94	255.62	347.59
“foodtime × Imm noncitizen”	--	--	--	.	56.43	78.71	83.75
“foodtime × Imm citizen”	--	--	--	.	61.72	76.00	56.17
“foodexpenditure × Native”	--	--	--	.	536.95	136.73	84.16
“foodexpenditure × Imm noncitizen”	--	--	--	.	10.04	12.72	13.41
“foodexpenditure × Imm citizen”	--	--	--	.	77.04	89.32	84.60

Note: Food production time compositions is in units of 10 hours and food expenditure is in units of 100 dollars. Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Chapter 4 Structural Food Security Dynamics in the United States

### 4.1 Introduction

FI persists as a significant challenge in the United States, affecting approximately one in every ten households annually since 1995, as reported by the United States Department of Agriculture (USDA). Recognized as a critical issue for many American households (Coleman-Jensen et al., 2018), FI, is associated with adverse economic, health, and social outcomes that subsequently impact household incomes, dietary behaviors, and future FS status (Ziliak & Gundersen, 2016). In 2022, the prevalence of FI in the United States reached 12.8% with 5.1% of households experiencing very low FS, both representing statistically significant increases from the 2021 rates of 10.2% and 3.8%, respectively (Rabbitt et al., 2023). While these alarmingly high prevalence estimates of household FS from the USDA Household FS Survey Measure (HFSSM)<sup>21</sup> capture only a momentary and static timepoint, FS is likely a dynamic condition. Households may persist in their current state or transition in and out of FS as their circumstances evolve (Grineski et al., 2018). A nuanced understanding of the dynamics of FS, particularly transitions triggered by adverse shocks, duration of insecurity, persistence, and vulnerability of specific subpopulations, is crucial for designing and evaluating effective policy interventions. In this study, we develop a

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<sup>21</sup> This official estimate is calculated from the affirmed number of self-reported responses to 18 questions per household (10 questions for households without children) that characterize households when they have difficulty meeting basic food needs, as shown in (Coleman-Jensen et al., 2018), developed by the USDA. Household FS status is assessed by counting affirmative responses to specific questions and standardizing these counts into 29 discrete scalar values ranging from 0.0 to 9.3 using a Rasch model. These values, or Rasch scores, are categorized into three levels—food secure, low FS, and very low FS—to facilitate comparisons between households with and without children.

method to examine the structural dynamics of FS through household financial assets for the long term.

Little attention has been devoted to the dynamics of FS at the household level in the United States, primarily due to the challenges of gathering long-term, reliable data. Specifically, it arises from the short duration of surveys tracking the same household and the discrete, ordinal nature of FS measure (Lee et al., 2023). Since 1995, the USDA's Household FS Survey Module (HFSSM) has been the key tool for evaluating FS, primarily in the annual December FS Supplement of the Current Population Survey (CPS-FSS), along with other longitudinal surveys such as the Panel Study of Income Dynamics (PSID), the Survey of Program Dynamics (SPD) and the Early Childhood Longitudinal Survey (ECLS). However, these surveys provide at most five observations per household, which substantially limits the analysis of long-term dynamics. The CPS-FSS data tracks the FS status of households only twice at most over 16 months. The PSID followed household FS across six intervals (1999, 2001, 2003, 2015, 2017, 2019), but a notable break was from 2003 to 2015. The SPD provides only early information on FS status from the HFSM from 1998 through 2002, rendering the dataset insufficient for assessing recent trends. The ECLS, which collected data during 1999-2007 and 2010-2016 periods, lacks comprehensive coverage of the HFSSM and is not nationally representative, focusing only on households with young children. Because of the limitations of these data, the following existing studies vary in the number of consecutive periods a household is food insecure, which is considered as experiencing persistent FI.

The existing literature on FS dynamics offers diverse estimates using these short-pan HFSSM datasets. Prevalent cohort studies examining temporal patterns suggest that persistent FI is not widespread, occurring in a small sample of households, and typically manifests as episodic

or transient phenomena. Specifically, Ryu & Bartfeld (2012) analyzed a longitudinal dataset of children from kindergarten through 8<sup>th</sup> grade, discovering that only 1% of the sample experienced FI for four consecutive years and 3% for three consecutive years. Similarly, Wilde et al. (2010), utilizing data from the 1998-2001 Survey of Program Dynamics panel, observed that a mere 1% of the U.S. population suffered from persistent FI across four or five consecutive years. In a study of two waves of the SPD (1997 and 1999), Hofferth (2004) reported that approximately 5% of households with children younger than 13 experienced persistent FI over this two-year interval. However, the prevalence of persistent FI is significantly higher among at-risk populations. Jansen et al. (2017) in a study involving a cohort of Head Start preschoolers in Michigan between 2011 and 2015, found that 54% of participants demonstrated persistent FI across two consecutive years, while 36% experienced it only once during the study period. Liese et al. (2021), examining two economically disadvantaged communities in South Carolina from 2013 to 2016, found that 37% of sampled households faced persistent FI over three years. Despite a broader understanding of the dynamics of FS, analyses based on datasets containing fewer than five observations per household may be confounded by measurement errors and transient shocks due to the dataset's short span (Dercon et al., 2007; Duffy & Zizza, 2016; Naschold & Barrett, 2011).

Additionally, analyses on the transition and persistence of FS dynamics using discrete categorical statuses from HFSM measures may not accurately capture the true dynamics and within-category variation in the severity of FI experienced by households. The broad categories of official and standardized FS status are invariant concerning the specific manifestations of food access. For example, in the cross-section dataset, households that affirm any questions but with the same number are classified as having the same status of FS by the HFSSM measure, despite the fact they may have potentially diverse and severe experiences of FI. Similarly, the FS status

for a household that affirms the same number of questions across two consecutive years will be the same over time, even if some conditions related to food access worsen during that period. So, this categorical measure estimated by the official HFSSM results in limited insights into the cross-sectional, and perhaps especially intertemporal, variation in the severity of FI for the study of household FS dynamics (Bickel et al., 2000; Lee et al., 2023).

To overcome the limitations of existing data and measures, a recent study of FS dynamics by (Lee et al., 2023) introduced a continuous measure of household FS based on food expenditures. This method, which examines the severity of FS dynamics in US households from 2001 to 2017, distinguishes between chronic and transient FI. Moving away from the categorical HFSSM data, this truly continuous measure relaxes the previously required strong assumptions necessitated by that categorical measure. It enables a more nuanced analysis of FS dynamics. Using 17 years of Panel Study of Income Dynamics (PSID) data (2001-2017), they found that while roughly two-thirds of households never experience FI, more than half of food-insecure households face chronic FI, not transient, meaning they're expected to be food insecure at every survey period. Even though they distinguish the chronic and transient components in the severity of the FI households experience, the new food expenditure-based measures still fail to distinguish between short-term, stochastic transitions—often driven by luck or unluck—and structural changes, which involve substantial shifts in asset accumulation or loss. So, we must provide a deeper nuanced view of FS dynamics by distinguishing the structural from stochastic FS dynamics.

Drawing on foundational poverty literature (Carter & Barrett, 2006; Carter & May, 2001), this study uses household asset holdings to examine FS dynamics comprehensively. While income and food expenditure are well-documented determinants of FS (Loopstra & Tarasuk, 2013), assets provide a buffer against income shocks and unforeseen expenses, thereby ensuring stable

consumption and long-term well-being (Carter & Barrett, 2006; Nam et al., 2008; Pirog et al., 2017). Additionally, accessible household financial assets are strong FS indicators (Chang et al., 2014; Guo, 2011). As Carter & Barrett (2006) put it, the asset-based FS measure will help identify the distinct sorts of experiences in the severity of FI. For instance, transitions from FS to FI may vary widely. For some households with minimal assets, transitioning to FI may merely signify a return to a typical standard of living following a temporary improvement due to favorable circumstances like participating in a food assistance program. For others, this change might result from stochastic events like unexpected setbacks in subsequent survey periods. Additionally, certain households experience a structural decline into FI due to significant asset loss from health issues or worsening economic conditions, such as the Great Recession. Extending the analysis by (Lee et al., 2023), our study dissects both stochastic and structural components of FS dynamics, thereby enhancing our understanding of the variations in the severity of FI that households experience.

This study aims to investigate the longer-run, structural nature of household FS dynamics in the United States. For this long-run analysis, we use the Panel Study of Income Dynamics (PSID) from 2001 to 2019, a nationally representative sample of approximately 21,660 survey responses from 2,166 households surveyed every two years over 19 years. This dataset is unique in its collection of detailed wealth data and the USDA's core FS module, which together enables an analysis of long-term FS trends not possible with other datasets. With this leading nationally representative panel dataset, our study makes two contributions to the literature on FS dynamics.

First, we utilize PSID data to develop a new continuous measure of asset-based household FS for long-term study. This measure, termed the Structural (asset-based) Probability of Food Security (SPFS or asset-based PFS), estimates the likelihood that a household's observed financial

asset holdings meet or exceed a threshold defined as 25% of the US Census Bureau's poverty line<sup>22</sup>. This asset threshold is a widely acknowledged criterion that covers basic necessities for three months (Haveman & Wolff, 2004). To estimate the SPFS, we adopt the econometric method outlined by Cissé & Barrett (2018), which has been utilized in various studies to examine FI across low-, middle-, and high-income countries (Knippenberg et al., 2019; Lee et al., 2023; Upton et al., 2016; Vaitla et al., 2020). Specifically, the SPFS is estimated using a conditional moments-based framework, where the conditional density of household assets is computed. Then we estimate the inverse cumulative density function for assets exceeding the minimal adequate threshold for each household and survey period and obtain the estimated household-year-specific SPFS.

Our SPFS measure is calibrated to align with the USDA Economic Research Service's (ERS) official HFSSM prevalence estimates, potentially as a complementary measure. The SPFS, derived from household financial asset holdings as a more targeted measure of liquidity constraints, correlates strongly with FS (Brewer, 2020; Chang et al., 2014; Grafova, 2011; Guo, 2011) but may not fully capture household FS resilience. Acknowledging this limitation, the construction of the SPFS incorporates responses based on financial assets and adjusts for home and vehicle ownership and household characteristics that are well-documented correlates of FS. As a result, the SPFS not only maintains a robust correlation with financial asset holdings but also reflects a meaningful relationship with household characteristics. Following Lee et al. (2023)'s methodology, we calibrate the SPFS to match the HFSSM-based FI prevalence estimates exactly. Comparative tests confirm that the SPFS is a viable alternative to the HFSSM, facilitating the exploration of structural FS dynamics that are not possible with the current measures and adaptable for longer panel studies.

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<sup>22</sup> The relevance of the U.S. Census Bureau's poverty threshold to our study stems from its foundation in minimal food cost. Its calculation will be detailed in the data part.

The second and main contribution of the study is to apply our asset-based FS measure to examine long-run U.S. household FS dynamics by distinguishing structural from stochastic dynamics from 2001 to 2019. We use two approaches from the poverty literature: the first is a spells approach, which provides the intertemporal dynamics of FS. Specifically, we focus on the dynamics of household transitions into and out of FI over time, distinguishing between structural and stochastic transitions. Additionally, we examine the spell length of FI, defined as uninterrupted intervals during which households are classified as food insecure. The second approach is the permanent approach, differentiating structural and stochastic FI based on year, household-specific histories. In addition to national estimates, we assess FS dynamics across various subgroups. Furthermore, this study also examines predictors of structural FI.

Estimates from our SPFS measure demonstrate that the vast majority of U.S. households with adequate financial assets consistently avoid FI, consistent with previous studies (Hofferth, 2004; Ryu & Bartfeld, 2012; Wilde et al., 2010). Notably, we find structural FI, primarily resulting from insufficient asset holdings, accounts for most of the observed variations in the estimated FI. To be more specific, using a transition matrix from a spell-based approach for the periods from 2001 to 2019<sup>23</sup>, we observe that 82.5% to 86.5% of the population maintain FS across consecutive survey waves. Conversely, 8.1% to 11.7% of households were persistently food insecure, and fewer than 5% transitioned into or out of FS annually with structural or stochastic mobility. Households that are both asset-poor and estimated food insecure—categorized as structurally food insecure—display significant immobility, with 65-71% remaining in FI. Furthermore, consistent with Lee et al. (2023), the duration of FI for a household correlate strongly with its difficulty in transitioning out of this state; longer spells are typically due to structural issues related to financial

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<sup>23</sup> Year 2001 is the base year for 2003.

assets, whereas stochastic shocks often trigger shorter spells. Our long-term analysis using the mean intertemporal SPFS over 19 periods confirm that most of U.S. households (78.7%) have never experienced FI, and among those affected, 84% suffer from structural FI. In contrast, Lee et al. (2023) reports that over half of all FI cases are chronic. This finding contrasts sharply with earlier cohort studies (Hernandez et al., 2014; Ryu & Bartfeld, 2012; Wilde et al., 2010) which describe FI primarily as episodic or transient, attributing this characterization to the small fraction of households that experience persistent FI. Additionally, economic downturns exhibit a significant positive correlation with the duration and the persistence of FI in the United States.

FS dynamics, as measured by the SPFS, exhibit significant variation across household characteristics. Aligning with the findings of Lee et al. (2023), this study highlights that households headed by non-white females without a high school diploma are particularly vulnerable, facing a heightened, persistent, and structural risk of severe FI. Households led by the disabled, single parents, SNAP recipients, and those without homeownership or vehicle ownership are also notably prone to structural and persistent FI due to their increased likelihood of structural immobility and downward mobility. Shocks such as the discontinuation of SNAP benefits notably lead to a substantial increase in the likelihood of newly transitioning into FI. Meanwhile, the loss of vehicle ownership or the onset of a disability is more likely to correlate with persistent FI. Collectively, race, income, participation in food assistance programs, and asset ownership (including homes and vehicles) account for over 60% of the variance in FI, particularly affecting structural FI. Further analysis reveals that factors such as educational attainment, Child Meal program participation, and unemployment shocks are more strongly linked to structural FI than to FI overall. Moreover, geographic factors significantly influence FI patterns, subject to various short-run and long-run regional shocks. The findings of this study are consistent with those of (Coleman-Jensen et al.,

2017), demonstrating that households in the South and Midwest are disproportionately affected by persistent and structural challenges.

In the following sections of this chapter, we start by summarizing the existing literature on FS and household asset holdings in Section 4.2. Next, we explain the conceptual framework for measuring FI using assets, known as SPFS, which is based on poverty research, in Section 4.3. Section 4.4 details the use of the Panel Study of Income Dynamics (PSID) data to analyze FI dynamics in the U.S. Building on recent studies in development resilience (Cissè and Barrett, 2018), we apply this new method to calculate the SPFS using household panel survey data. Following this, we describe our approach to examine household dynamics in Section 4.5. The findings are presented in Section 4.6, and the study concludes with a discussion in Section 4.7.

## **4.2 Assets as Predictors of FS: A Literature Review**

FI arises when households lack adequate access to food due to limited economic resources. Although household income is frequently employed as a proxy for consumption and significantly affects FS (Loopstra & Tarasuk, 2013), emerging research underscores the vital role of asset holdings. Assets bolster financial resilience against income fluctuations and unforeseen expenses, thus maintaining stable food consumption and promoting long-term well-being (Pirog et al., 2017). Consequently, household assets are essential for fostering self-sufficiency, securing food availability, and mitigating material deprivation (Beverly et al., 2008; Ribar & Hamrick, 2003).

Although the significance of assets in mitigating FI is well-recognized, comprehensive studies on this relationship are scarce. Historically, research shows a positive correlation between food expenditures and asset levels (Ogaki & Atkeson, 1997; Zimmerman & Carter, 2003). Investigations typically focus on tangible assets such as homeownership, vehicles, savings, and investment portfolios (Gundersen & Gruber, 2001; Guo, 2011; Ribar & Hamrick, 2003). Notably,

owning a home or vehicle is associated with reduced FI (De Marco & Thorburn, 2008; Fitzpatrick & Ver Ploeg, 2010; Furness et al., 2004). Guo (2011) found that particularly for low-income families, assets—especially savings—serve as the most reliable indicators of FS. Moreover, Chang et al. (2014) illustrated that asset-rich but liquidity-poor households are more vulnerable to FI, despite stable incomes when other variables are controlled.

Household financial assets, especially liquid assets as a household's readily available financial resources are the most effective predictors of FS, outperforming traditional metrics such as total asset value or net worth, which often overlook the specific challenges faced by financially constrained households (Brewer, 2020; Guo, 2011; West & Price, 1976). While traditional measures assess overall wealth, they fail to capture the immediate financial vulnerabilities crucial for maintaining basic living standards, including FS (Grafova, 2011). Chang et al. (2014) further validates this by employing Haveman & Wolff (2004)'s asset poverty framework, which highlights vulnerabilities that exacerbate FI. Moreover, research consistently shows that households with inadequate financial assets below the asset poverty line are more likely to suffer material hardship following income shocks (McKernan et al., 2020).

### **4.3 Conceptual Framework — Static Asset-Based FI**

Drawing upon the theoretical foundations of asset-based poverty measures, as Carter & Barrett (2006) outlined, this section introduces a conceptual framework for assessing asset-based household FS through household financial asset holdings and elucidates FS dynamics by distinguishing structural from stochastic dynamics over two periods in Figure 4.1.

In Figure 4.1, the vertical axis is the structural probability of food security (PFS) estimated by household asset holdings. The threshold probability of classifying a household as food secure is denoted by  $\underline{P}$ , enabling the differentiation between FS (above  $\underline{P}$ ) and FI (below  $\underline{P}$ ). The

horizontal axis reflects accessible financial assets to households, correlating with the likelihood of FS. The "asset FI line", represented as  $\underline{A}$ , marks the minimum asset level required for a household to meet basic living standards and ensure FS. This threshold, in conjunction with the FI line  $\underline{P}$  facilitates the distinction between structural and stochastic FI within a single period, as delineated by Carter & May (2001) and Carter & Barrett (2006). A household is deemed structurally food insecure (FI) if its asset holdings fall below  $\underline{A}$  and its anticipated or estimated SPFS is also below  $\underline{P}$  (for example, a household observed at point  $\hat{P}(A')$  in Figure 4.1). Conversely, a household is considered to experience stochastic FI if its assets exceed the asset line  $\underline{A}$  but the actual estimated SPFS unexpectedly drops below  $\underline{P}$  (illustrated by point B in Figure 4.1). Similarly, households can be categorized as structurally food secure (FS) ( $\hat{P}(A'')$  in Figure 4.1) or stochastically FS (point C in Figure 4.1), depending on their asset holdings and the realized PFS.

Figure 4.1 also illustrates the decomposition of FI transitions into structural and stochastic events. Although the actual FI threshold  $\underline{P}$  and asset FI line  $\underline{A}$  may vary over time, for simplicity, we assume they are constant and static. The dashed curve,  $\tilde{P}(A)$ , represents the dynamic relationship between FI and asset levels, which may shift from  $\hat{P}(A)$  over time due to factors like price fluctuations or technological advancements affecting productivity. For instance, a transition from FS to insecurity over two periods can occur through either structural or stochastic mechanisms. A transition for a household from point C to  $\hat{P}(A')$  in Figure 4.1 exemplifies a stochastic transition back to its expected status if it crosses below the FI threshold ( $\underline{P}$ ) with consistently low financial assets. Conversely, a structural transition is exemplified by a household moving from  $\hat{P}(A'')$  to  $\hat{P}(A')$ , indicating a shift from FS to insecurity due to asset depletion. Likewise, transitions from FI to security, crossing above the threshold  $\underline{P}$ , can be classified as either stochastic or structural, depending on asset holdings.

Asset-based FI provides a framework for categorizing transitions between food secure and insecure statuses as either structural or stochastic. This approach underscores structural FI as a condition where households fall below the FI threshold due to consistently low or, on average, insufficient assets. Unlike traditional FS classifications, this asset-based perspective emphasizes the impact of inadequate financial assets on the mobility of households' FS statuses.

#### **4.4 Data**

To examine the dynamics of FI in the United States using asset-based measures, this study employs data from the Panel Study of Income Dynamics (PSID) from 2001 to 2019 (Panel Study of Income Dynamics, 2023). Initiated in 1968, the PSID has provided longitudinal data on American families, transitioning from annual to biennial surveys post-1997. Since 1984, the survey has meticulously collected detailed household wealth data, capturing both reported and imputed values across various asset components. This wealth data, collected biennially over the last two decades, forms the bedrock for constructing a longitudinal panel dataset pivotal for our asset-based FI analysis. Additionally, the PSID's integration of the USDA's core food security module during the 1999-2003 and 2015-2017 waves positions it as a critical tool for validating our new asset-based measure against the USDA's official FS metrics derived from CPS data. This unique combination of longitudinal wealth data and FS metrics enables a comprehensive analysis of FI dynamics.

As a first step in our exploration of this dataset, this study only includes two core independent samples in PSID: an over-sample of low-income families from the study of Survey of Economic Opportunity (the "SEO sample") and a nationally representative sample designed by the Survey Research Center (the "SRC sample"). These combined two samples constituting a national probability sample of U.S. families account for 93% of the PSID sample. We did not include the new immigrant refresher sample of PSID added in 1990, 1997, and 2017, because its

representativeness concerning FS status has not yet been validated (Lee et al., 2023; Tiehen et al., 2020). To create the longitudinal panel data using the structure of PSID, our study limits its dataset to families in which the head of the household's identity did not vary throughout the period by omitting attrited and split-of units. Finally, we keep a consistent dataset of 21,660 observations from 2,166 families monitored across ten waves between 2001 and 2019. We report the summary statistics of all used variables in Table 4.1, which are consistent with the summary statistics of Lee et al. (2023). To prevent bias due to PSID's complex design (stratification, clustering, weighting), all reported parameter estimates and standard errors are robust and adjusted using the primary sampling unit method as recommended by Heeringa et al. (2011).

The household financial assets in the wealth module are the key information in our study of FI dynamics. Chang et al. (2014) underscores the significance of non-pension financial assets, delineating them as a household's immediately accessible financial reserves. These reserves are crucial for sustaining consumption and ensuring FS when adverse shocks disrupt regular income streams. We construct our financial asset measure using a simple summation of all non-pension financial assets on any given year, including liquid assets, equity in stock, mutual funds, investment trusts, other liquid assets such as bond funds, cash value in life insurance, valuable collections for investment purposes, and rights in a trust or estate. The inherent shortcoming of this wealth data is its pronounced inequality, particularly manifest in the distribution's tails. This disparity often results in estimations being disproportionately skewed by outlier observations. To mitigate this bias and enhance the robustness of our analysis, we exclude the top and bottom one percent of financial asset outliers, as suggested by the literature (Pfeffer et al., 2016).

After getting our financial asset measure, we use the concept of asset poverty to define the recommended minimal asset threshold to meet basic living standards and ensure FS. A candidate

threshold for a static asset line, illustrated in Figure 4.1 of Section III, is 25% of the US Census Bureau’s poverty line, designed to cover basic necessities for three months. This echoes a widely referenced criterion in the asset-based poverty literature (Haveman & Wolff, 2004). The relevance of the U.S. Census Bureau’s poverty threshold to our study stems from its foundation in minimal food cost<sup>24</sup>, making our chosen asset threshold—25% of the poverty line—a symbolic representation of the financial resources needed for a household to support its basic food needs over a quarter-year, thus directly linking to FS objectives. This threshold also aligns with benchmarks used by policymakers in setting Supplemental Nutrition Assistance Program (SNAP) eligibility criteria, emphasizing its practical relevance for assessing household FS (Ratcliffe et al., 2016). In applying this threshold to our analysis, we utilize the PSID data, specifically a variable labeled “Census Needs Standard” derived from the Census Bureau’s documentation, which reflects annual household poverty thresholds adjusted for family size, the number of children under 18, and the age of the household head, thereby allowing us to establish a nuanced, household-year-specific asset threshold.

Figure 4.2 depicts the distribution of households’ FS status, categorized by economic conditions—namely, income poverty, asset poverty, both, or neither. This distribution is visualized through a histogram with two main dimensions: the x-axis distinguishes between food insecure and food secure households, while the y-axis quantifies the proportion (as a percentage) of households in each economic category. Within the categories of FI and security, the histogram further segregates households based on their economic status, displaying four distinct groups: 1) those not classified as income or asset-poor, 2) those identified as income-poor but not asset-poor,

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<sup>24</sup> It is calculated based on the economy food budget, specifically three times the cost of a minimum food diet from 1963 (adjusted for today's prices).  
[https://www.census.gov/content/dam/Census/library/visualizations/2021/demo/poverty\\_measure-how\\_print.pdf](https://www.census.gov/content/dam/Census/library/visualizations/2021/demo/poverty_measure-how_print.pdf)

3) those considered asset poor but not income poor, and 4) those recognized as both income and asset poor. The data reveal that 36.95% of food-insecure households fall below the income poverty threshold, encompassing income-poor (regardless of asset status) households. Conversely, nearly 90.37% of food-insecure households fall below the asset poverty threshold, including those asset-poor regardless of income status. In contrast, 93.53% of food-secure households are above the income poverty threshold, whereas 38.11% are still below the asset poverty threshold. This pattern, where the asset poverty line includes a larger proportion of food-insecure households even among those who are not income poor, suggests that assets, which provide a buffer against economic shocks, offer a more comprehensive measure of food insecurity.

## **4.5 Empirical Model and Methods**

### **4.5.1 Construct the Structural Probability of Food Security (SPFS)**

In the theoretical framework outlined in Section III, we propose establishing a relationship between household assets and the likelihood of FI, aiming to predict the probability of FS based on household financial assets holdings. Nevertheless, the USDA's core food security module within the PSID dataset is constrained by its sample coverage, limited to 1999-2003 and 2015-2017. This discontinuity restricts our ability to conduct a direct regression analysis of FS status against asset holding across the entire dataset. To devise our new asset-based structural probability of food security (SPFS), we employ an econometric approach for estimating resilience at the individual or household level from panel data, as introduced by Cissé & Barrett, 2018; Lee et al., 2023; Upton et al., 2016.

Intuitively, this approach utilizes a conditional moments-based framework, enabling the estimation of the expected probability of a household's FS, given that its asset holdings are sufficient to provide a buffer against FI. Specifically, this technique models the household's FS,

as inferred from asset holdings, to behave as a random variable with its distribution across periods. This is crucial for detecting wealth-dependent, heterogeneous responses to shocks, acknowledging the nonlinear durability of such shocks, accounting for heteroscedasticity and the variability of higher-order central moments in path dynamics. The procedure for constructing the SPFS involves a series of conditional moment functions, detailed as follows:

First, for household  $i$ , in state  $j$  and year  $t$ , we parametrically estimate the conditional mean of the FS indicator, household non-pension financial asset in period  $t$  ( $A_{ijt}$ ), on a polynomial function of lagged values in prior period ( $A_{ijt-1}$ ) and a vector of household level covariates ( $X_{ijt}$ ), including shocks directly experienced by household  $i$  or risks to which household  $i$  is exposed:

$$A_{ijt} = \sum_{\gamma=1}^n \beta_{M\gamma} A_{ijt-1}^{\gamma} + \delta_M X_{ijt-1} + \theta_{Mj} + \eta_{Mt} + \mu_{Mijt} \quad (4.1)$$

In Equation (4.1),  $A_{ijt}$  is the aggregated annual household per capital non-pension financial asset for household  $i$ , in state  $j$  and year  $t$ . It is constructed using annual household non-pension financial divided by family size. The variable  $X_{ijt}$  encompasses various household characteristics and dynamics. It incorporates household demographics (age and its square for lifecycle effects, gender, race, education of the head), employment and disability status, family size, child proportion, food assistance (SNAP, WIC, Child Meal, Elderly Meal) participation, asset ownership (housing, vehicle), and non-transfer income. Additionally, the model accounts for changes since the last survey in key areas: employment and marital status, disability status, SNAP participation, and changes in home and vehicle ownership.  $\theta_j$  and  $\eta_t$  are the year and state fixed effects to absorb time and spatially invariant unobservable variables. The  $M$  subscript helps distinguish the parameters from the conditional mean.

The predicted dependent variable  $\hat{A}_{ijt}$  is the conditional mean of household per capita non-pension financial assets. We assume the assets follow the Gamma distribution because it is continuous and non-negative<sup>25</sup>. We therefore estimate a generalized linear model (GLM) logit link regression for Equation (4.1). We use the Akaike information criterion (AIC) and t-tests on the equality of means between the predicted values of the higher-order specifications to decide the order of the polynomial function, reported in Table 4.2. By testing various polynomial specifications in Table 4.2, we observe a decline in the AIC value with increasing polynomial order, indicating that a specification of a higher order might be preferable. However, the estimated coefficients of the higher-order lagged terms of well-being are effectively zero, suggesting a minimal impact on the model. Concurrently, a t-test examining the mean equality of predicted values from higher-order specifications reveals that differences become statistically non-significant at and beyond the sixth order. Thus, this analysis supports selecting the sixth-order polynomial function of  $A_{ijt-1}$  as the optimal choice.

Next, to estimate the conditional variance ( $\hat{\sigma}_{ijt}^2$ ) of household financial assets, we utilize the residuals derived from the conditional mean Equation (4.1). Given the assumption that the random error term  $\mu_{Mijt}$  in Equation (4.1) has a zero mean ( $E[\mu_{ijt}] = 0$ ), the expected value of squared residuals,  $E[\mu_{ijt}^2]$ , corresponds to the conditional variance. Consequently, by regressing these squared residuals from the conditional mean equation against the covariates, we obtain the regression model for the conditional variance of household financial assets. This model uses the same basic specification outlined in Equation (4.1):

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<sup>25</sup> The mean of the outcome differs significantly from its variance in our sample, so we do not use a Poisson distribution, which requires the mean equals the variance.

$$\hat{\sigma}_{ijt}^2 = (\hat{\mu}_{ijt} - E[\hat{\mu}_{ijt}])^2 = \hat{\mu}_{ijt}^2 = \sum_{\gamma=1}^n \beta_{v_\gamma} A_{ijt-1}^\gamma + \delta_v X_{ijt} + \theta_{vj} + \eta_{vt} + \mu_{vijt} \quad (4.2)$$

Where  $V$  denotes conditional variance. We apply the same generalized linear model (GLM) with a logit link function as specified in Equation (4.1) to Equation (4.2).

Assuming household financial asset  $A_{ijt} \sim \text{Gamma}(\alpha, \beta)$ , we calibrate the parameters of the household-and-period-specific cumulative density function (CDF)  $F(\cdot)$  using the predicted conditional moments such that  $(\alpha = \frac{\hat{A}_{ijt}^2}{\hat{\sigma}_{ijt}^2}; \beta = \frac{\hat{\sigma}_{ijt}^2}{\hat{A}_{ijt}})$ .

Finally, we can estimate SPFS using household assets' complementary cumulative density function (CCDF)<sup>26</sup>, the inverse of CDF. For the survey time series defined by  $t \geq 0$ , we can define a household's FS resilience as the estimated complementary cumulative probability above the asset threshold based on the sequence of estimated probabilities  $(\hat{\rho}_{ijt})_{t=1}^T$ :

$$\hat{\rho}_{ijt} = P(A_{ijt} \geq \underline{A}_{ijt} | A_{ijt-1}, X_{ijt}) = \bar{F}(X_{ijt}, A_{ijt-1} | \underline{A}_{ijt}) = 1 - F(X_{ijt}, A_{ijt-1} | \underline{A}_{ijt}) \in [0, 1] \quad (4.3)$$

Where  $F(\cdot)$  is the assumed CDF and  $\bar{F}(\cdot)$  is the corresponding CCDF. The SPFS as defined by  $\rho$  is our asset-based Household FS Survey Measure representing the probability that household  $i$ 's non-pension financial assets in period ( $t$ ) is equal or above the asset FI thresholds.  $\underline{A}_{ijt}$  is the static asset threshold illustrated in Figure 4.1. We adopt asset thresholds based on a household-year-specific calculation, which equates to 25% of the annual poverty line as reported by the US Census Bureau. This threshold is designed to cover basic needs for three months in our FS analysis, with the calculation methodology detailed in the data section of this paper.

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<sup>26</sup> The Complementary Cumulative Distribution Function (CCDF) is formally defined as the probability that a random variable  $X$  assumes a value greater than a specific threshold  $x$ . This definition underpins its application in forecasting SPFS by household asset holdings.

The SPFS measure can categorize households as food secure or insecure using a minimum threshold probability,  $\underline{P}_t$ , an externally defined cut-off. Following Lee et al. (2023), we use the USDA's annual FI prevalence to set this threshold, aligning the PFS cutoff with the USDA's reported rates. For instance, if 12% of households are reported as food insecure by the USDA in year  $t$ , the 12<sup>th</sup> percentile SPFS in the weighted sample becomes the threshold  $\underline{P}_t$  for that year. This approach ensures our FI prevalence estimates align with the official USDA figures, adhering to the Household FS Survey Measure (HFSSM).

We further employ a series of crucial tests, as suggested by Boateng et al. (2018) and Lee et al. (2023), to validate the SPFS measure as a representative measure of FS. Our analysis includes: (1) comparing the distribution of SPFS and official HFSSM measure, (2) examining the concordance in household classifications as food secure or insecure by these measures, (3) assessing the correlations between SPFS and the official HFSSM measures through estimation of rank correlations and regression of SPFS on HFSSM, and (4) evaluating whether the associations between SPFS or HFSSM and household characteristics exhibit similarity.

#### **4.5.2 Structural FS dynamics**

Using the static asset threshold,  $\underline{A}_{ijt}$ , and the cut-off probability of FS (SPFS),  $\underline{P}_t$ , as outlined by Carter & May (2001), we commence our analysis by categorizing household  $i$  in period  $t$  based on the estimated FS status by SPFS, delineating between structural and stochastic components. This classification framework is depicted in Figure 4.1, which presents the conceptual underpinnings of our approach.

- 1) Structural FI: Identified by its possession of financial assets insufficient to cover the basic needs for a minimum of three months (i.e., below the static asset threshold), coupled with a SPFS indicating a lack of resilience to achieve FS ( $A_{ijt} < \underline{A_{ijt}}$  And  $SPFS < \underline{P_t}$ ).
- 2) Stochastical FI: Characterized by adequate financial assets to meet the minimum three-month basic needs yet encountering FI due to unfavorable circumstances ( $A_{ijt} \geq \underline{A_{ijt}}$  and  $SPFS < \underline{P_t}$ ).
- 3) Structural FS: Defined by financial assets exceeding the static threshold and a SPFS measure above the FS cut-off, indicating resilience ( $A_{ijt} \geq \underline{A_{ijt}}$  and  $SPFS \geq \underline{P_t}$ );
- 4) Stochastical FS: Describes a household achieving the estimated FS following a positive shock, despite its assets being below the FI threshold for a single period ( $A_{ijt} < \underline{A_{ijt}}$  and  $SPFS \geq \underline{P_t}$ ).

### ***Spell-based approach***

After identifying each household's asset-based FS status from 2001 to 2019, we first adopt the spell-based approach borrowing from poverty literature (Jo Bane & Ellwood, 1983) to study household-level dynamics. The spell-based approach explicitly provides the intertemporal dynamics of FI, focusing on its transitions and durations.

First, we aim to elucidate the dynamics of household transitions into and out of FI over time, distinguishing between structural and stochastic transitions, as depicted in Figure 4.3. This approach diverges from the conventional classifications found in the literature (Lee et al., 2023; Ziliak & Gundersen, 2016), which categorize transitions as remaining food insecure across two successive waves (Still FI); transitioning from FI to FS (New FS); moving from FS to FI (New FI); and remaining FS across both waves (Still FS). Instead, we adopt the theoretical framework

proposed by Carter & May (2001), which allows for a more nuanced analysis of both stochastic and structural transitions.

We classify a household as stochastically upwardly mobile depending on the estimated structural FS statuses by SPFS. A household is deemed stochastically upwardly mobile if it is estimated to transition from being food insecure in year  $t-1$  to food secure in year  $t$ , or if it was food insecure and becomes stochastically food secure in year  $t$ . Conversely, a household is deemed stochastically downwardly mobile if it moves from food secure to stochastically food insecure, or from stochastically food secure to food insecure, showcasing a deterioration in FS status due to stochastic elements. A household remains stochastically immobile if it was stochastically food insecure in both consecutive periods. Lastly, households whose mobility or immobility cannot be solely attributed to stochastic factors fall into the structurally mobile (or immobile) category, suggesting that deeper, structural issues shape their FS status.

Using the transition probability matrix, we derive the joint distributions of the specified categories, as illustrated in Figure 4.3, across periods for the full sample and for distinct subpopulations. This provides a nuanced decomposition of these distributions into components attributable to structural and stochastic mobilities. Furthermore, we quantify the persistence rate of FI, defined as the conditional probability that a household experiencing FI in one survey wave will continue to do so in the subsequent wave. Complementarily, the entry rate represents the conditional probability that a household transitions to a state of FI in the next wave, given its initial state of FS. Consequently, the exit rate is calculated as one minus the persistence rate. An analytical

comparison is also conducted between the estimated persistence and entry rates<sup>27</sup>, distinguishing between stochastic and structural FI at the initial period.

In the subsequent phase of our analysis, we identify spells of FI, defined as uninterrupted intervals during which households are classified as food insecure. We proceed to characterize the distribution of the lengths of these FI spells, in conjunction with an assessment of conditional persistence—specifically, the probability that a household will continue to be food insecure, given the duration of its current spells of FI. Furthermore, an exploration into the distribution of spell lengths, as delineated by asset holdings and the estimated FS status as determined by SPFS, is conducted within each delineated spell length. This investigation is designed to shed light on the role of structural determinants, focusing on household asset holdings, in influencing the duration and the persistence of FI spells.

### ***Permanent approach***

Compared to the spell approach, the permanent approach—also known as the component approach and representing the second method for analyzing household-level FS dynamics—distinguishes between the structural and stochastic components. These components are estimated using the mean intertemporal SPFS. It is less vulnerable to measurement error and more flexible with data truncation and survey intervals (Lawson & McKay, 2002) than the estimates from the spell-based approach. Moreover, it is feasible to use panel data to identify those unlikely to escape economic hardship like poverty and FI permanently over a significant period based on their relevant characteristics. Following the permanent approach from Jalan & Ravallion (1998, 2000), structural

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<sup>27</sup> The persistence rate for stochastic (alternatively, structural) FI quantifies the conditional probability that a household, identified as being stochastically (or structurally) food insecure in one survey wave, will continue to exhibit FI in the subsequent survey wave. Similarly, the entry rate for stochastic (or structural) FI is defined as the conditional probability that a household, initially food secure, transitions into a state of stochastic (or structural) FI in the following survey period.

FI is identified by mean intertemporal (the average over the observed periods) SPFS and stochastic FI is identified by deviations from the household specific intertemporal mean.

First, we define the total FI for household  $i$  using the observed sequence of SPFS measures based on the static asset line, denoted as  $TFI_i$ . Then we denote  $SFI_i$  as its structural component. So, the difference between  $TFI_i$  and  $SFI_i$  is the stochastic component:

$$TFI_i(\alpha, SPFS_{i1}, \dots, SPFS_{it}) = \frac{1}{T} \sum_{t=1}^T \left( 1 - \frac{\min(SPFS_{it}, \underline{P}_t)}{\underline{P}_t} \right)^\alpha \quad (4.4)$$

$$SFI_i(\alpha, SPFS_{i1}, \dots, SPFS_{it}) = \left( 1 - \min \left[ 1, \frac{\sum_{t=1}^T SPFS_{it}}{\sum_{t=1}^T \underline{P}_t} \right] \right)^\alpha \quad (4.5)$$

Where  $TFI_i$ , the total FI over the period for each household, is the weighted sum of TFI over the component sub-periods. When  $SFI_i > 0$ , this indicates the average SPFS (or the average probability to reach the static asset threshold over time) is below the FS threshold ( $\underline{P}_t$ ). Therefore, the household  $i$  could be viewed as structurally food insecure. It also means that this household is expected to be structurally (asset-based) food insecure in any observed period or the full period. Conversely,  $SFI_i = 0$  suggests a household is not structurally food insecure.

$TFI_i$  and  $SFI_i$  are created based on the Foster-Greer-Thorbecke (FGT) poverty measure. There is an important modification that they are aggregated over time within households, whereas the usual FGT measure is aggregated over households within a specific time period. The aversion parameter  $\alpha$ , usually used in FGT style measure, reflects the weight placed on the severity of gaps between asset-based  $SPFS_{it}$  and  $\underline{P}_t$  with the value of 0, 1, 2. The estimated structural FI with  $\alpha = 0$  indicates the frequency (headcount ratio) of structural FI. Higher order measures with  $\alpha = 1, 2$  represent the gap of FI and the severity of such shortfalls for each household. Different values of help explain how the changes in the parameter under this component approach affect this aggregate FI dynamics estimation.

Under this permanent approach measure of  $TFI_i$  and  $SFI_i$ , we can distinguish stochastic and structural FI households from FI households by mean intertemporal SPFS and categorize them into four categories. First, if  $SFI_i > 0$  and  $SPFS_{it} < \underline{P}_t \forall t$ , a household is structurally persistent food insecure. If  $SFI_i > 0$  and  $\exists t$  such that  $SPFS_{it} \geq \underline{P}_t$ , the household is structurally but not persistently food insecure. The third one is stochastically food insecure households, i.e.,  $SFI_i = 0$  and  $\exists t$  such that  $SPFS_{it} < \underline{P}_t$ . Finally, households are never food insecure or persistently food secure if  $TFI_i = SFI_i = 0$ .

On the 19-year, household-specific histories of PSID panel data, this permanent approach helps us distinguish structurally food insecure households whose mean intertemporal assets predict a standard of living to be food insecure from households with stochastically food insecure whose circumstance, on average, predicts a food secure future standard living. We then conducted a correlation analysis to explore the relationship between household characteristics and FS dynamics, measured by TFI and SFI. We then compared coefficients to evaluate the different relationships of these predictors to TFI and SFI. Finally, we utilize the Shapley decomposition method to identify the sources of variation in these measures, TFI and SFI.

## 4.6 Results

### 4.6.1 The SPFS Measure & Validation

With the PSID household panel survey data from 2001-2019, we first report the resilience measurement of household-period-specific FI probability, SPFS, using a system of conditional moment functions of household assets illustrated in Equation (4.1)-(4.3).

Columns (1) and (2) of Table 4.3 present the marginal effects estimates for household assets' mean and variance equations using generalized linear model (GLM) logit link regression.

One unit increase of lagged asset holding (in the ten-thousands) positively correlates with an average increase of 4.489 (in the ten-thousands) in household financial assets and a 168.838 higher variance. Notably, the dynamics of household asset holdings exhibit significant nonlinearity, as indicated by the adoption of a sixth-order polynomial function for lagged assets in Table 4.2, which we have discussed it in Section 4.5 empirical model and methods. Controlling for other factors, the data show that households led by males, those with higher-educated heads (at least some college), employed household heads, higher income, smaller family sizes, and homeownership are statistically linked with greater financial asset holdings. Furthermore, households receiving benefits from SNAP, Child Meal, or Elderly Meal programs tend to have higher financial assets. Conversely, households experiencing a cessation of SNAP are associated with reduced asset holdings. Additionally, the covariates correlated with the predicted mean value of financial assets are significantly associated with larger conditional variance. The analysis also indicates reduced variance associated with WIC participation and shocks such as unemployment or loss of vehicle ownership.

Using conditional mean and variance estimates derived from columns (1) and (2) in Table 4.3, we then calculate the probability density function (pdf) of each household's financial assets using a gamma distribution for each period and estimate each household's probability of achieving the static minimum asset holding ( $\underline{A_{ijt}}$ ) for each period. The resulting probabilities (SPFS), specific to each household and period, range between 0 and 1. These SPFS scores are then regressed on the same regressors (see Table 4.3, column (3)), uncovering a non-linear link between past asset holdings and FS probabilities. Specifically, Figure 4.4 depicts a rapid increase in FS probabilities with increases in non-pension financial assets per capita up to a point beyond which the increase plateaus or slightly decreases. Statistically, the estimated higher probabilities of FS

(SPFS) correlate with households led by older, white, male, or more educated individuals and those with fewer members but more children, owning homes and vehicles, participating in food assistance programs, or not facing recent adverse events (e.g., losing SNAP benefits or vehicle ownership). Contrary to expectations (Ziliak & Gundersen, 2016), households experiencing unemployment, divorce, or loss of homeownership also showed higher estimated FS probabilities.

Although these associations from GLM models indicate a sensible relationship between SPFS and household characteristics, it is imperative to ascertain the alignment of the SPFS measure with the official USDA’s HFSSM measure. To facilitate this comparison, we adjust the HFSSM scale to range from 0 to 1, with higher values indicating greater FS<sup>28</sup>.

We conduct validity tests proposed by Boateng et al. (2018) and Lee et al. (2023). First, this study contrasts SPFS and HFSSM distribution patterns and examines the concordance in household classifications as food secure or insecure by these measures. Figure 4.5 illustrates the density distributions of SPFS and HFSM, revealing a higher concentration of observations within the lower PFS range (0-0.6), predominantly among households identified as food insecure. This pattern suggests that, due to its sensitivity to asset ownership, the SPFS might more accurately capture variations in FI compared to the HFSSM. Regarding classification accuracy, the analysis indicates that 1.93% of households are deemed food secure by our SPFS measure but food insecure by the HFSSM, while 8.78% are categorized as food insecure by SPFS yet food secure by HFSSM. In contrast, Lee et al. (2023) reports that 3.2% of households are classified as food secure based on their food expenditure-based measure but food insecure by HFSSM, and 10.0% are classified

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<sup>28</sup>  $HFSSM_{\text{rescaled}} = \frac{9.3 - HFSSM_{\text{scale score}}}{9.3}$  where  $HFSSM_{\text{scale score}}$  denotes the household FS scale score ( $fs_{\text{scale}}$ ) that varies from 0 to 9.3, as reported in the USDA Household FS Survey Measure.

as food insecure by their measure yet food secure by HFSSM. Overall, our asset based SPFS demonstrates greater alignment with the HFSSM measure in classifying FS.

Second, we investigate the existence of a statistically significant and positive correlation between the HFSSM and SPFS. Initially, we utilize two non-parametric rank correlation coefficients: Kendall's tau and Spearman's rho. These analyses produce correlation coefficients of 0.32 for tau and 0.40 for rho, both statistically significant and different from zero. Hence, we reject the null hypothesis of no correlation between SPFS and HFSSM. The moderate correlations observed may partly stem from the methodological differences in constructing these measures: the HFSSM is derived from a Rasch model applying categorical variables, whereas the SPFS is a continuous probability measure. Subsequently, the HFSSM scale's regression on SPFS, detailed in Table 4.4, corroborates the statistically significant positive association between HFSSM and SPFS. This conclusion holds under both linear and quadratic model specifications and remains robust after adjusting for state and year-fixed effects, notwithstanding the positive skewness inherent in both measures.

Finally, we compare the correlations between household characteristics and FS, as measured by the Household FS Module (HFSSM) scale and SPFS. Our analysis uses continuous representations of these measures in columns (1) and (2) and binary representations in columns (3) and (4). Most covariates display consistent directional estimates, albeit with magnitude and statistical significance variations. Statistically significant covariates associated with both FSSS and SPFS—and exhibiting identical directional relationships—include high school completion, household income, disability status, the proportion of children in the household, participation in food stamp/SNAP programs, homeownership, and experiencing housing instability. Conversely, certain variables, such as racial status, marital status, gender, education level beyond high school,

family size, receipt of WIC benefits, receipt of elderly meal benefits, and housing tenure status, demonstrate significant associations with SPFS but not with HFSSM. Nonetheless, these associations align with prior research findings (Coleman-Jensen et al., 2018; Liese et al., 2021; Ziliak & Gundersen, 2016).

The significant positive correlation between the SPFS measure and the USDA's Household FS Module (HFSSM) scale, alongside the widespread alignment in their associations with household characteristics, indicates that the SPFS serves as a valuable complement of FS measure to the USDA's measure in the United States.

#### **4.6.2 Structural FS Dynamics Based on Static Asset Threshold.**

##### ***FI Prevalence Predicted by SPFS***

We first show the distribution of FS status and structural FS status estimated by our SPFS in Figure 4.6. In Figure 4.6a, our findings reveal that the prevalence rates of FI, as gauged by the SPFS, align with the annual reports on prevalence issued by the USDA (Rabbitt et al., 2023). Specifically, during periods of economic stability, such as 2001-2005 and 2015-2019, approximately 88.2% to 89.5% of U.S. households were found to be food secure, leaving an estimated 10.5% to 11.8% experiencing FI at some point within these years. However, the incidence of FI rose to between 14.3% and 14.7% during and following the Great Recession, highlighting the impact of economic cycle on household FS.

Figure 4.6b categorizes the estimated FS into structural and stochastic components. Structurally food secure households, making up 62.3%-69.5% of the food secure, have sufficient financial assets to maintain FS, covering 72%-77% of overall FS prevalence. Stochastically food-secure households, accounting for 19.2%-25.4%, are temporarily food secure due to positive shocks despite being asset-poor. On the other hand, 8.9%-13% of the population are structurally

food insecure, lacking adequate financial assets for FS and representing over 85% of all food-insecure cases. This finding is further substantiated by the descriptive results presented in Figure 4.2, where nearly 92% of these structurally food-insecure households are shown to fall below the asset poverty threshold. The remaining 15% of food-insecure households are stochastically insecure, facing adverse shocks despite being not asset-poor.

Interestingly, an examination of prevalence rates over time reveals that the rate of structural FS remains relatively stable, even during the Great Recession (GR) period. Conversely, the prevalence of stochastically food-secure households, characterized by insufficient financial assets, is significantly impacted by economic downturns, experiencing a decline of approximately 3%-4.5% during the GR period. As the economy recovers post-GR, households with the recovery of income are more likely to slowly accumulate assets above the threshold required for FS (Mitchell, 2020), leading to an increase in the prevalence of structural FS and a decrease in stochastic FS. During the economic downturn associated with the GR (2007-2013), the prevalence of structural FI rose from 9.7% to 13.0%, a trend that persisted until 2013. This pattern suggests that the GR led to a significant loss of financial assets (McKernan et al., 2014), contributing to heightened structural FI. Concurrently, certain households, initially possessing adequate assets but detrimentally impacted by negative economic shocks during the Great Recession (GR), regained FS.

In summary, our estimates of the prevalence of FS and insecurity, utilizing the SPFS measure, reveal that a significant portion of U.S. households achieve FS supported by adequate asset holdings. Conversely, the primary proportion of FI is structural, rooted in inadequate financial assets. While structural FS—characterized by sufficient financial assets and FS—exhibits resilience over time, including during the Great Recession, this period also witnessed a marked

increase in structural FI. Additionally, there were fluctuations in stochastic FS and insecurity, underscoring the intricate influence of economic conditions on the various dimensions of FS.

### ***Structural FS Dynamics by Spells approach***

#### *i. Transition Matrix of FS Status Across Two Waves*

Utilizing the transition matrix from the spells approach in Figure 4.3, Table 4.6 offers a detailed examination of transition in FS status across two successive waves within the U.S. population, disaggregated by annual data and household characteristics. This analysis categorizes households into four distinct groups: those remain food secure (Still FS), those transitioning from food insecure to secure (New FS), those persisting in FI (Still FI), and those newly experiencing FI (New FI) between the two observation periods. The proportions of these joint distributions are detailed in columns (2), (3), (6), and (11), respectively. Moreover, we further dissect these transitions into structural and stochastic components, with their respective proportions detailed in columns (4)–(5) for New FS, (7)–(10) for Still FI, and (12)–(13) for New FI.

Table 4.6 illustrates that a significant majority of the population, between 82.6% and 86.8%, maintained their FS across two consecutive waves from 2003 to 2019. Concurrently, a smaller segment of the population exhibited fluctuations in FS status, underscoring transitions both into and out of FS or staying in FI. Specifically, it is estimated that 8.8% to 11.7% of U.S. households consistently remained food insecure, whereas fewer than 5% of households transitioned into newly food secure or newly food insecure statuses annually.

Figure 4.7a depicts these transition trends across time, where the top of each bar aligns with FI prevalence rates reported by the USDA and those estimated by our SPFS measure. Notably, households that remained FI from one wave to the next accounted for approximately 61-80% of the FI rate at each subsequent measurement, while less than half transitioned from FS in one wave to new FI in the next. "Still FI" rates were relatively stable at about 8.4-8.8% before the Great

Recession, surging to 9.2% and 11.7% in 2009 and 2011, respectively, then gradually returning to 8.1% by 2019. The incidence of becoming newly food insecure exhibited a similar stability pre-recession, around 2.4%, doubling to 5.1% in 2009, before swiftly declining post-2013.

Decomposing these transitions within Table 4.6 into structural and stochastic mobility reveals that, in the given year, 75%-92% of households achieving new FS status benefited from stochastic upward mobility, while a smaller fraction achieved FS through structural upward mobility. This pattern indicates that transitions to FS were predominantly driven by stochastic variations, moving from stochastic FI in the preceding year to FS in the current year or transitioning from FI to stochastic FS. Moreover, this analysis places a ceiling of 25% (in the economically favorable year of 2019) on these “New FS” households upward transitioning from structural FI to structural FS, facilitated by asset accumulation.

For current FI households, transitions are detailed in columns (6) to (13) of Table 4.6 and visualized in Figure 4.7b, showcasing its mobility trends over the years. Households “still FI” may exhibit one of four mobilities: stochastic FI immobile, structural FI immobile, structurally upward mobile, or structurally downward mobile. Within the PSID sample, 6.8%-9.8% of households remained in structural FI across two waves, peaking in 2011 and 2013, then gradually decreasing by 2017. Meanwhile, transitions in other “still FI” categories accounted for about 1% of U.S. households, respectively. The majority of the variation in households that remain food insecure (“still FI”), approximately 65-71%, can be attributed to those classified as “structurally immobile”, who cannot overcome asset poverty and FI. This reflects the broader trend observed in the persistence of FI. For “new FI” households, over 90% experienced stochastic downward mobility, indicating temporary negative shocks that led to FI without substantial financial asset loss.

In our analysis of transitions by diverse household characteristics, as delineated in Table 4.6, we observe a significantly higher prevalence of remaining food insecure ( “still FI”) and transitions into FI (“new FI”) among households led by non-Whites, female, individuals lacking a high school diploma, the disabled, single-parent households with children, SNAP/food stamp benefits, those lacking homeownership and vehicle ownership, and residents of the South and Midwest. For shocks, households ceasing to receive SNAP benefits exhibit a 53.9% probability of remaining food insecure across two observation periods. Furthermore, these demographic groups exhibit a higher propensity towards “structural immobility” and “structural downward mobility” indicating a sustained or worsening FI status.

Figure 4.8 illustrates the dynamics of FS across demographic subgroups, categorized by education level, gender, and race. This analysis distinguishes between households newly facing FI due to stochastic downward mobility (Panel A) and those experiencing persistent FI without mobility (Panel B), emphasizing variations within these demographic segments. Households led by individuals with a high school education or less, comprising 38% of the population, represent approximately 50-65% of the newly food insecure (stochastic downward mobility) and 70-80% of the persistently food insecure (immobile) groups. This indicates a pronounced correlation between lower educational attainment and higher rates of FI, particularly among persistently food-insecure households. Additionally, female-headed and non-white households exhibit greater variability in persistent FI, whereas male-headed and white households show more variation among those newly experiencing FI due to stochastic downward mobility. Notably, households led by non-white females without a college degree, making up 4.4% of the population, are disproportionately vulnerable, accounting for about 30% of the persistently food insecure group. In contrast,

households led by white males without a college degree constitute a larger share of those newly food insecure due to stochastic downward mobility.

The trends depicted in Figure 4.8 reinforce the conclusion that particularly vulnerable subgroups, notably non-white females with only a high school education, have exhibited relatively stable rates of FI, with a pronounced emphasis on structural immobility, in the periods before and after the recession. Additionally, it can be inferred that the Great Recession primarily precipitated a significant asset loss among less vulnerable groups like white males with college degrees, leading to their transition into a state of structural and persistent FI (structurally food insecure immobility). This finding aligns with the findings of Smeeding (2012), who reported that the middle classes experienced the most significant proportional losses in wealth during the Great Recession.

In our estimation of persistent and entry rates of FI—conditional on the FS status in the preceding year, as presented in Table 4.7, we observe that households previously identified as food insecure exhibit a greater than 80% average probability of remaining food insecure (persistent rate) in the subsequent wave, with this likelihood peaking at 85.4% in 2009 during the Great Recession (GR). This finding contrasts with earlier research; for instance, Lee et al. (2023) analysis using food expenditure to measure FS indicates a lower persistence range of 51% to 72%. Households classified as structurally food insecure, with asset holdings below the threshold, demonstrate an 80% - 88.3% likelihood (reaching 88.3% in 2009) of persisting in FI in the following wave. Conversely, households initially deemed stochastically food insecure, possessing assets above the threshold but being food insecure, show a 25.2% - 67.2% probability (highest during the GR) of remaining food insecure. The GR notably exacerbates the likelihood of persistent FI among households initially categorized as stochastically FI.

Conversely, for households that were food secure in the previous year, the entry rate (probability of transitioning to FI) in the current wave ranges between 1.5% and 5.8%, peaking during the GR. This rate of transition into FI notably contrasts with the findings of Ziliak & Gundersen (2016), who report an entry rate from full FS (FFS) to marginal FI (MFI) of 6%-8%<sup>29</sup>. Similarly, Lee et al. (2023)'s study suggests an entry rate of 5 - 8%. Our analysis further distinguishes between transitions into stochastic FI (0.4% - 1.1% transition rate) and structural FI (1.0% - 4.4% transition rate), with both categories peaking in 2009 among households initially food secure, according to SPFS estimates.

Persistent and entry rate analysis reveals that households led by non-Whites, women, individuals without a high school diploma, the disabled, single parents, SNAP recipients, and those lacking homeownership or vehicle ownership, particularly in the South and Midwest, are significantly more likely to persist in or transition into FI. Notably, households experiencing the loss of vehicle ownership or onset of disability exhibit the highest rates of persistent FI, at 96.6% and 94.4% respectively, with the former also facing the highest entry rate into FI at 27.5%. Additionally, discontinuing SNAP benefits is associated with a relatively high entry rate into FI at 15.5%. These findings again highlight the profound impact of socio-economic status and shocks on FS, underscoring the need for targeted interventions to address the structural vulnerabilities that heighten the risk of persistent FI.

*ii. Spell Length*

Analyzing the distribution of FI spell lengths alongside the estimated conditional persistence and the differentiation between structural and stochastic FS statuses reveals nuanced insights into

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<sup>29</sup> Our study defines FI strictly as low FS (LFS) and very low FS (VLFS) following the guidance of USDA, unlike Ziliak & Gundersen (2016) which also includes marginal FS (MFS). This different definition likely accounts for the differing values observed.

household experiences of FI from 2001-2019 (Table 4.8). Given the biennial nature of PSID data, a single wave spell can represent up to 4 years of persistent FI for a household between survey waves. Conversely, a household could experience FI less than a year, captured just after the entry, indicating shorter spell lengths.

Our analysis first reveals that less than half (43.08%) of sample households experience FI for a single wave (1-4 years). This finding suggests that spells of FI in the U.S. are more likely to be persistent, not stochastic. Moreover, the conditional persistence of FI increases, albeit weakly and statistically, with the spell's duration. This pattern implies that the longer a household experiences FI, the more challenging it becomes to escape. Specifically, after a household has been identified as food insecure for two consecutive waves, there is at least an 80% chance that it will continue to be food insecure until the following PSID (Panel Study of Income Dynamics) wave.

Within the subset of each spell length, a distribution based on asset holdings and estimated FS status by SPFS further delineates the severity of FI. Initially, stochastically food-secure households account for a significant proportion of households (47.70%) experiencing one-year spells of FI, indicating stochastically positive shocks in food access despite being asset-poor. In contrast, 40.17% of households within the same spell length enjoy structural FS, benefiting from adequate asset holdings that ensure stable access to food.

However, as FI spells extend, the landscape shifts markedly. The percentage of households identified as stochastically food secure decreases gradually, dropping to 0% by the tenth wave. Simultaneously, the prevalence of structural FI escalates, peaking at 95.25% for households enduring spells of five waves or longer, pointing to a deep-rooted link between long-term persistent FI and asset poverty. The proportion of households facing stochastic FI initially rises with spell length, reaching a peak before stabilizing, while structurally food-secure households dramatically

decline to zero, highlighting the complex dynamics that underpin FS status over time. This evidence suggests a critical role of asset holdings in shaping the trajectory and persistence of FI, with longer spells reinforcing the impact of insufficient asset holdings and the challenge of escaping FI.

Figure 4.9 presents the distribution of the duration of FI spells (measured in years) among households, conditional on the initial year of FI status. We reveal notable distinctions in the durations of FI spells, influenced significantly by the business cycle and categorized by stochastic and structural beginnings. Analysis of spell lengths starting from 2003 to 2017 indicates a wide variance in short-term FI (1 wave spanning 2 years), with incidences peaking at over 70% in 2017—a period marked by economic stability and full recovery from the Great Recession (GR)—and dropping to their lowest at the onset of the GR in 2007. This variation underscores the influence of macroeconomic stability on the prevalence of short-term (one wave) FI. Furthermore, the data exhibit a persistent long tail of FI beyond a single wave, highlighting the persistent impacts of FI. Unconnected dots at the distribution’s right extreme represent households with ongoing FI as of the 2019 Panel Study of Income Dynamics (PSID) wave, indicating right-censored data and the potential for even longer spells. Particularly, households initially classified as food insecure during the GR (in 2007 and 2009) or its aftermath (in 2011 and 2013) exhibited a significantly higher proportion of spells exceeding 6 years. This persistence suggests a pronounced business cycle effect on the duration and continuity of FI in the United States. The spell lengths for households entering FI in 2003 and 2005 also expanded during and following the GR, further evidencing the cyclic impact.

To corroborate the hypothesis that structurally food-insecure households are more likely to experience persistent FI, Figures 4.9b and 4.9c delineate the spell length distributions for stochastic

and structural FI in the initial years, respectively. As anticipated, households with stochastic FI predominantly exhibit single-wave spells, comprising around 60% of the distribution. Exceptions exist for those entering FI during or after the GR (2007-2013), who show a near-zero distribution for extended spell lengths. Conversely, households with structural FI at the onset in Figure 4.9c follow a similar pattern with households with FI at the onset in Figure 4.9a and show a higher propensity for enduring longer spells. These findings emphasize that insufficient financial asset holdings—a key structural reason—contribute to prolonged periods of FI.

### ***Structural FS Dynamics by Permanent approach***

The results of examining household-level FI dynamics employing the permanent approach with mean intertemporal SPFS measure are detailed in Table 4.9. Using the methodology delineated by Equations (4.4) and (4.5), we derive the average period-specific total FI (TFI) alongside its mean intertemporal structural component (SFI) for each household, employing an FGT style metric with the parameter  $\alpha$  set to zero<sup>30</sup>. The summarized outcomes, encompassing the total households and subgroups, are in columns (1) through (4) of Table 4.9. Column (3) details the stochastic component, while column (4) indicates the proportion of household FI considered structural. Moreover, we integrate SFI estimates with SPFS-determined FI statuses, enabling the classification of households into four groups based on their mean intertemporal, not period-specific, FI experiences: structurally persistently food insecure, structurally not persistently food insecure, stochastically food insecure, and never food insecure. The distribution is presented in columns (5) through (8) of Table 4.9.

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<sup>30</sup> We also derive the average period-specific total FI (TFI) alongside its mean intertemporal structural component (SFI) with  $\alpha = 2$  in Appendix Table D. There are similar results.

From 2001 to 2019, an estimated 78.7% of U.S. households never experienced FI (Table 4.9, column (8)). This persistence ratio exceeds Lee et al. (2023) estimate of 67% based on food expenditure but is comparable to the 87.6% calculated using the official USDA's HFSSM measurement<sup>31</sup>. This difference can be attributed to household assets being a more reliable indicator of long-term welfare, such as FS. Moreover, the asset-based SPFS measure, which spans ten waves from 2001 to 2019 and includes the Great Recession period, may yield estimates that our persistent ratio of FS is smaller than the USDA's HFSSM estimate which is confined to five waves in PSID data (2001, 2003, 2015, 2017, and 2019) and excludes the recession years. Importantly, among those experiencing FI, 84% face structural challenges, as column (4) shows, aligning closely with the percentages of structural FI and structural mobility in Figure 4.6 and Table 4.6.

Furthermore, our analysis using the permanent approach suggests 11.8% of households encounter stochastic FI, with 4.4% facing structurally persistent and 5.2% facing non-persistent structural FI from 2001-2019, as indicated in columns (5) to (7) of Table 4.9. This intertemporal distribution diverges from the period-specific findings in Figure 4.6, where 62.3% - 69.5% are structurally FS, and 19.2% - 25.4% experience stochastic FS, 8.9% - 13% are structurally FI and 1.4 - 2.1% are stochastically FI. The variation between the permanent and period-specific approaches reflects their differing methodologies. The former emphasizes stable, long-term household characteristics to derive average trends, potentially overlooking the impact of short-term fluctuations. In contrast, illustrated in Figure 4.6, period-specific estimations capture FS distributions over time, factoring in asset and FI status changes, though they may encounter measurement errors.

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<sup>31</sup> It is roughly calculated using the available HFSSM data during 2001, 2003, 2015, 2017 and 2019 in PSID.

The subgroup analysis, employing a permanent approach with time-invariant variables as presented in Table 4.9, corroborates that households led by females, non-whites, individuals with lower educational attainment (notably those without a high school diploma), or those living in the South and Midwest regions, exhibit significantly higher TFI indices and a greater propensity to encounter FI—particularly structural and persistent FI—compared to their counterparts (males, whites, individuals with at least a high school education, and residents of other regions). Furthermore, the observed range of SFI as a percentage of TFI, spanning 87% to 100%, underscores that households within these disadvantaged demographic cohorts are not only more susceptible to FI but also to a substantially greater risk of enduring structural FI, compounded by insufficient financial assets, in contrast to other groups.

In Figure 4.10, we further illustrate this trend by comparing TFI and SFI across subgroups delineated by gender, race, and education levels. It becomes evident that households led by individuals who are non-white, female, or possess a high school diploma or less constitute the most disadvantaged segment, exhibiting the highest indices of TFI and SFI, along with the largest proportion of the structural component of FI. Holding education level constant, households headed by non-white and female individuals continue to face a heightened risk of enduring structural FI compared to their counterparts with equivalent educational achievements. This underscores that non-white and female groups are particularly vulnerable and should be prioritized in policy interventions. Furthermore, education, particularly attainment beyond a high school diploma, is crucial in mitigating FI and its structural aspects, even among these highly vulnerable groups.

We subsequently conducted a correlation analysis to investigate the relationship between household characteristics and dynamics of FI, as measured by TFI and SFI (Table 4.10). As anticipated, significant predictors of TFI and SFI include household characteristics such as race,

gender, education level, family size, participation in the Supplemental Nutrition Assistance Program (SNAP), child meals programs, and asset ownership, including housing and vehicles. Regarding economic shocks, the discontinuation of SNAP benefits is associated with increased TFI and SFI rates. An unemployment shock is linked to a rise in SFI rates at the 10% significance level, with no significant association observed for TFI. Intriguingly, a higher percentage of children within a household is associated with reduced rates of TFI and SFI, potentially attributable to eligibility for additional government assistance and social programs designed to mitigate child FI or poverty. Furthermore, the loss of important assets, such as houses and vehicles, is linked to lower rates of TFI and SFI, possibly due to increased cash flow from these transactions.

Upon examining the differences in coefficients between TFI and SFI, our analysis reveals that the lack of home ownership, particularly among renters, is more strongly associated with an increase in TFI than SFI. This suggests that home ownership is more closely linked to general FI than to structural FI. Conversely, receiving child meal benefits is significantly more associated with an increase in SFI than TFI at the 10% significance level, indicating that households benefiting from such programs experience FI and are also at a heightened risk of enduring severe FI. Notably, even after controlling for other variables, higher educational attainment (at least a high school degree) significantly reduced rates of severe structural FI more than general FI at the 5% significance level, underscoring the critical role of education in mitigating persistent FI challenges. Furthermore, unemployment shocks were found to have a stronger association with increases in structural FI. These findings highlight the potential effectiveness of policies targeting education attainment, child nutrition programs, and unemployment insurance for low-income households in reducing both structural and persistent FI.

Figure 4.11 elucidates the coefficient estimates and corresponding confidence intervals for state/regional effects derived from the model presented in Table 4.10. Spatial variations exist in TFI and SFI, particularly in the South and Midwest regions of the U.S. The majority of state/regional effects on TFI and SFI do not reach statistical significance, with the exceptions being North Carolina/South Carolina (NC/SC) and Georgia (GA) in the South, and Indiana (IN) and Michigan (MI) in the Midwest. Notably, SFI in these states, where significant regional effects are observed, exceeds TFI. This indicates that households experiencing FI in these regions are structurally and persistently food insecure. Such findings imply that both short-run and long-run shocks may impact regions differently. It also suggests that FI, especially structural FI, is intricately linked to both household characteristics and geographical location.

Finally, we employed a Shapley decomposition, detailed in Table 4.11, to elucidate the sources of variation in SFI and TFI in Table 4.10. Significantly, variables such as race, income, participation in food assistance programs, and ownership of housing and vehicles collectively account for approximately 60% of the variations in both the SFI and TFI, with the largest contribution stemming from racial disparities. Regional fixed effects explain around 8.7% and 8.3% of the variation in the SFI and TFI, respectively. This finding aligns with evidence suggesting that spatial disparities correlate with FI and structural FI, as demonstrated in Figure 4.11. Further analysis reveals that educational attainment and food assistance program participation account for a greater proportion of the variation in the SFI than in the TFI. This distinction underscores these factors' critical role in mitigating structural FI.

## **4.7 Conclusions and Discussion**

In conclusion, the primary objective of this study was to examine the structural dynamics of FS in the United States. Building on advances in poverty research, we utilized asset holdings—

highlighting structural barriers to economic mobility—to develop a new measure of household FS. This asset-based measure, informed by methodologies from existing literature, enables an exploration of the structural aspects of FI. We define household FS through the SPFS (or asset based PFS), calculated as the likelihood that a household’s financial assets meet or exceed the minimum financial resources required to meet basic needs for at least three months. Furthermore, we validate the SPFS against the USDA’s official HFSSM based estimates through a series of tests. This measure allows us to comprehensively delineate the structural dynamics of FS by examining structural and stochastic mobility of the dynamics, analyzing the persistence and duration of FI episodes, decomposing these phenomena into their structural and stochastic components, and identifying the most vulnerable subgroup.

Using the newly measured SPFS and PSID data from 2001-2019, we estimate that approximately 80% of the representative sample successfully maintained food secure, bolstered by adequate financial asset holdings, without experiencing intermittent FI. Among the 20% of households that experience FI, about 85% face structural rather than stochastic challenges attributable to inadequate financial assets, with over half suffering from FI for at least two survey waves (exceeding three years).

U.S. households that are structurally food insecure—defined as both asset-poor and food insecure—are more likely to experience immobility during transitions between FS statuses and to suffer from persistent FI over the long term. Furthermore, the duration of FI in a household directly correlates with increased difficulty of escaping it. Stochastic shocks to food access typically trigger short-term FI, but the longer spell lengths primarily arise from a lack of financial assets—a fundamental structural barrier. Additionally, pronounced business cycles are significantly and positively associated with the duration and persistence of FI in the United States.

The findings also reveal that households headed by non-Whites, female, individuals without a high school diploma, the disabled, single parents, SNAP recipients, and those lacking homeownership or vehicle ownership show a greater tendency towards structural immobility and downward mobility compared to their counterparts, significantly elevating their risk of persistent and structural FI. Negative shocks, such as ending SNAP participation, are linked to a high entry rate into FI. Furthermore, the loss of vehicle ownership or the onset of a disability is associated with the highest rates of persistent FI. Race, income, food assistance participation, and asset ownership (home and vehicles) together explain over 60% of the variance in the estimated FI by SPFS, particularly structural FI. Notably, educational attainment, Child Meal program participation, and unemployment shocks are more closely associated with structural FI than overall FI. Beyond these household characteristics, FI—especially structural FI—is intricately linked to geographical locations, subject to various short-run and long-run regional shocks.

Our study enhances the understanding of FI's intertemporal dynamics and persistence. In accordance with the recent studies (Lee et al., 2023; Ryu & Bartfeld, 2012), we confirm that most U.S. households never experience FI, and the persistence of FI is positively associated with their current duration and economic downturns. Additionally, the links between FI and predictors such as educational attainment, gender, race, income, and food assistance programs align with existing literature. A key novelty of our study is its emphasis on structural FI, estimated through household financial asset holdings from 2001 to 2019. We find approximately 85% of FI cases are structural, originating from inadequate financial assets and consequently more likely to experience persistent FI with longer spell length. This finding starkly contrasts with those of Lee et al., who report that over half of the cases are chronic, and with Jansen et al. (2017), who identifies 54% of FI cases as persistent within particularly disadvantaged populations. Conversely, prior cohort studies

(Hernandez et al., 2014; Ryu & Bartfeld, 2012; Wilde et al., 2010) using official HSFM typically describe FI as episodic or transient on three or more consecutive assessments of FI. Our findings underscore the critical role of financial assets holdings in maintaining FS among U.S. household.

Our study establishes that structural barriers, rather than stochastic shocks, are the primary drivers of FI among U.S. households, underscoring the necessity for targeted policy interventions. Notably, non-white females with high school education or less are the most vulnerable, consistently experiencing structural immobility even during recession periods. Policies aimed at dismantling these barriers for these at-risk groups should enhance economic support and asset accumulation like family tax credits, reduce racial disparities, promote educational attainment, and ensure the availability of essential resources such as housing and food assistance programs (including SNAP, WIC, Child Meal, and Elderly Meal Programs). Interestingly, groups traditionally viewed as less vulnerable, such as white males with college degrees, have also faced significant wealth losses during the Great Recession, potentially leading to persistent FI. Targeting these individuals with programs designed to provide short-term safety nets like food assistance and unemployment insurance, could be effective. Additionally, the variability of FI across regions suggests the need for localized policies that consider unique economic conditions and structural vulnerabilities.

It is essential to recognize the limitations of this study and suggest some directions for future studies. First, the sample does not include the immigrant subpopulations, who are generally more prone to FI than their native counterparts; this omission could introduce an upward bias in our estimates of FI. Second, our analysis is limited to households with a consistent head; however, changes such as marital status alterations, deaths, or household splits may influence FI. Controlling for differences in local food prices, housing prices or state-specific assistance programs may

further reduce spatial variation. Additionally, incorporating vehicle and home mortgage status, along with credit card debt, into our model might be necessary. But Brewer (2020) found that credit card and housing debt is weakly linked to reduced food insecurity when controlling for individual and household characteristics. And our model already accounts for changes in home and vehicle ownership, reflecting variations in the related disposable financial resources. However, we should consider including unpaid medical bills and other unsecured debts (Brewer, 2020), such as student loans, in our model to improve its accuracy in predicting household food insecurity. Finally, our SPFS measure is based on the static asset threshold which is an arbitrarily defined living standard and fail to reflect potential changes in asset values and future returns. Consequently, it cannot reliably predict whether households currently in FI will persist so in the long run. Future research could follow the poverty literature to investigate those trapped in FI by finding a dynamic asset threshold. Further studies can explore how assistance programs variably impact structural versus stochastic FI.

Tables and Figures

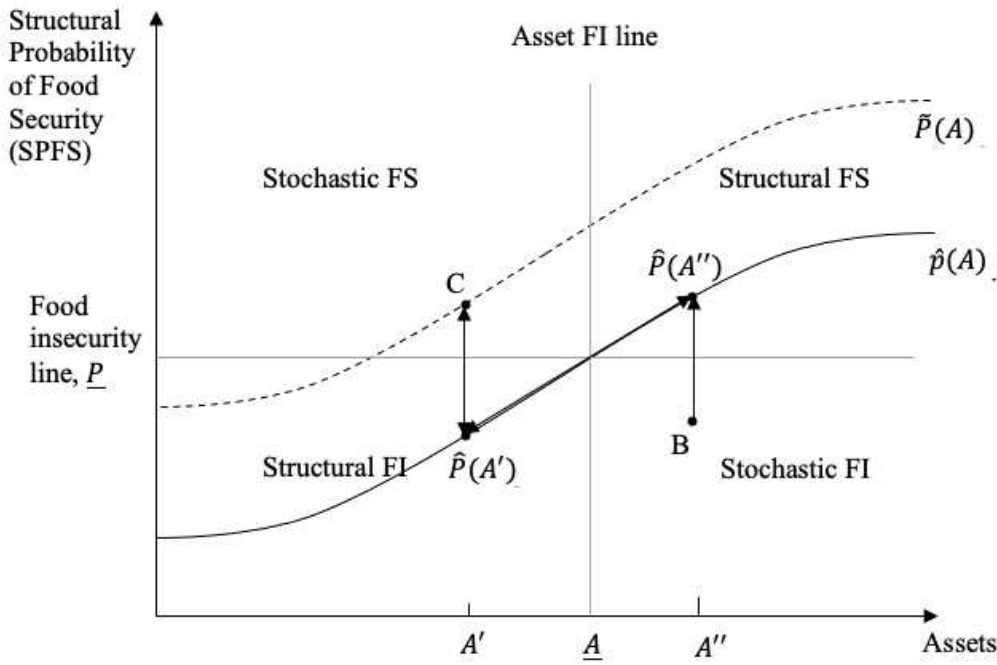
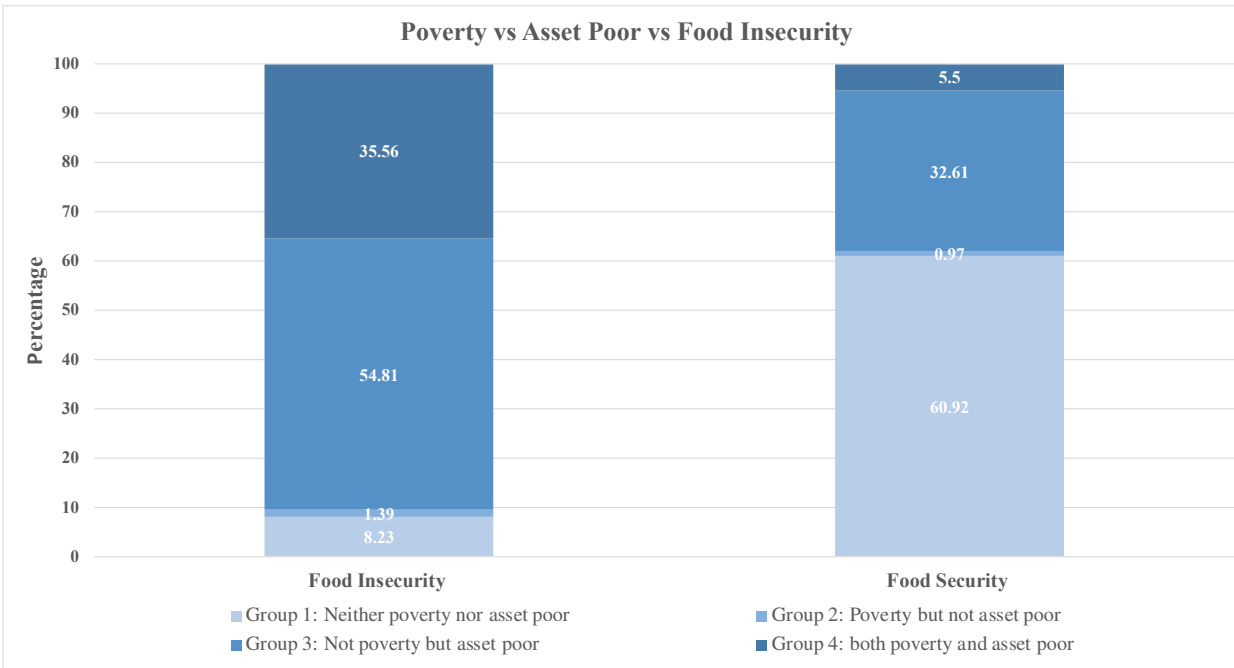


Figure 4.1. Conceptual Framework of SPFS and Static Asset FI at Single Period.



**Figure 4.2. The Distribution of Households' FS Status by Different Economic Conditions.**

*Note:* This distribution uses the PSID sample in 2001, 2003, 2015, 2017 and 2019 during which the Household FS Survey Measure (HFSSM) is included. The household poverty is defined by the household-year specific US Census Bureau's poverty line. The asset poor is defined by whether household financial asset per capital is above or below the asset poverty line (25% of US Census Bureau's poverty line).

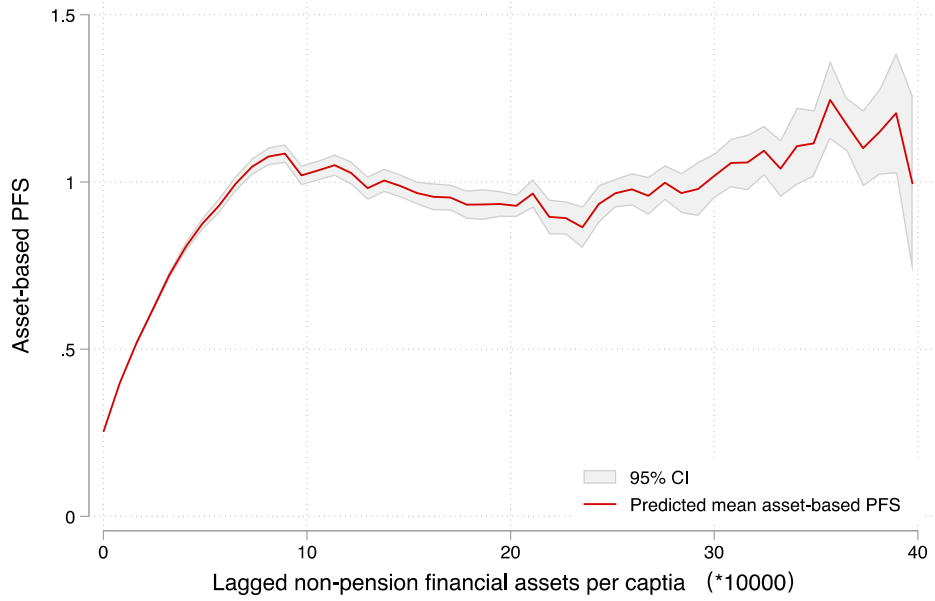
Period t-1		Period t			
		Food insecurity (FI)		Food security (FS)	
		Stochastic FI	Structural FI	Stochastic FS	Structural FS
FI	Stochastic FI	—	↓	↑	↑
	Structural FI	↑	—	↑	↑
FS	Stochastic FS	↓	↓	<b>Never FI</b>	
	Structural FS	↓	↓		

—Immobile;

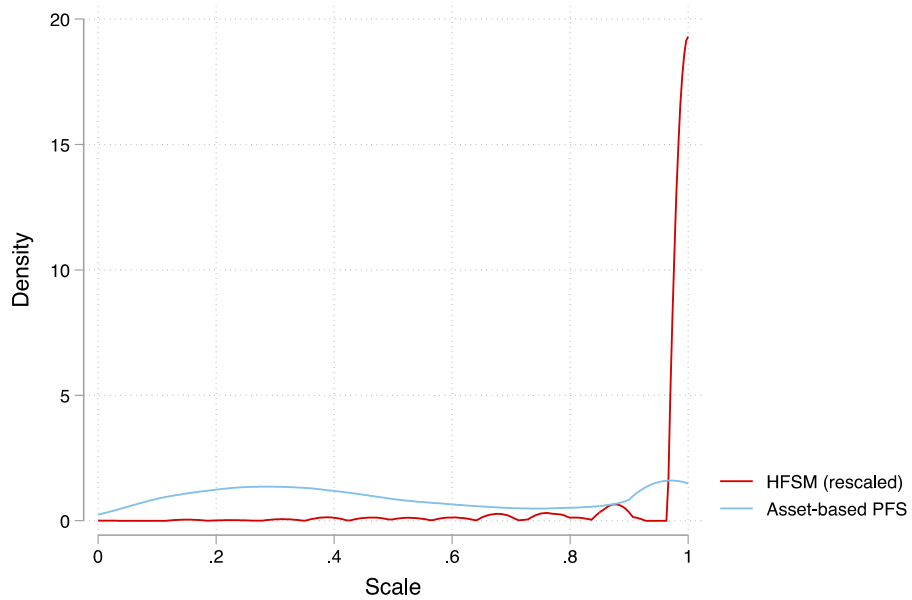
**Bold Arrow in bold:** structural mobile;

**Not bold Arrow:** stochastic mobile

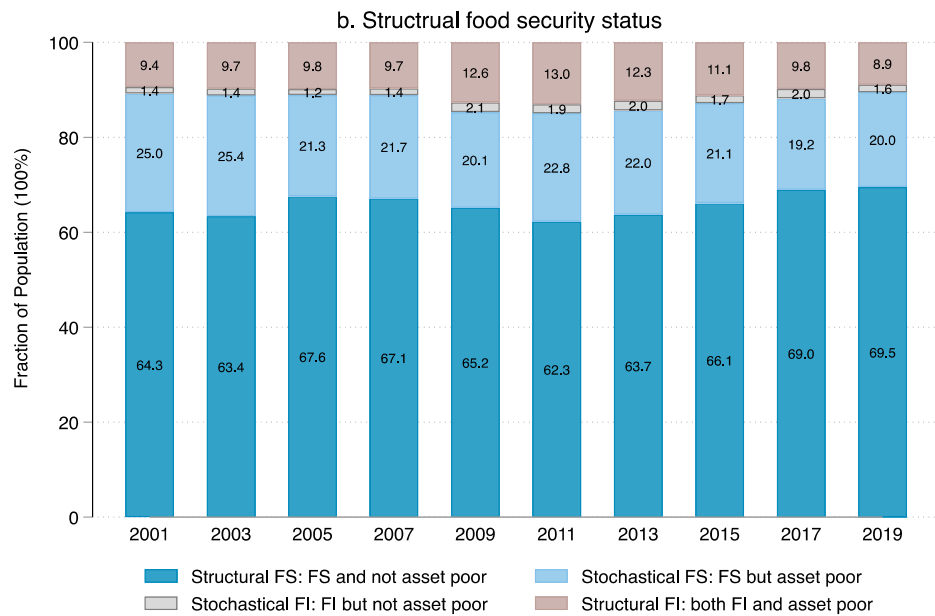
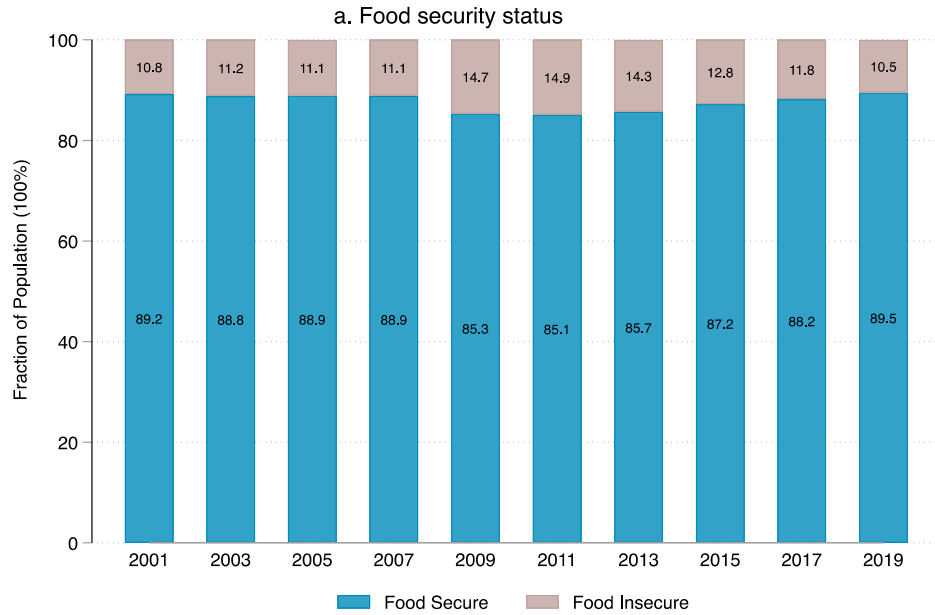
**Figure 4.3. Decomposition of FI Transitions Based on Static Asset threshold**



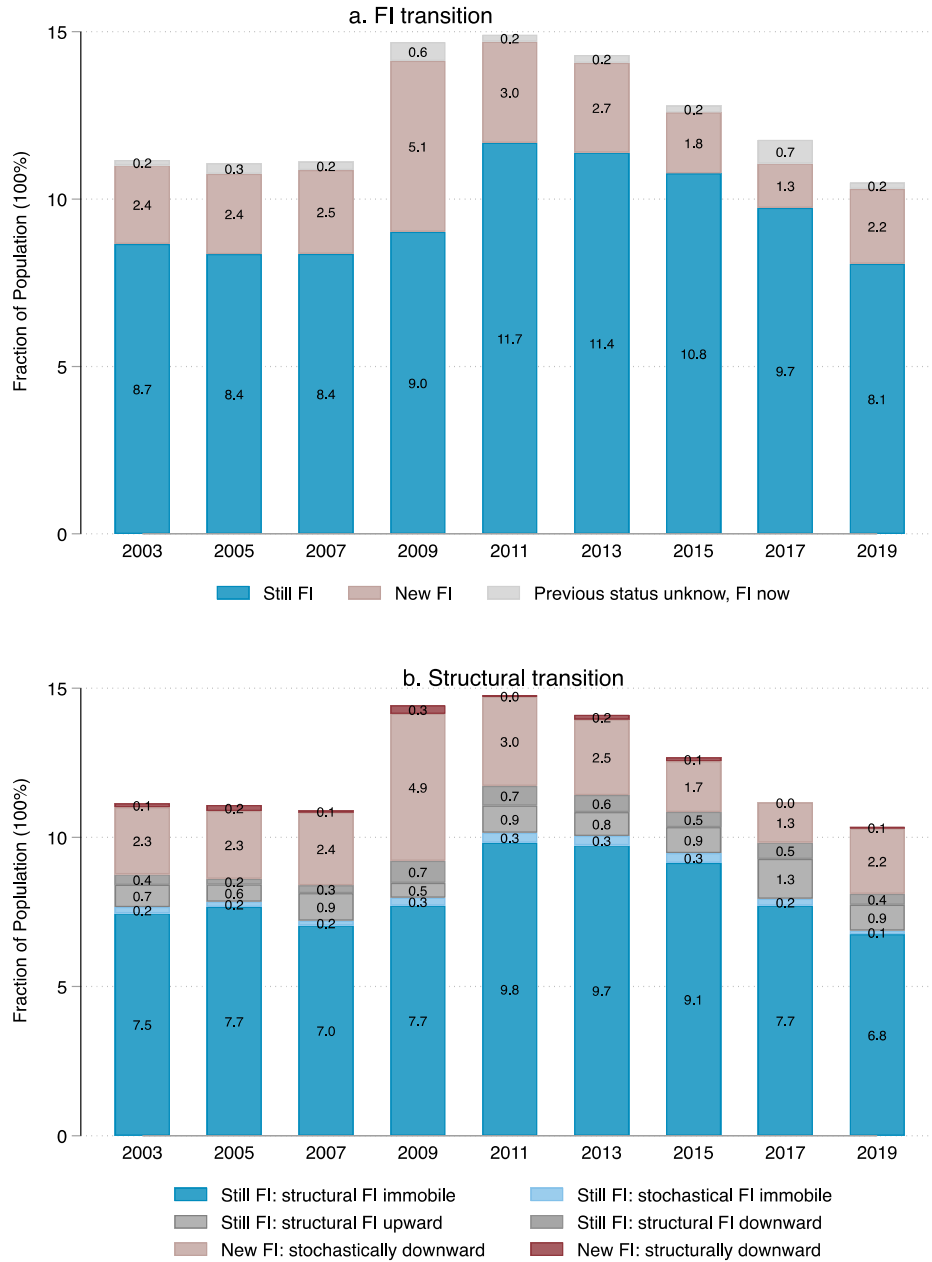
**Figure 4.4. Estimated SPFS Dynamics.**



**Figure 4.5. Density Distribution of FS Indicators.**

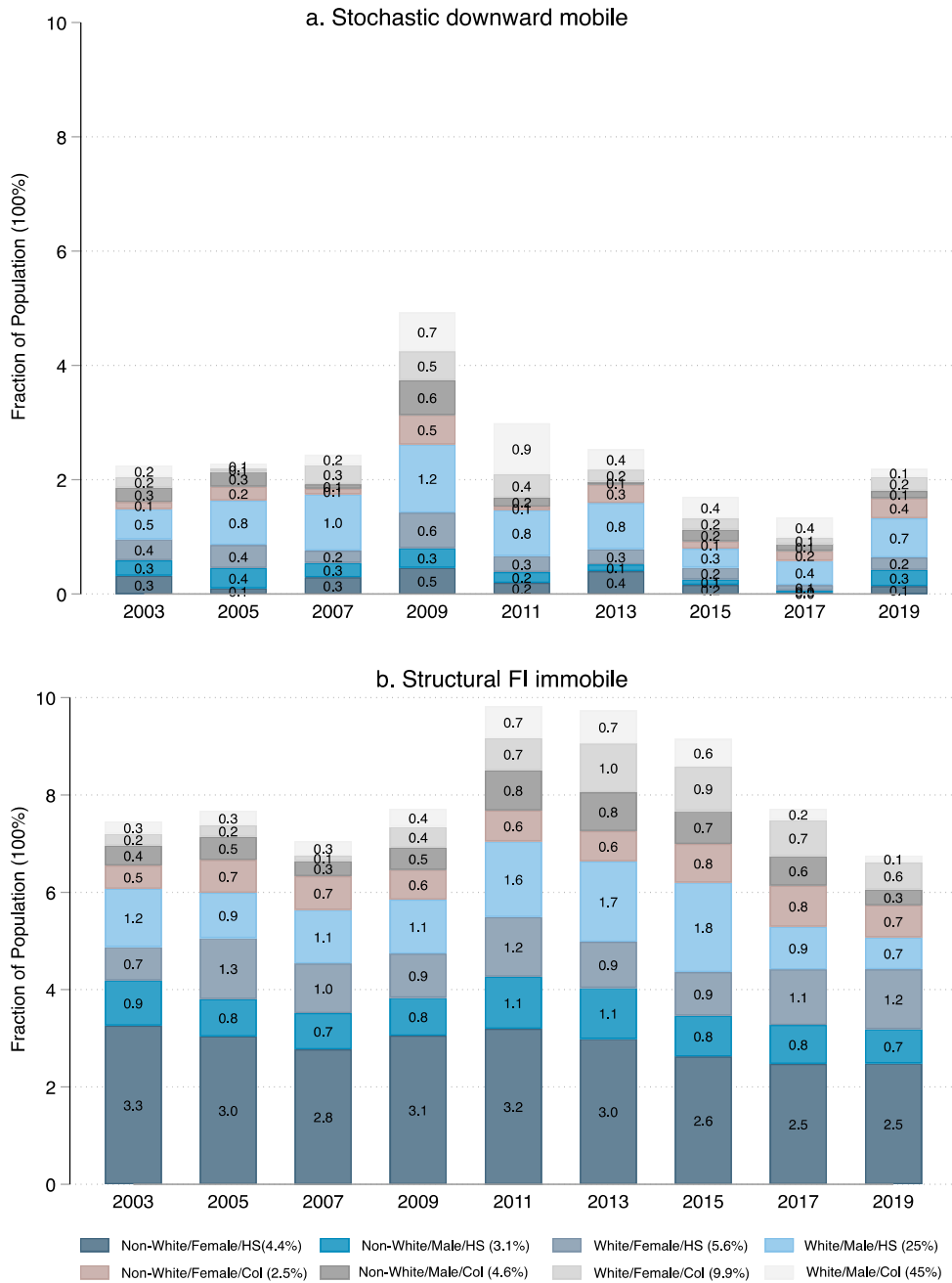


**Figure 4.6. Prevalence of FS Status and Structural FS Status Estimated by SPFS.**



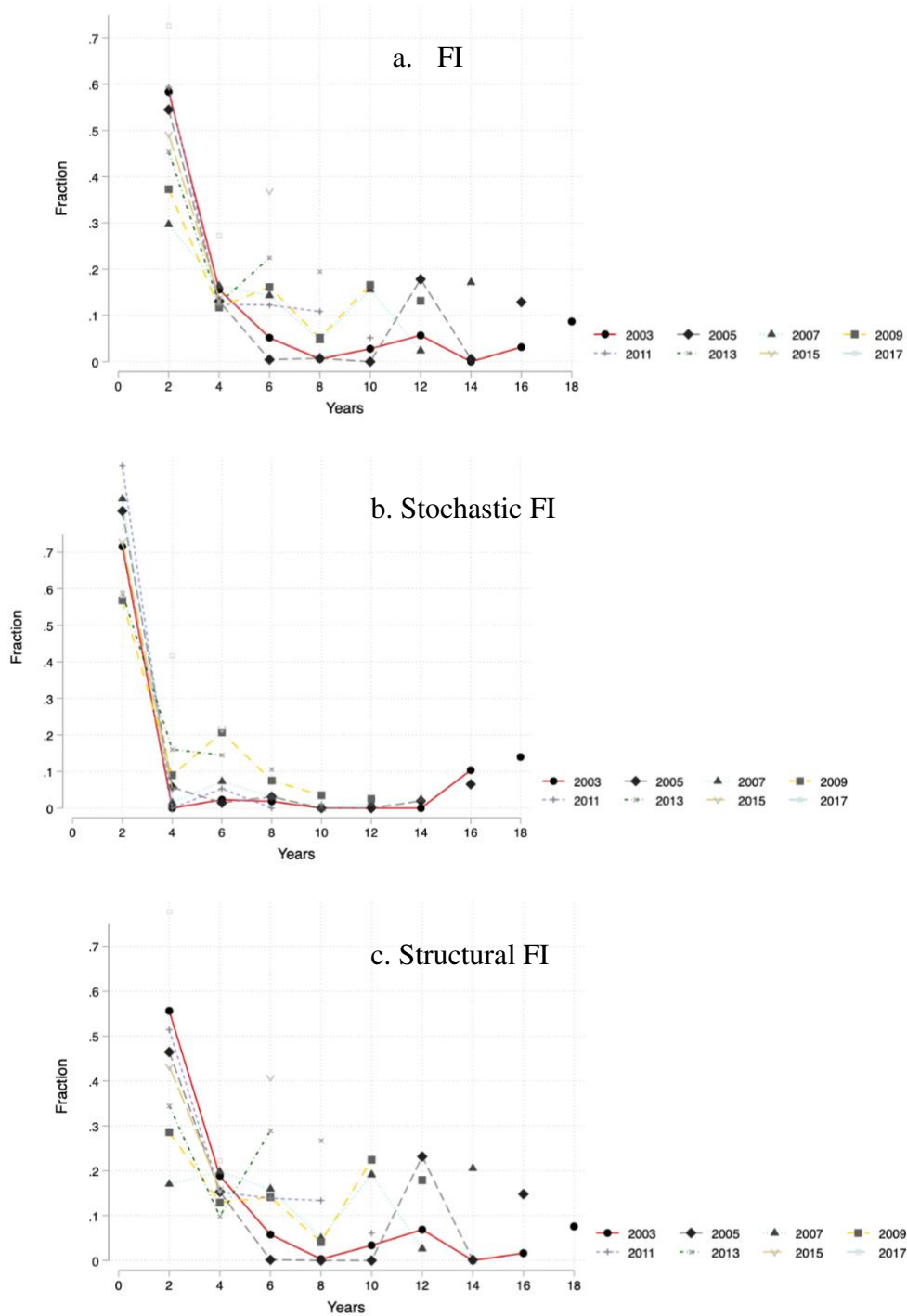
**Figure 4.7. Change in Estimated Structural FI Status.**

*Note:* Sample includes households from 2003 to 2019. “Still FI” and “New FI” refer to households that were or were not estimated to be food insecure under the SPFS (Section 5 has the detailed explanation of how we categorize FI status with the SPFS) in the preceding survey wave, respectively. “Previous status unknown” refers to households whose SPFS in the preceding wave is missing. We further decompose the changes in FS status into structural and stochastic mobile based on Figure 4.7b. The prevalence reported at the top of each bar matches the official FSSS by construction.



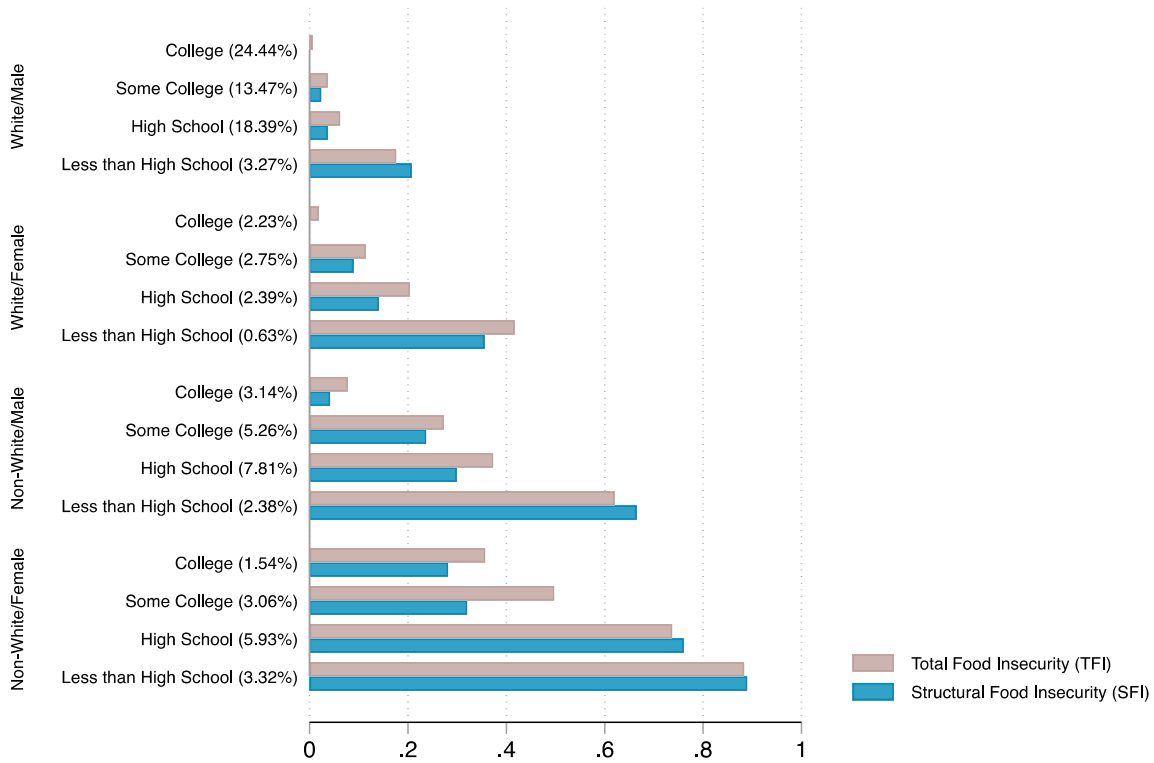
**Figure 4.8. Estimated Stochastic Downward Mobile and Structural FI Immobile by Subgroups.**

*Note:* “stochastic downward mobility” (Panel A) and “structural FI immobile” (Panel B), capture most of variations in “Newly FI” and “Still in FI”, respectively. A household is deemed stochastically downwardly mobile if it moves from FS to stochastical FI, or from stochastical FS to FI. A household remains structurally immobile if it was structurally food insecure in both consecutive periods. “HS” indicates the head has no education beyond high school. “Col” indicates that the head has at least some college education. “Non-White” indicates the head’s race is not White. Percentages in parentheses report each category’s share of the total population.



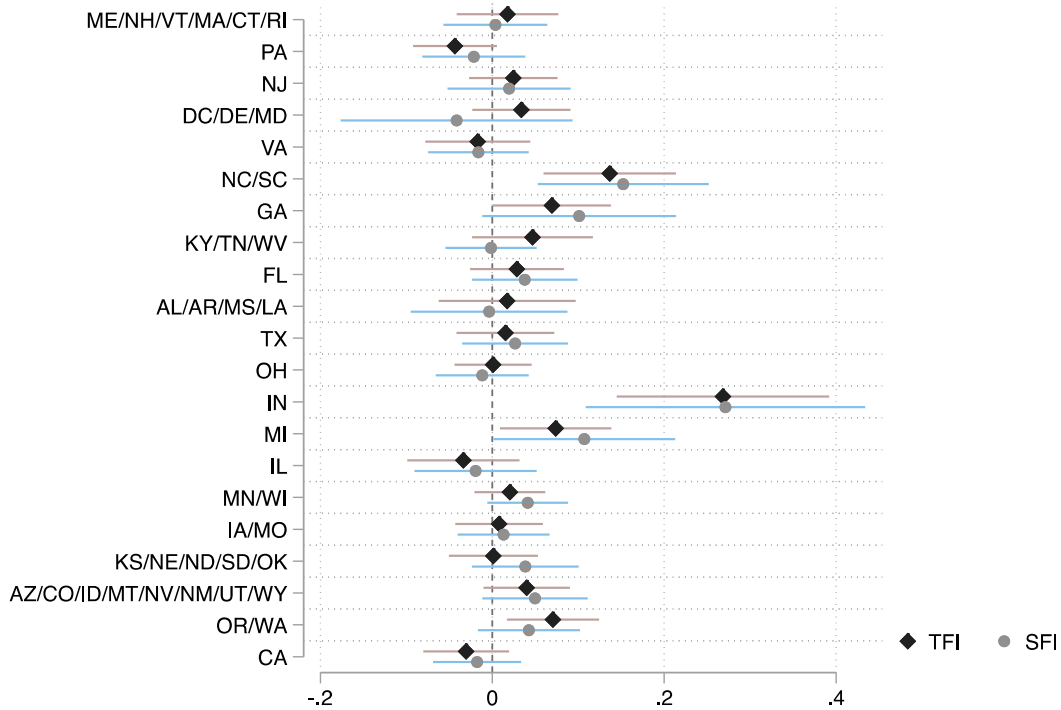
**Figure 4.9. Spell Length of Estimated FI by SPFS Measure (2003–2019).**

*Note:* Sample includes households with SPFS observations from 2001 to 2019. The unconnected rightmost dots reflect the right-censored share. The different panels from a to c represents the estimated FI status at initial period.



**Figure 4.10. Estimated Structural FI by Subgroups.**

*Note:* Sample include households with non-missing SPFS for 5 or more years from 2001 to 2019. The horizontal axis indicates the estimated mean of TFI and SFI for each subgroup. The vertical axis shows the categories or subgroup to which household heads belong. The percentage in parentheses indicates that category’s population share. “Some college” indicates the household head at least attended college. “College” indicates the household head earned at least a bachelor’s degree. Because PSID does not report educational status for every individual in every round, we base the head’s educational status on the earliest available status recorded for that individual in the 2001–2019 period.



**Figure 4.11. Spatial Variation of TFI/SFI.**

*Note:* TFI and SFI are estimated total FI and structural FI by permanent approach. Base region is NY. AK, HA, and other U.S. territories are excluded. We aggregate states with a limited number of observations with neighboring states that exhibit similar economic characteristics, thereby creating a consolidated region for analysis (so for example, we combine Delaware, Maryland, and Washington DC into one region).

**Table 4.1. Description of Variables and Summary Statistics.**

Variable	Description	Total	
		Mean	SD
<b>Age</b>	household head's age	57.45	12.97
<b>Race</b>			
White	binary, =1 if household head is White	0.85	0.35
Non-white	binary, =1 if household head is non-White	0.15	0.35
<b>Female</b>	binary, =1 if household head is female	0.22	0.42
<b>Highest Education Degree</b>			
Less than high school	binary, =1 if household head neither completed high school nor achieved GED	0.08	0.26
High school	binary, =1 if household head completed high school but did not attend college (attended school 12 years)	0.30	0.46
Some college	binary, =1 if household head attended college but did not hold the bachelor's degree (attended school between 13 to 15 years)	0.25	0.43
College	binary, =1 if household head completed the bachelor's degree (attended school 16 years or longer)	0.37	0.48
<b>Employed</b>	binary, =1 if household head is employed	0.66	0.47
<b>Disabled</b>	binary, =1 if household head self-report as physical or nerous condion that limit them work	0.19	0.39
<b>Income per captia</b>	Total annual household income per capita (thousand dollars)	41.67	34.68
<b>Household financial assets per capita</b>	Total annual household financial assets per capita (ten thousand dollars)	5.86	13.89
<b>Family Size</b>	Total number of people in household	2.25	1.24
<b>% of children</b>	Percentage of the number of children (0-17) to total number of family members	0.10	0.19
<b>Household composition</b>			
Single without child	binary, =1 if single household without children	0.33	0.47
Single with children	binary, =1 if single household with children	0.04	0.19
Married without children	binary, =1 if married household without children	0.44	0.50
Married with child	binary, =1 if smarried household with children	0.19	0.39
<b>Food stamp/SNAP recipient</b>	binary, =1 if household received food stamp/SNAP any time this year	0.05	0.22

<b>WIC recipient</b>	binary, =1 if household received WIC any time this year	0.01	0.10
<b>Elderly Meal recipient</b>	binary, =1 if household received Elderly Meal any time this year	0.01	0.08
<b>Home ownership</b>			
Own	binary, =1 if household own home	0.78	0.41
Rent	binary, =1 if household rent home	0.19	0.39
Neither	binary, =1 if household neither own or rent home	0.03	0.18
<b>Vehicle ownership</b>	binary, =1 if household own vehicle	0.92	0.26
<b>Shocks</b>			
No longer received stamp/SNAP	binary, =1 if household receive SNAP in previous wave (2 years ago) but not receive in current wave	0.26	0.12
No longer employed	binary, =1 if household was employed in previous wave (2 years ago) but not employed in current wave	0.04	0.19
No longer married	binary, =1 if household was married in previous wave (2 years ago) but not married in current wave	0.01	0.11
Became disabled	binary, =1 if household was not disabled in previous wave (2 years ago) but disabled in current wave	0.07	0.26
no longer own home	binary, =1 if household owned home in previous wave (2 years ago) but not own in current wave	0.02	0.15
no longer own vehicle	binary, =1 if household owned vehicle in previous wave (2 years ago) but not own in current wave	0.02	0.14
<b>Region</b>			
Northeast	binary, =1 if household is in ME/NH/VT/MA/CT/RI/NY	0.10	0.30
Mid-Atlantic	binary, =1 if household is in PA/NJ/DC/DE/MD/VA	0.15	0.36
South	binary, =1 if household is in NC/SC/GA/KY/TN/WV/FL/AL/AR/MS/LA/TX	0.25	0.43
Midwest	binary, =1 if household is in OH/IN/MI/IL/MN/WI/IA/MO	0.27	0.44
West	binary, =1 if household is in KS/NE/ND/SD/OK/AZ/CO/ID/MT/NV/NM/UT/WY/OR/WA/CA	0.22	0.42
<b>SPFS</b>	The Probability of FS ([0, 1]) estimated by household financial asset holdings	0.51	0.31

*Note:* The PSID sample consists of the households from the SRC and the SEO sample surveyed from 2001 to 2019. Top and bottom 1% values of income and household assets values are winsorized.

**Table 4.2. Estimates of Annual Per Capita Household Financial Assets (Ten Thousand).**

	$A_{ijt}$	$A_{ijt}$	$A_{ijt}$	$A_{ijt}$	$A_{ijt}$	$A_{ijt}$	$A_{ijt}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$A_{ijt-1}$	0.057*** (0.004)	0.143*** (0.006)	0.242*** (0.010)	0.371*** (0.016)	0.507*** (0.023)	0.645*** (0.033)	0.796*** (0.047)
$A^2_{ijt-1}$		-0.001*** 0.000	-0.006*** 0.000	-0.018*** (0.001)	-0.038*** (0.002)	-0.067*** (0.005)	-0.111*** (0.010)
$A^3_{ijt-1}(*10^2)$			0.005*** 0.000	0.035*** (0.003)	0.124*** (0.009)	0.324*** (0.027)	0.744*** (0.076)
$A^4_{ijt-1}(*10^4)$				-0.021*** (0.002)	-0.173*** (0.013)	-0.747*** (0.071)	-2.555*** (0.291)
$A^5_{ijt-1}(*10^7)$					0.857*** (0.069)	8.145*** (0.839)	46.408*** (5.663)
$A^6_{ijt-1}(*10^9)$						-3.363*** (0.372)	-42.370*** (5.433)
$A^7_{ijt-1}(*10^{11})$							15.294*** (2.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	86.581	82.932	81.350	80.350	79.678	79.311	79.004
T-test <sup>a</sup>	0.000***	0.000***	0.000***	0.000***	0.000***	0.291	

Note: Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

<sup>a</sup> P-value of the t-test on the equality of means between predicted values from the specific estimation and the 7th order polynomial specification.

**Table 4.3. Marginal Effects—Generalized Linear Model Estimates.**

VARIABLES	Financial Assets per capita (1)	Variance (financial Assets per capita) (2)	SPFS (3)
(Lagged) Financial Assets per capita	4.489*** (0.330)	168.838*** (29.072)	0.161*** (0.0002)
Age	0.113 (0.105)	0.159 (8.007)	0.007*** (0.0000)
Non-white	0.420 (0.970)	227.898 (137.679)	-0.116*** (0.0001)
Married	-0.091 (0.726)	-107.975 (80.919)	0.081*** (0.0001)
Female	-1.354* (0.710)	-83.629* (47.099)	-0.008*** (0.0000)
High school	1.308* (0.667)	59.086** (22.459)	0.022*** (0.0000)
Some college	2.121*** (0.650)	84.234*** (23.621)	0.056*** (0.0001)
College	4.107*** (0.737)	192.012*** (37.223)	0.071*** (0.0001)
Employed	1.024* (0.590)	-76.222** (35.077)	0.006*** (0.0000)
Disabled	-1.099 (0.788)	-53.958 (52.479)	-0.018*** (0.0000)
ln(income per capita)	1.619*** (0.330)	41.235* (21.694)	0.051*** (0.0001)
Family size	-0.964*** (0.267)	-34.992 (25.852)	-0.020*** (0.0000)
% of children	0.108 (1.656)	-49.731 (119.003)	0.044*** (0.0001)
Received Food Stamp/SNAP	-2.739* (1.374)	-75.072 (88.302)	-0.275*** (0.0220)
Received Child Meal	-3.763*** (0.416)	-165.131*** (23.416)	-0.172*** (0.0092)
Received WIC	-1.133 (1.379)	-156.368*** (38.584)	0.173*** (0.0002)
Received Elderly Meal	-4.364*** (0.677)	-183.161*** (31.173)	-0.015 (0.0308)
Rent	-2.373*** (0.589)	-117.526*** (33.052)	-0.062*** (0.0001)
Neither owns nor rents	-2.813*** (0.979)	-149.202*** (42.854)	-0.048*** (0.0001)
Not own vehicle	0.066 (1.765)	93.798 (136.739)	-0.075*** (0.0001)
No longer receive Food	-5.259***	-354.054***	-0.159***

Stamp/SNAP	(1.262)	(94.767)	(0.0331)
No longer employed	-0.716	-137.854***	0.049***
	(0.811)	(50.528)	(0.0001)
No longer married	1.199	-51.801	0.087***
	(1.277)	(84.741)	(0.0001)
Became disabled	1.256	146.225*	-0.048***
	(1.007)	(83.342)	(0.0001)
No longer own home	2.230***	99.628	0.067***
	(1.062)	(75.588)	(0.0001)
No longer own vehicle	-4.345*	-276.487**	-0.012***
	(2.198)	(134.990)	(0.0000)
N	21,115	21,115	21,114
Population size	482,367.48	482,367.48	482,363.27

*Note:* Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Gamma distribution is assumed for Column (1) and (2). For (3), a binomial distribution is assumed.

**Table 4.4. Regression of the HFSSM on SPFS.**

VARIABLES	HFSSM (1)	HFSSM (2)	HFSSM (3)	HFSSM (4)
SPFS	0.102*** (0.009)	0.481*** (0.048)	0.108*** (0.010)	0.515*** (0.050)
SPFS <sup>2</sup>		-0.334*** (0.036)		-0.356*** (0.037)
Constant	0.916*** (0.007)	0.842*** (0.014)	0.943*** (0.009)	0.853*** (0.016)
Subpop. no. obs	10,505	10,504	10,505	10,504
Subpop. size	255,552.09	255,547.87	255,552.09	255,547.87
R-squared	0.086	0.140	0.106	0.163
State & year FE	NO	NO	YES	YES

*Note:* Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 4.5. FS Indicators and Their Correlates.**

VARIABLES	Continuous HFSSM (1)	Continuous SPFS (2)	Binary HFSSM (1=Food Secure) (3)	Binary SPFS (1=Food Secure) (4)
Age	-0.001 (0.001)	0.007*** (0.002)	-0.002 (0.002)	0.000 (0.002)
<i>Age</i> <sup>2</sup> /1000	0.021*** (0.006)	-0.002 (0.014)	0.034** (0.013)	0.031 (0.019)
Non-white	0.002 (0.006)	-0.135*** (0.013)	0.012 (0.011)	-0.189*** (0.019)
Married	0.004 (0.006)	0.115*** (0.014)	0.007 (0.012)	0.056*** (0.013)
Female	-0.016* (0.009)	-0.022 (0.014)	-0.027* (0.014)	-0.041** (0.017)
High school	0.020** (0.009)	0.027* (0.014)	0.037** (0.017)	0.066*** (0.019)
Some college	0.017 (0.011)	0.076*** (0.014)	0.028 (0.021)	0.094*** (0.021)
College	0.017 (0.010)	0.169*** (0.015)	0.031* (0.018)	0.094*** (0.018)
Employed	0.011*** (0.004)	-0.060*** (0.009)	0.017** (0.008)	0.016* (0.008)
Disabled	-0.033*** (0.007)	-0.069*** (0.009)	-0.048*** (0.011)	-0.035*** (0.013)
ln(income per capita)	0.019*** (0.004)	0.110*** (0.007)	0.030*** (0.007)	0.045*** (0.006)
Family size	0.001 (0.003)	-0.041*** (0.005)	0.000 (0.006)	-0.017*** (0.005)
% of children	0.044*** (0.012)	0.079*** (0.024)	0.074*** (0.026)	0.123*** (0.026)
Received Food Stamp/SNAP	-0.090*** (0.017)	-0.024 (0.017)	-0.153*** (0.032)	-0.418*** (0.036)
Received Child Meal	-0.018 (0.015)	0.006 (0.016)	-0.043 (0.031)	-0.196*** (0.024)
Received WIC	-0.014 (0.021)	0.141*** (0.022)	-0.035 (0.043)	0.167*** (0.028)
Received Elderly Meal	-0.008 (0.030)	-0.155*** (0.032)	-0.027 (0.053)	-0.037 (0.047)
Rent	-0.027*** (0.007)	-0.094*** (0.012)	-0.043*** (0.014)	-0.079*** (0.015)
Neither owns nor rents	-0.012 (0.014)	-0.083*** (0.018)	-0.013 (0.028)	-0.063** (0.024)
Not own vehicle	-0.000	-0.036**	-0.017	-0.154***

	(0.019)	(0.017)	(0.037)	(0.032)
No longer receive Food Stamp/SNAP	-0.034**	-0.037**	-0.065*	-0.191***
	(0.017)	(0.016)	(0.036)	(0.033)
No longer employed	-0.020	0.078***	-0.045**	0.017
	(0.012)	(0.014)	(0.020)	(0.015)
No longer married	-0.019	0.064***	-0.045**	0.072***
	(0.014)	(0.018)	(0.021)	(0.022)
Became disabled	0.021**	-0.012	0.020	-0.040**
	(0.009)	(0.011)	(0.016)	(0.016)
No longer own home	0.011	0.048**	0.028	0.083***
	(0.013)	(0.019)	(0.021)	(0.025)
No longer own vehicle	-0.024	-0.025	-0.011	-0.024
	(0.026)	(0.023)	(0.045)	(0.043)
Constant	0.756***	-0.963***	0.617***	0.406***
	(0.043)	(0.085)	(0.088)	(0.097)
Subpop. no. obs	10,505	10,504	10,505	10,504
Subpop. size	255,552.09	255,547.87	255,552.09	255,547.87
R-squared	0.208	0.632	0.164	0.600
State FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

*Note:* Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 4.6. Transitions in Estimated Structural FS Status Over Two Consecutive Waves.**

	N	Still FS	New FS			Still FI					New FI		
			All	Stoc upward mobile	Struc upward mobile	All	Stoc FI immobile	Struc FI immobile	Struc upward mobile	Struc downward mobile	All	Stoc downward mobile	Struc downward mobile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
<b>Year</b>													
2003	2010	0.868	0.021	0.020	0.001	0.088	0.002	0.075	0.007	0.004	0.024	0.023	0.001
2005	2021	0.864	0.025	0.022	0.003	0.086	0.002	0.077	0.006	0.002	0.025	0.023	0.002
2007	2088	0.868	0.023	0.021	0.002	0.084	0.002	0.070	0.009	0.003	0.025	0.024	0.001
2009	2080	0.840	0.016	0.013	0.002	0.092	0.003	0.077	0.005	0.007	0.052	0.049	0.003
2011	2131	0.826	0.026	0.024	0.002	0.117	0.003	0.098	0.009	0.007	0.030	0.030	0.000
2013	2113	0.826	0.033	0.031	0.002	0.114	0.003	0.097	0.008	0.006	0.027	0.025	0.002
2015	2102	0.849	0.024	0.022	0.002	0.109	0.003	0.091	0.009	0.005	0.018	0.017	0.001
2017	2105	0.858	0.030	0.026	0.004	0.098	0.002	0.077	0.013	0.005	0.013	0.013	0.000
2019	2102	0.864	0.033	0.028	0.005	0.081	0.001	0.068	0.009	0.004	0.023	0.022	0.001
<b>Gender</b>													
	1473												
Male	9	0.911	0.021	0.019	0.002	0.048	0.001	0.038	0.005	0.003	0.020	0.019	0.001
Female	4013	0.642	0.043	0.039	0.004	0.269	0.006	0.232	0.019	0.012	0.046	0.044	0.002
<b>Race</b>													
	1279												
white	7	0.918	0.019	0.017	0.002	0.044	0.001	0.037	0.003	0.002	0.019	0.019	0.000
Non-white	5955	0.448	0.066	0.061	0.005	0.420	0.010	0.348	0.039	0.022	0.066	0.061	0.005
<b>Highest Education Degree</b>													
< HS	1714	0.504	0.057	0.050	0.007	0.376	0.004	0.334	0.025	0.012	0.063	0.060	0.003
HS	6412	0.792	0.033	0.031	0.002	0.141	0.004	0.117	0.013	0.007	0.035	0.033	0.002
some Col	4629	0.853	0.033	0.029	0.004	0.087	0.002	0.072	0.008	0.004	0.027	0.027	0.001
Col	5997	0.964	0.011	0.008	0.002	0.015	0.001	0.010	0.002	0.002	0.010	0.010	0.000
<b>Disability</b>													
Yes	3274	0.723	0.036	0.032	0.004	0.188	0.004	0.159	0.018	0.007	0.052	0.050	0.003
No	1547												
	8	0.883	0.024	0.021	0.002	0.074	0.002	0.062	0.006	0.004	0.019	0.018	0.001
<b>Household composition</b>													
single w/o chid	4895	0.721	0.046	0.042	0.004	0.183	0.004	0.154	0.016	0.009	0.050	0.047	0.002
single w/ chidren	1293	0.352	0.052	0.052	0.000	0.548	0.012	0.471	0.040	0.024	0.047	0.045	0.002

married w/o children	8365	0.971	0.010	0.008	0.001	0.012	0.000	0.010	0.001	0.001	0.007	0.007	0.000
married w/ child	4199	0.878	0.027	0.023	0.004	0.069	0.003	0.056	0.006	0.004	0.026	0.025	0.001
<b>Food stamp/SNAP recipient</b>													
Yes	1560	0.138	0.053	0.050	0.003	0.693	0.014	0.606	0.047	0.027	0.115	0.108	0.007
	1718												
No	4	0.893	0.024	0.022	0.003	0.062	0.002	0.051	0.006	0.003	0.021	0.020	0.001
<b>Home ownership</b>													
	1430												
Own	5	0.928	0.016	0.014	0.002	0.042	0.002	0.033	0.005	0.002	0.013	0.013	0.001
Rent	3907	0.552	0.059	0.054	0.005	0.319	0.005	0.277	0.023	0.014	0.069	0.066	0.003
Neither	540	0.614	0.091	0.075	0.016	0.208	0.000	0.179	0.016	0.013	0.087	0.083	0.004
<b>Vehicle ownership</b>													
	1708												
Yes	6	0.888	0.024	0.021	0.002	0.067	0.002	0.055	0.007	0.003	0.020	0.019	0.001
No	1666	0.372	0.056	0.049	0.007	0.477	0.006	0.413	0.032	0.024	0.095	0.090	0.005
<b>Region</b>													
Northeast	1344	0.928	0.019	0.018	0.001	0.034	0.000	0.025	0.006	0.003	0.019	0.017	0.002
Mid-Atlantic	2545	0.893	0.021	0.018	0.004	0.063	0.001	0.054	0.006	0.002	0.022	0.021	0.000
South	5907	0.784	0.035	0.033	0.002	0.149	0.005	0.123	0.014	0.007	0.033	0.032	0.001
Midwest	4724	0.831	0.027	0.023	0.003	0.115	0.003	0.097	0.009	0.006	0.027	0.024	0.002
West	3515	0.901	0.021	0.018	0.003	0.057	0.000	0.051	0.003	0.002	0.021	0.021	0.000
<b>Shocks</b>													
No longer received food stamp/SNAP	427	0.163	0.219	0.175	0.043	0.589	0.002	0.512	0.060	0.014	0.030	0.030	0.000
No longer employed	777	0.764	0.091	0.075	0.016	0.130	0.002	0.114	0.012	0.001	0.015	0.015	0.000
No longer married	251	0.857	0.058	0.057	0.001	0.065	0.001	0.065	0.000	0.000	0.020	0.017	0.003
Became disabled	1240	0.746	0.009	0.009	0.000	0.156	0.004	0.131	0.013	0.007	0.089	0.086	0.003
No longer own house	487	0.795	0.071	0.070	0.001	0.098	0.003	0.083	0.010	0.003	0.036	0.035	0.001
No longer own vehicle	455	0.502	0.010	0.010	0.000	0.297	0.007	0.270	0.006	0.015	0.191	0.183	0.008

*Note:* Column (1) report the number of observations in each subgroup. The transition shares of column (2), (3), (6) and (11) sum up to one. The sum of structural and stochastic transition shares in column (2), (4), (5), (7)-(10) and (12)-(3) also equal to one. These transition shares are calculated by the weighted joint distribution.

**Table 4.7. Persistent and Entry Rate Across Two Consecutive Waves.**

	Persistent Rate			Entry Rate		
	FI	Stochastical FI	Structural FI	FI	Stochastical FI	Structural FI
<b>Year</b>						
2003	0.809	0.393	0.872	0.027	0.005	0.022
2005	0.776	0.252	0.855	0.028	0.006	0.022
2007	0.783	0.379	0.830	0.028	0.004	0.024
2009	0.854	0.672	0.883	0.058	0.015	0.044
2011	0.817	0.483	0.872	0.035	0.007	0.028
2013	0.776	0.463	0.822	0.032	0.011	0.021
2015	0.821	0.447	0.883	0.021	0.005	0.016
2017	0.764	0.447	0.814	0.015	0.005	0.010
2019	0.712	0.257	0.804	0.025	0.007	0.018
<b>Gender</b>						
Male	0.692	0.352	0.762	0.021	0.005	0.016
Female	0.863	0.500	0.908	0.067	0.015	0.051
<b>Race</b>						
white	0.691	0.329	0.749	0.020	0.004	0.016
Non-white	0.864	0.490	0.923	0.128	0.039	0.089
<b>Highest Education Degree</b>						
less than high school	0.869	0.475	0.904	0.111	0.020	0.091
high school	0.811	0.468	0.865	0.042	0.010	0.032
some college	0.726	0.328	0.797	0.031	0.008	0.023
college	0.586	0.391	0.661	0.011	0.003	0.007
<b>Disability</b>						
Yes	0.839	0.432	0.894	0.068	0.017	0.051
No	0.759	0.413	0.819	0.021	0.005	0.016
<b>Household composition</b>						
single without child	0.799	0.410	0.859	0.065	0.014	0.050
single with children	0.913	0.555	0.957	0.118	0.034	0.084
married without children	0.557	0.264	0.616	0.007	0.002	0.005
married with child	0.723	0.433	0.782	0.029	0.008	0.021

<b>Food stamp/SNAP recipient</b>						
Yes	0.929	0.604	0.961	0.454	0.095	0.359
No	0.718	0.368	0.785	0.023	0.006	0.017
<b>Home ownership</b>						
Own	0.725	0.377	0.805	0.014	0.004	0.010
Rent	0.844	0.498	0.883	0.112	0.026	0.086
Neither	0.696	0.290	0.767	0.124	0.017	0.106
<b>Vehicle ownership</b>						
Yes	0.739	0.374	0.805	0.022	0.006	0.016
No	0.895	0.567	0.932	0.203	0.035	0.168
<b>Region</b>						
Northeast	0.641	0.382	0.685	0.020	0.003	0.017
Mid-Atlantic	0.747	0.247	0.827	0.024	0.005	0.019
South	0.810	0.434	0.875	0.040	0.010	0.030
Midwest	0.813	0.496	0.862	0.031	0.008	0.023
West	0.734	0.324	0.786	0.023	0.006	0.017
<b>Shocks</b>						
No longer received food stamp/SNAP	0.729	0.216	0.783	0.155	0.016	0.139
No longer employed	0.588	0.126	0.644	0.020	0.005	0.014
No longer married	0.531	0.029	0.683	0.023	0.008	0.015
Became disabled	0.944	0.668	0.974	0.106	0.024	0.083
No longer own house	0.580	0.172	0.681	0.043	0.004	0.039
No longer own vehicle	0.966	0.751	0.988	0.275	0.049	0.226

*Note:* Persistence  $Pr = (FI_t|FI_{t-1})$ ; Entry  $Pr = (FI_t|FS_{t-1})$ ; The persistence rate for stochastic (alternatively, structural) FI quantifies the conditional probability that a household, identified as being stochastically (or structurally) food insecure in one survey wave, will continue to exhibit FI in the subsequent survey wave. Similarly, the entry rate for stochastic (or structural) FI is defined as the conditional probability that a household, initially food secure, transitions into a state of stochastic (or structural) FI in the following survey period.

**Table 4.8. Spell Length Distribution.**

Spell length survey waves	Proportion	Conditional Persistence (Std.Error)	Proportion of estimated structural FS status			
			Structural FS	Stochastical FS	Stochastical FI	Structural FI
1 (1-4 years)	43.08%	0.58 (0.03)	40.17%	47.70%	4.59%	7.54%
2 (3-6 years)	11.01%	0.8 (0.02)	25.73%	45.15%	9.12%	20.00%
3 (5-8 years)	10.18%	0.79 (0.03)	15.68%	41.12%	10.90%	32.30%
4 (7-10 years)	3.61%	0.92 (0.03)	13.20%	28.34%	12.60%	45.86%
5 (9-12 years)	5.73%	0.8 (0.04)	6.86%	31.85%	8.71%	52.57%
6 (11-14 years)	5.94%	0.84 (0.04)	4.22%	21.69%	8.50%	65.59%
7 (13-16 years)	2.11%	0.96 (0.01)	3.57%	15.97%	7.00%	73.47%
8 (15-18 years)	3.21%	0.87 (0.04)	5.00%	12.73%	15.90%	66.37%
9 (17-20 years)	1.78%	0.92 (0.04)	4.83%	7.46%	3.96%	83.75%
10 (20+ years)	13.35%		0.00%	0.00%	4.75%	95.25%

*Note:* Sample consists of the balanced panel of households with SPFS estimates from 2001 to 2019. Duration reflects the number of consecutive (biennial) survey waves and years households experienced FI. As data are right censored, there is no upper limit on the range for the spell length of nine survey waves, the entire study period. Other spell lengths can likewise be right censored if the household was food insecure in 2019.

**Table 4.9. Estimated Structural FS Status from the Permanent Approach.**

Category	N	TFI	SFI	TFI-SFI	(SFI/TFI)	Structural & persistent FI	Structural, but not persistent FI	Stochastical FI	Never FI
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	21064	0.122	0.103	0.020	0.839	0.044	0.052	0.118	0.787
<b>Gender</b>									
Male	16512	0.067	0.054	0.014	0.794	0.014	0.036	0.098	0.852
Female	4552	0.314	0.274	0.040	0.872	0.151	0.110	0.188	0.550
<b>Race</b>									
White	14326	0.062	0.045	0.017	0.729	0.010	0.031	0.102	0.856
Non-white	6738	0.483	0.446	0.037	0.922	0.252	0.179	0.214	0.355
<b>Highest Education Degree</b>									
Less than high school	2316	0.418	0.429	-0.011	1.027	0.221	0.192	0.195	0.392
High school	7335	0.162	0.131	0.031	0.807	0.049	0.074	0.159	0.718
Some college	4934	0.105	0.077	0.028	0.737	0.033	0.039	0.128	0.800
College	6067	0.019	0.008	0.011	0.425	0.002	0.006	0.056	0.937
<b>Metropolitan area</b>									
Metro	15910	0.121	0.101	0.021	0.830	0.044	0.050	0.117	0.789
Non-metro	5064	0.127	0.111	0.017	0.870	0.043	0.059	0.121	0.777
<b>Region</b>									
Northeast	1514	0.051	0.022	0.029	0.429	0.015	0.005	0.112	0.868
Mid-Atlantic	2846	0.084	0.058	0.027	0.683	0.021	0.034	0.109	0.837
South	6625	0.185	0.161	0.024	0.870	0.076	0.075	0.141	0.709
Midwest	5319	0.140	0.128	0.012	0.917	0.058	0.062	0.112	0.769
West	3953	0.077	0.062	0.015	0.807	0.013	0.045	0.105	0.837

Note: Sample include households with non-missing SPFS for 5 or more years from 2001 to 2019. It is the headcount ratio (HCR) of FI measure using the SPFS following the method from Jalan and Ravallion (2000). The last four columns describe the distribution of households' status which add up to one. SFI can be greater than TFI, like household head with Less than high school degree. That's the very definition of a household that is structurally food insecure but occasionally food secure (i.e., structurally but not persistently food insecure).

**Table 4.10. Regression of TFI and SFI on Characteristics.**

VARIABLES	TFI (1)	SFI (2)
Age	-0.002 (0.00)	-0.003 (0.00)
Age <sup>2</sup>	-0.017 (0.02)	-0.015 (0.02)
Non-white	0.222*** (0.02)	0.213*** (0.03)
Married	-0.056*** (0.01)	-0.045** (0.02)
Female	0.061*** (0.02)	0.050** (0.02)
High school	-0.072*** (0.02)	-0.117*** (0.03)
Some college	-0.109*** (0.02)	-0.150*** (0.03)
College	-0.116*** (0.02)	-0.156*** (0.03)
Employed	-0.008 (0.01)	-0.010 (0.01)
Disabled	0.046*** (0.01)	0.041** (0.02)
ln(income per capita)	-0.036*** (0.00)	-0.033*** (0.01)
Family size	0.013*** (0.00)	0.013* (0.01)
% of children	-0.109*** (0.02)	-0.114*** (0.03)
Received Food Stamp/SNAP	0.250*** (0.03)	0.261*** (0.04)
Received Child Meal	0.138*** (0.02)	0.171*** (0.03)
Received WIC	0.0153 (0.02)	-0.0215 (0.03)
Received Elderly Meal	-0.031 (0.03)	-0.019 (0.03)
Rent	0.081*** (0.01)	0.045** (0.02)
Neither owns nor rents	0.074*** (0.02)	0.029 (0.03)
Not own vehicle	0.152*** (0.03)	0.140*** (0.04)
No longer receive Food Stamp/SNAP	0.181*** (0.02)	0.187*** (0.03)
No longer employed	0.010 (0.01)	0.021* (0.01)
No longer married	-0.018 (0.02)	-0.009 (0.02)
Became disabled	-0.018 (0.01)	-0.017 (0.01)
No longer own home	-0.042*** (0.01)	-0.026 (0.02)
No longer own vehicle	-0.087*** (0.03)	-0.078** (0.04)
N	21064	21064
Population size	481,819.72	481,819.72
R <sup>2</sup>	0.666	0.517

*Note:* Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Sample include households with non-missing SPFS for 5 or more years from 2001 to 2019. The FI measure for TFI and SFI is the headcount ratio (HCR) using the SPFS.

**Table 4.11. Shapley Decomposition of the TFI and the SFI.**

Component	TFI		SFI	
	R <sup>2</sup>	Share	R <sup>2</sup>	Share
Region	0.064	0.087	0.050	0.083
Age	0.020	0.027	0.014	0.023
Race	0.165	0.225	0.122	0.206
Marriage status	0.062	0.084	0.046	0.078
Sex	0.055	0.074	0.043	0.073
Education	0.053	0.073	0.051	0.087
Income	0.081	0.110	0.066	0.111
Food assistance (SNAP, WIC, child meal and Elderly meal)	0.092	0.126	0.086	0.145
House and vehicle ownership	0.095	0.130	0.075	0.127
Others	0.043	0.059	0.037	0.062
Total	0.729	0.993	0.590	0.994

*Note:* This decomposition is from the unadjusted (unweighted, no panel data adjustment) regression. Sample include households with nonmissing SPFS for 5 or more years from 2001 to 2019. “Others” include family size, % of children, employment, disability, and change in status. Variation from time FE (less than 0.06) is omitted from this table.

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## Appendix

### A. Robustness Check of Bartik Instrument

**Table A: The Effect of Economic Cycle on Household Food Insecurity Using Alternative Bartik Instruments.**

VARIABLES	Household food insecurity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Instrument</i>	<i>Baseline</i>	<i>Baseline</i>	<i>Simple demeaning growth rate</i>	<i>Simple demeaning growth rate</i>	<i>Top five industries Only</i>	<i>Top five industries Only</i>	<i>Share-Year Dummy Interaction Instrument</i>	<i>Share-Year Dummy Interaction Instrument</i>
<b>URmsa</b>	<b>0.011***</b> <b>(0.001)</b>	<b>0.010***</b> <b>(0.001)</b>	<b>0.047***</b> <b>(0.011)</b>	<b>0.027***</b> <b>(0.009)</b>	<b>0.014***</b> <b>(0.001)</b>	<b>0.011***</b> <b>(0.001)</b>	<b>0.008***</b> <b>(0.002)</b>	<b>0.009***</b> <b>(0.002)</b>
1.hh_img	0.053*** (0.006)	0.048*** (0.005)	0.052*** (0.005)	0.049*** (0.005)	0.053*** (0.006)	0.048*** (0.005)	0.053*** (0.006)	0.047*** (0.005)
Constant	0.057*** (0.008)	0.481* (0.247)	-0.189** (0.077)	-3.237* (1.686)	0.033*** (0.009)	0.271 (0.223)	0.070*** (0.012)	0.608 (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	249.25	249.11	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.

## B. 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 et al. (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:

$$UR_{lt} = \lambda B_{lt} + \mu_{lt} \quad (9)$$

$$y_{lt} = \beta \widehat{UR}_{lt} + \epsilon_{lt} \quad (10)$$

Equation (9) is the first stage; Equation (10) represents 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 (10). 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:

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

Following the decomposition process of the Bartik instrument estimator suggested by Goldsmith-Pinkham et al. (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:

$$\hat{\beta}_k^{bartik} = \frac{Z_k'Y}{Z_k'X} \quad (12),$$

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:

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

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  $X_k^{bartik'X}$  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 B. Panels A and B report the variation in Bartik instruments among industries and years. Panel C summarizes the distribution of Rotemberg weights<sup>32</sup>. Panel D shows the correlation between the Rotemberg weights ( $\hat{\alpha}_k$ ), industry national employment growth rate ( $\hat{g}_k$ ), the just identified coefficient estimates ( $\hat{\beta}_k$ ), the first stage F- statistics of the industry share ( $\hat{F}_k$ ) and the variance of local industry shares ( $Var(z_k)$ ). This panel shows that the Rotemberg weights and industry employment

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<sup>32</sup> Goldsmith-Pinkham et al. (2020) indicate that negative Rotemberg weights are possible resulting from outlying point estimates, which raises the possibility (but does not necessarily imply) non-convex weights on the just-identified instrumental variable estimator. In this case the overall Bartik estimate does not have a LATE-like interpretation as a weighted average of treatment effects.

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 B. 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  $\alpha_k$** 

	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**

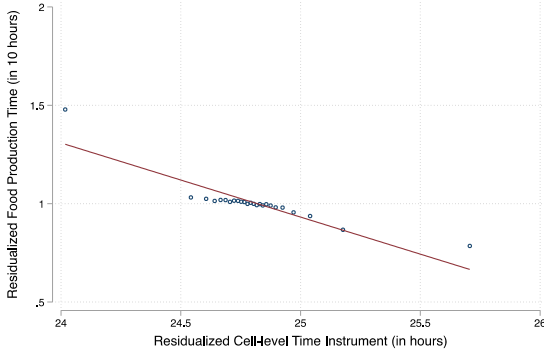
	Sum	Mean	Share
Negative	-1.311	-0.187	0.362
Positive	2.311	0.385	0.638

**Panel D: Correlations of Industry Aggregates**

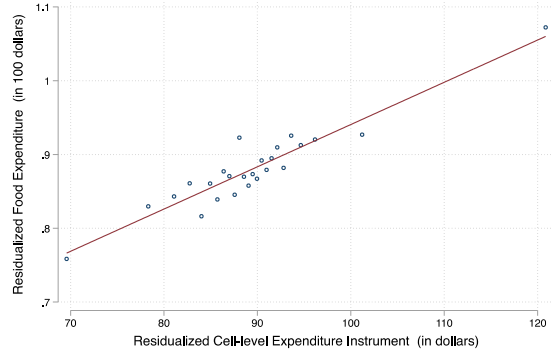
	$\widehat{\alpha}_k$	$g_k$	$\widehat{\beta}_k$	$\widehat{F}_k$	Var( $z_k$ )
$\widehat{\alpha}_k$	1				
$g_k$	-0.170	1			
$\widehat{\beta}_k$	-0.055	0.636	1		
$\widehat{F}_k$	0.328	-0.307	0.019	1	
Var( $z_k$ )	-0.097	-0.284	0.314	-0.214	1

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  $\widehat{\beta}_k^{bartik}$  estimated from equation (12). Following the suggestion from Goldsmith-Pinkham et al. (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.

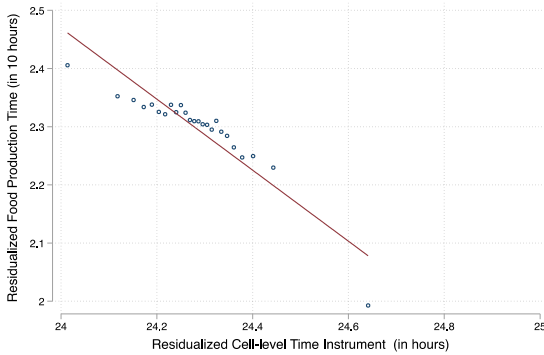
**C. First Stage Effects of Cell-level Instruments on Weekly Time and Money Use Separately for Single and Married Households.**



**a. First stage effect of cell-level Instrument on Food Production Time for Single Households**



**b. First stage effect of cell-level Instrument on Food Expenditure for Single Households**



**c. First stage effect of cell-level Instrument on Food Production Time for Married Household**



**d. First stage effect of cell-level Instrument on Food Expenditure for Married Households**

**Figure C. First Stage Effects of Cell-level Instruments on Weekly Time and Money Use Separately for Single and Married Households.**

*Note:* The figure is a visual representation of the first stage regressions about the residualized cell-level instruments and weekly food production time and food expenditure for single and married households separately. The residualized y- and x-axis variables are generated by the regression of predicted weekly food production time or food expenditure on its corresponding cell-level instrument for single and married households with full set of the same control variables as in the IV estimations of the effect of time and money inputs on household FI. We then group the values of residualized cell-level instruments for time and money into equal sized bins, compute the mean of instruments and time (or money) residuals within each bin, and create a scatterplot of these data points. Finally, the red lines are the plotted the best linear fit lines for time and money inputs, constructed from the OLS regressions of the y-residuals on the x-residuals. The slopes of the fit lines match the first-stage regression coefficients on the cell-level instruments for single and married households.

*Source:* Authors' calculations, Current Population Survey, and American Time Use Survey.

**D. Estimated Structural FS Status from the Permanent Approach using SFIG.**

**Table D. Estimated Structural FS Status from the Permanent Approach using SFIG.**

Category	N	TFI	SFI	TFI-SFI	(SFI/TFI)	Structural & persistent FI	Structural, but not persistent FI	Stochastical FI	Never FI
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total	21064	0.027	0.019	0.007	0.722	0.044	0.052	0.118	0.787
<b>Gender</b>									
Male	16512	0.011	0.005	0.005	0.514	0.014	0.036	0.098	0.852
Female	4552	0.085	0.069	0.016	0.813	0.151	0.110	0.188	0.550
<b>Race</b>									
White	14326	0.008	0.004	0.004	0.477	0.010	0.031	0.102	0.856
Non-white	6738	0.138	0.112	0.026	0.811	0.252	0.179	0.214	0.355
<b>Highest Education Degree</b>									
Less than high school	2316	0.133	0.106	0.027	0.794	0.221	0.192	0.195	0.392
High school	7335	0.029	0.020	0.009	0.692	0.049	0.074	0.159	0.718
Some college	4934	0.019	0.012	0.007	0.645	0.033	0.039	0.128	0.800
College	6067	0.003	0.001	0.002	0.449	0.002	0.006	0.056	0.937
<b>Metropolitan area</b>									
Metro	15910	0.027	0.019	0.007	0.722	0.044	0.050	0.117	0.789
Non-metro	5064	0.028	0.020	0.008	0.724	0.043	0.059	0.121	0.777
<b>Region</b>									
Northeast	1514	0.010	0.006	0.004	0.616	0.015	0.005	0.112	0.868
Mid-Atlantic	2846	0.017	0.012	0.005	0.707	0.021	0.034	0.109	0.837
South	6625	0.041	0.032	0.010	0.768	0.076	0.075	0.141	0.709
Midwest	5319	0.035	0.026	0.009	0.757	0.058	0.062	0.112	0.769
West	3953	0.014	0.007	0.007	0.484	0.013	0.045	0.105	0.837

*Note:* Sample include households with non-missing SPFS for 5 or more years from 2001 to 2019. It is the FI measure using the SPFS with  $\alpha = 2$  following the method from Jalan and Ravallion (2000). The last four columns describe the distribution of households' status which add up to one. SFI can be greater than TFI, like household head with Less than high school degree. That's the very definition of a household that is structurally food insecure but occasionally food secure (i.e., structurally but not persistently food insecure).