Topics on Food Insecurity

by

Akash Issar

(Under the Direction of Travis A. Smith)

Abstract

We explore two aspects of food insecurity in this study. In both study, we use the Food Security Supplement to the Current Population Survey to measure food insecurity. In our first study, *Empirical Analysis of The Black-White Food Insecurity Gap* , we explore the factors behind Black households experiencing higher food insecurity relative to a White household. We find that returns to SNAP are experienced primarily by White households. Decomposition analysis suggests that 57.32% of the Black-White food insecurity gap is explained by observable demographics. And our heterogeneity analysis on the effect of race on food insecurity highlights lack of home ownership, low education and poverty to be crucial factors explaining the gap. Our second study, *Food Insecurity And Unemployment*, explores the relationship between unemployment and food insecurity. We apply the *front-door criterion* and argue that the effect of unemployment on food insecurity is completely mediated by resource (monetary) deficiency. We find that householder's unemployment causes the probability of being food insecure by 1.1 percentage points. And if all family members are unemployed the effect is 1.8 percentage points. Further analysis examines food severity and unemployment and finds that unemployment increases food insecurity at the intensive margin, too.

Index words: Food Insecurity, Racial Disparity, Supplemental Nutrition Assistance Program, Decomposition Analysis, Sorted Partial Effects, Front-Door Criterion, Mediator, Unemployment

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Dedication

Dedicating this to my past and future self. To my past, you made it this far and in this beautiful country that was your dream and prayers. And, to my future self, learn and explore as there is a lot to uncover and keep working on yourself to defeat what holds you back.

Acknowledgments

Dear Dr. Travis Smith,

I pen this letter as my acknowledgement to you for being an integral part of my Ph.D. journey. Looking back, you have been my advisor, mentor and teacher. Professor, this dissertation is a culmination of five years of exploration, apprehension, frustration and elation. My doctoral journey began with thirst for a better education and evolved into a thirst for a well rounded knowledge. There is still a long way to go, with ebbs and flows, as the past five years have only revealed a fraction of what defines a researcher and an academician. Dr. Smith, my Ph.D. journey has been bolstered by your support and my expression of gratitude towards you with these words don't seem enough. I have gathered and learnt the essentials of being an economist and a teacher with our interactions, meetings and discussions. I am not sure what the future holds, but I hope I do you proud.

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Dr. Smith, since our first meet in 2017 to the present , you have supported and guided my educational development by providing me amazing opportunities. And, in the next stage of my career, I will definitely push myself to make progress on doing amazing research and do you proud. Thank you for all that you've done and provided me in this doctoral journey.

Yours faithfully, Akash Issar

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Chapter 1

Introduction And Literature Review

1.1 Introduction

In the chapter, *Empirical Analysis of The Black-White Food Insecurity Gap*, we explore the factors behind the differential experience in food insecurity between Black & White households. Black households experience, on average, 11 percentage points higher food insecurity relative to a White household for the period under study (2005-2016). Our instrumental variables results highlight that returns to SNAP reduces food insecurity primarily for White households than Black households. We employ a modified Kitagawa-Oaxaca-Blinder decomposition using DiNardo et al., 1996 re-weighting factor. Decomposition results provide evidence that 57.3% of the difference between these two groups is explained by differences in mean observable household characteristics. Thus, aiding policymakers to target public policies to address part of the food insecurity problem. Next, we move beyond the averages in exploring the heterogeneity in the partial effects of being black on the probability of being food insecure. We estimate the average partial effect and sorted partial effect using Chernozhukov et al., 2018 methodology on the Food Security Module of the Current Population Survey data covering 2005-2016. The average partial effect of being black on food insecurity is 4 percentage points. The *sorted effects* curve graphically depicts the heterogeneity in this summary measure showing that the effects range from 1 to 6 percentage points. Households are classified into having the largest and smallest effects, respectively. One of the observable characteristics that make these two households differ is the low home ownership rate among the households that experience higher food insecurity.

In the chapter, *Food Insecurity And Unemployment*, we explore the relationship between unemployment & household's food hardships measured using both *food insecurity* and *food severity* status. We begin by exploring the association between householder being unemployed and food insecurity outcome and we find that an unemployed householder's household is associated with 7.2 percentage points higher probability of being food insecure than an employed householder's household. Our data includes the working age population using the Food Security Supplement of the Current Population Survey for the years 2001 to 2020. We argue that the total effect of unemployment on food insecurity is fully mediated by the lack of monetary resources that translates into higher food insecurity. To estimate the indirect effect of unemployment on food insecurity, we employ the *front-door criterion* estimation proposed by Pearl, 1995, 2009 with an economic application as used by Bellemare et al., 2021. We use *resource (monetary) deficiency* as the mechanism (a mediator) that translates unemployment into food insecurity. We find that the indirect effect of householder's unemployment on the the probability of being food insecure increases by 1.1 percentage points. And the impact increases to 1.8 percentage points if all family members in the labor force are employed. On *food severity*, measured by the count of responses to the food security questions, we find that both householder's and family members' unemployment status increases the responses to the food insecurity experiences. The analysis of the paper could suggest to policymakers the need to strengthen the local labor market to address a part of the food insecurity problem.

1.2 Literature on Racial Disparity & Food Insecurity

Food insecurity severity and widening racial disparities in the USA have been reignited since the onset of the global pandemic despite reaching low food insecurity rates in 2019 to rates prevalent prior to the Great-Recession of 2008 Coleman-Jensen et al., 2021. Lack of access to adequate and nutritious food is associated with both financial and health hardships. The United States Department of Agriculture (USDA) characterizes *food insecurity* as households lacking the resources necessary for a consistent and dependable access to food. Since the onset of the pandemic, food stress and food-related hardships has hit low-income households hard. As of September 2020, Blacks and Hispanics families with school-aged children have experienced higher rates of food insecurity than a similar White family Gupta et al., 2020. However, prior to the onset of the pandemic in 2020, in 2014 one in seven households experienced food insecurity and 40% among them were *very low food secure* Furman et al., 2015. Coleman-Jensen et al., 2020 report that in 2019 10.5% of US households reported food insecurity over the year (down from 11.1% in 2018) out of which 4.1% were very low food secure (statistically insignificant from 4.3% in 2018). Furthermore, 2019 was the first time that food insecurity fell below the 2007 level.

The USDA measures food insecurity by the responses to eighteen survey questions (ten for adults and 8 additional for households with children). Some of the questions asked about the food situation in a household are : 1) *"We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?*; 2) *In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)* (see, Coleman-Jensen et al., 2021 page 5 for the complete list of the 18-item questionnaire). Tanaka et al., 2020 provide a detailed description on how food insecurity is measured in the USA and what the responses tell us about households food hardships.

Food insecurity and health outcomes have been shown to have a strong association. The following study in the medical and health arena have shown a negative association of food insecurity with diabetes (Liese et al., 2020). Cassidy-Vu et al., 2022 provide evidence of strong correlation between food insecurity and infant mortality for North Carolina residents. Gundersen and Ziliak, 2018 provides a great overview on where we are on food insecurity in the US and where the research needs to move forward. Supplemental Nutrition Assistance Program (SNAP), a cornerstone of the federal food assistance program, provides additional resource to the low-income households to be able to have access to food for a healthy life. In other words, SNAP is a first line of defense against hunger Ratcliffe et al., 2011. SNAP is administered by the U.S. Department of Agriculture's (USDA's) Food and Nutrition Service (FNS) and has been reauthorized in every Farm Bill since 1973 Aussenberg, 2018a; Aussenberg and Billings, 2018[1]. Prior work has addressed the policy question on how effective is SNAP in addressing food insecurity. A key policy question is : how effective is SNAP in reducing the food insecurity gap between Blacks and Whites? Understanding the role of SNAP in further addressing the disparity between the two groups is important for federal and state SNAP officials to address the food-related hardships among low-income households. Oliveira et al., 2018 examine the reasons behind the changes to the SNAP program and the major challenges facing SNAP program. Mills et al., 2014 find that Blacks are part of the SNAP demographics with higher rates of SNAP churn in a year.

[1] See Aussenberg and Billings, 2018; Aussenberg et al., 2019 for other major nutrition programs in the USA aside from SNAP that were recently updated in the 2018 Farm Bill. See, Aussenberg, 2018b for a primer on SNAP eligibility requirements and how benefits are calculated.

We add to the discussion of racial disparities in food insufficiency and food insecurity as provided in Flores-Lagunes et al., 2018a; McDonough et al., 2020; Ziliak, 2021 by exploring the differential returns to SNAP participation among Black & White households, decomposing the food insecurity gap among the two groups and examining the factors contributing to the heterogeneous effect of race on food insecurity. Our analysis uses the December supplement to the Current Population Survey, *Food Security Supplement* (CPS-FSS) for the years 2005-2016.

The causal impact of returns to SNAP participation on food insecurity faces an econometric identification problem as SNAP participation is an endogenous variable where the endogeneity arises from the non-random selection into participation. SNAP participants differ from non-participating eligible households because of un-observable factors that drive the participation decision. To address the endogeneity of SNAP participation, we use the instrumental variable (IV) approach by instrumenting the SNAP participation decision with variation in state-level SNAP policies (2005-2016) that impact eligibility and access to the program. We exploit both the state & temporal variation in policy helps in identifying the causal relationship. This IV analysis tell us that SNAP reduces food insecurity mostly for the White households. The Black households' food insecurity does not differ with SNAP participation. Thus, we highlight that despite the broad consensus that *SNAP matters* (Gundersen et al., 2015) , there exists differential returns to SNAP in reducing food insecurity among Black and White households.

We explore the factors behind the differential experience of race on food insecurity. Black households experience, on average, 11 percentage points higher food insecurity relative to a White household for the period under study (2005-2016). We decompose this mean food insecurity gap into explained and unexplained components using a modified Kitagawa-Oaxaca-Blinder decomposition method. Decomposition methods have been used in various fields from sociology to economics. Kitigawa-Blinder-Oaxaca decomposition method (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) has been used in labor economics to explain the factors that have contributed to the gender (or racial) wage gap (see, Blau and Kahn, 1997; Heckman et al., 2000; Ochsenfeld, 2017; J. P. Smith and Welch, 1989). In the food policy sphere, T. A. Smith et al., 2019 decompose the increase in diet quality over the period of 1994-2010 and the contribution of changes in food choice in explaining the gap. DiNardo et al., 1996 decomposition method (using re-weighted Black households as our counterfactual group) provides evidence that 57.3% of the difference between these two groups is explained by observable household characteristics. Thus, aiding policymakers to target public policies to address part of the food insecurity problem. Furthermore, the detailed decomposition here, too, highlights that differences in SNAP participation rates among the two groups pf households does not contribute to the explained component of the food insecurity gap.

In our final analysis, we move beyond the averages in exploring the heterogeneity in the partial effects of race (here, being black) on the probability of being food insecure. We estimate the average partial effect and sorted partial effect using Chernozhukov et al., 2018 methodology. The average partial effect of being black on food insecurity is 4 percentage points. This tells us that, even after controlling for demographic and household characteristics, Black households are 4 percentage points more likely to experience food insecurity relative to a White household. This singular summary measure masks the heterogeneity in the effect of race on food insecurity. To explore the heterogeneity in the effect of race on food insecurity we employ the *sorted effects* methodology. The *sorted effects* curve graphically depicts the heterogeneity in this summary measure showing that the effects range from 1 to 5 percentage points. Households are, further, classified into having the largest and smallest effects, respectively and the factors that differentiate these two classified households are examined. One of the observable characteristics that make these two households differ is the low home ownership rate among the households that experience higher food insecurity.

1.3 Literature on Unemployment & Food Insecurity

Unemployment and job instability has been a huge macro and micro-economic shock as a result of the global pandemic. Economically vulnerable households, as a result, have been distressed in many aspects of daily life and loss of a job/paycheck has been at the center (Kalil et al., 2020). We explore the causal impact of unemployment on food insecurity and severity. Food insecurity is a major health concern in the USA. A recent report by the United States Department of Agriculture (USDA) by Coleman-Jensen et al., 2018a states that in the year 2017, 11.8% of households were food insecure at least some time during that year. Although a decrease from 2016 , when the number was 12.3%, the percentage of food insecure households is still large. By the definition of *food insecurity*, this indicates that there were households that at some point in the year had limited access to food owing to lack of money or other resources to obtain food. On the other hand, many regions of the United States suffer from low levels of labor force participation. Recent studies have begun to show a link between economic distress (e.g. unemployment) and health outcomes (see Betz and Jones, 2018). However, there still remains a question as to what extent unemployment affects a household's food insecurity status. The connection between job-loss and the resulting socio-economic outcomes is well hypothesized by Wilson, 2011 that declining job prospects have a wider impact on social outcomes like marriage, single parenthood, crime, drug use and health. We posit that *food insecurity* be also considered as a dimension of socio-economic outcomes an economically vulnerable household faces. The task of the researcher is to uncover the mechanisms that drive this causal relationship.

This paper studies how unemployment affects food insecurity among low-income individuals. Intuitively, unemployment leads to loss of a paycheck and this directly would affect an individual's basket of food making an individual feel less food secure. Nord et al., 2014 observe that household food insecurity and unemployment rate has been moving in tandem upto a few years since the financial crisis of 2008 but since 2010 even though unemployment rate has shown modest improvement food insecurity has remained high. Anderson et al., 2016 in examining very low food security status of low-income households with children, find that labour force patterns among potential workers in a household matters. That is, children in households where the adult works a larger fraction of the year are less likely to have a very low food secure (VLFS) status. This causal relationship between unemployment and food insecurity is studied using an aggregated state level analysis of unemployment rate and state food insecurity status by Gundersen et al., 2017. They find the elasticity of food insecurity rate with respect to the unemployment rate is greater and statistically significant than poverty rate. This highlights the importance of examining unemployment status and its impact on the incidence and severity of food insecurity.

It has been well documented in the food policy literature on the role of education and household income as determinants of household food insecurity. Bartfeld et al., 2006 have shown correlation between household-level characteristics as well as macroeconomic conditions on the household's food insecurity status. The household level determinants examined are income, education , race, number of children , employment status of the adult, household member with disability, etc. . The state-level characteristics examined are unemployment rate , SNAP participation rate, cost of rental housing, average wages, etc. Despite these descriptive associations the direction of causality is not yet well understood. In this paper, we aim to explore the negative causal relationship between unemployment status and food insecurity.

Job displacement, an economic shock that affects an individual's wages, through either a mass layoff or plant closures have a significant impact on individual's health outcomes. Studies on Sweden and Denmark show smaller effect of job displacement on mortality (Browning and Heinesen, 2012; Eliason and Storrie, 2009). Sullivan and von Wachter, 2009 show that displaced workers can also experience higher rates of mortality. They use unemployment insurance administrative data on quarterly earnings and employment histories of male workers from Pennsylvania in the 1970s and 1980s as well as death records from the Social Security Administration from 1980-2006 anywhere in the US. Sullivan and von Wachter, 2009 find that high-tenured male workers displaced experienced a significant increase in mortality rates of 50-100% increase in the immediate period and that converges to 10-15% increase in the hazard rate. This implies a decline in life-expectancy of 1.0-1.5 years for displaced workers in middle age.

It has been well documented the negative association between unemployment and health. However, the direction of causality needs can go both ways. Job displacement affects health through various mechanisms. Firstly, a negative wage shock affects consumption and exercise. Second, job displacement increases stress known to have negative effects on cardiovascular health. Bergemann et al., 2011 show that job displacement on diabetes incidence increased in Sweden for single men and women with children. A recent study by Black et al., 2015 use a rich detailed health survey form Norway matched with administrative register data from 1986-1999. Their sample consists of of men and women in their early 40s and compare displaced and non-displaced workers' health from 5years before to 7 years after displacement. The health outcomes the authors observe are cholesterol, blood pressure, smoking and an index of risk of heart disease. Black et al., 2015 find that the exact nature of displacement matters for health - downsizing versus plant closure - and find that the effect of plant closure on smoking dominate downsizing with differences large for women.

This paper addresses the endogeneity issue using and explores the impact of unemployment on two measures of food-related hardships, *food insecurity* and *food severity* (Flores-Lagunes et al., 2018b). We examine the *food insecurity incidence*, captured by the binary indicator of household's food insecurity status; and *food severity*, captured by the count of the affirmative responses in the food security module. The official statistics of food insecurity in the United States are based on a Food Security Supplement to the Current Population Survey (CPS-FSS). Our sample covers working-age respondents of the CPS-FSS who pass the common screening questions and report some level of food hardships. The individuals are of working age (18 - 64 years old) and in the labor force (i.e. currently working or actively searching for a job when unemployed). The sample consists of 60,292 person-year observations for the period of 2001-2020. We also, measure unemployment either via the unemployment status of the householder or share of unemployed family members (conditional on being in the labor force). The latter definition of unemployment attempts to address the stress a family as a whole undergoes with a loss of a paycheck.

We address the identification issue arising from the endogeneity of unemployment status (possibly, simultaneity bias arising from the relationship between food insecurity and unemployment) to identify the causal relationship by using Pearl, 1995, 2009 's *front-door criterion* (and with a recent economic application by Bellemare et al., 2021). We use *resource (monetary) deficiency* as the mechanism (a mediator) that translates unemployment into food insecurity. We argue that the total effect of unemployment on food insecurity is completely mediated by lack of (monetary) resources and this resource deficiency impacts food insecurity (and severity). We find that a householder being unemployed increases the probability of being food insecure by 1.1 percentage points. And the impact increases to 1.8 percentage points if all family members in the labor force are employed. On *food severity*, measured by the count of responses to the food security questions, we find that both householder's and family members' unemployment status increases the responses to the food insecurity experiences. The analysis of the paper could suggest to policymakers the need to strengthen the local labor market to address a part of the food insecurity problem.

Chapter 2

Empirical Analysis of The Black-White Food Insecurity Gap

2.1 Introduction

Food insecurity severity and widening racial disparities in the USA have been reignited since the onset of the global pandemic despite reaching low food insecurity rates in 2019 to rates prevalent prior to the Great-Recession of 2008 (Coleman-Jensen et al., 2021). Lack of access to adequate and nutritious food is associated with both financial and health hardships. The United States Department of Agriculture (USDA) characterizes *food insecurity* as households lacking the resources necessary for a consistent and dependable access to food. Since the onset of the pandemic, food stress and food-related hardships has hit low-income households hard. As of September 2020, Blacks and Hispanics families with school-aged children have experienced higher rates of food insecurity than a similar White family (Gupta et al., 2020). However, prior to the onset of the pandemic in 2020, in 2014 one in seven households experienced food insecurity and 40% among them were *very low food secure* (Furman et al., 2015). Coleman-Jensen et al., 2020 report that in 2019 10.5% of US households reported food insecurity over the year (down from 11.1% in 2018) out of which 4.1% were very low food secure (statistically insignificant from 4.3% in 2018). Furthermore, 2019 was the first time that food insecurity fell below the 2007 level.

Ziliak, 2021 provide evidence of exacerbation of food insufficiency with the onset of the pandemic. They observe that one in five Black adults reported food insufficiency compared to one in 11 White adults. Figure 2.1 show the the food insecurity rates and the Supplemental Nutrition Assistance Program (SNAP) participation rates of our Black and White households (non-Hispanic) from 2005 to 2019, respectively. We see that Black households' mean food insecurity rates being higher relative to a White households over the years. On average, this difference is about 11 percentage points. Figure 2.1 overlays the mean SNAP participation rates with the food insecurity rates and indicates that Black households have higher SNAP participation than White households (a difference of 15 percentage points, on average). Thus, Black households are more likely to be **On SNAP** but still experience **higher *food insecurity*** than a White household. This paper delves deeper behind the differential experience in Black-White food insecurity and explores the following questions: 1) Does SNAP have differential returns in reducing food insecurity among Black and White households?; 2) How much of the mean food insecurity gap is explained by observable characteristics?; 3) And how does the effect of race on food insecurity differ across households?

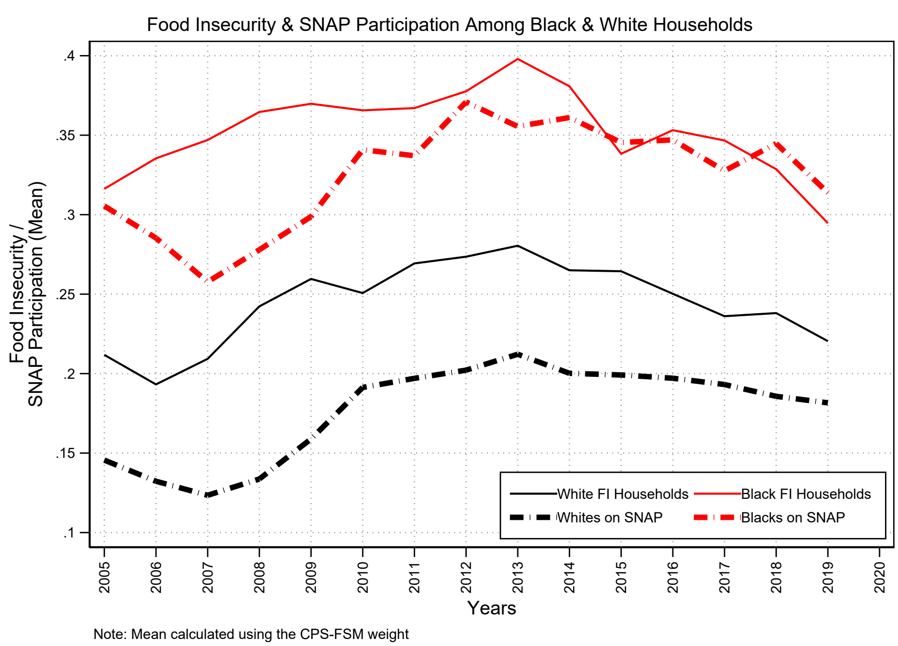

Figure 2.1: Mean SNAP participation rates & food insecurity rates among Black & White households using the Current Population Survey- Food Security Module (CPS-FSM) data for 2005-2019. These are non-Hispanic Black and White households. The solid lines are the food insecurity rates and the dashed lines are the SNAP participation rates.

The USDA measures food insecurity by the responses to eighteen survey questions (ten for adults and 8 additional for households with children). Soem of the questions asked about the food situation in a household are : 1) *"We* *worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?*; 2) *In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)* (see, Coleman-Jensen et al., 2021 page 5 for the complete list of the 18-item questionnaire). Tanaka et al., 2020 provide a detailed description on how food insecurity is measured in the USA and what the responses tell us about households food hardships.

Food insecurity and health outcomes have been shown to have a strong association. The following study in the medical and health arena have shown a negative association of food insecurity with diabetes (Liese et al., 2020). Cassidy-Vu et al., 2022 provide evidence of strong correlation between food insecurity and infant mortality for North Carolina residents. Gundersen and Ziliak, 2018 provides a great overview on where we are on food insecurity in the US and where the research needs to move forward. Supplemental Nutrition Assistance Program (SNAP), a cornerstone of the federal food assistance program, provides additional resource to the low-income households to be able to have access to food for a healthy life. In other words, SNAP is a first line of defense against hunger (Ratcliffe et al., 2011). SNAP is administered by the U.S. Department of Agriculture's (USDA's) Food and Nutrition Service (FNS) and has been reauthorized in every Farm Bill since 1973 (Aussenberg, 2018a; Aussenberg and Billings, 2018)[2]. Prior work has addressed the policy question on how effective is SNAP in addressing food insecurity. A key policy question is : how effective is SNAP in reducing the food insecurity gap between Blacks and Whites? Understanding the role of SNAP in further addressing the disparity between the two groups is important for federal and state SNAP officials to address the food-related hardships among low-income households. Oliveira et al., 2018 examine the reasons behind the changes to the SNAP program and the major challenges facing SNAP program. Mills et al., 2014 find that Blacks are part of the SNAP demographics with higher rates of SNAP churn in a year.

[2] See Aussenberg and Billings, 2018; Aussenberg et al., 2019 for other major nutrition programs in the USA aside from SNAP that were recently updated in the 2018 Farm Bill. See, Aussenberg, 2018b for a primer on SNAP eligibility requirements and how benefits are calculated.

We add to the discussion of racial disparities in food insufficiency and food insecurity as provided in Flores-Lagunes et al., 2018a; McDonough et al., 2020; Ziliak, 2021 by exploring the differential returns to SNAP participation among Black & White households, decomposing the food insecurity gap among the two groups and examining the factors contributing to the heterogeneous effect of race on food insecurity. Our analysis uses the December supplement to the Current Population Survey, *Food Security Supplement* (CPS-FSS) for the years 2005-2016.

The causal impact of returns to SNAP participation on food insecurity faces an econometric identification problem as SNAP participation is an endogenous variable where the endogeneity arises from the non-random selection into participation. SNAP participants differ from non-participating eligible households because of un-observable factors that drive the participation decision. To address the endogeneity of SNAP participation, we use the instrumental variable (IV) approach by instrumenting the SNAP participation decision with variation in state-level SNAP policies (2005-2016) that impact eligibility and access to the program. We exploit both the state & temporal variation in policy helps in identifying the causal relationship. This IV analysis tell us that SNAP reduces food insecurity mostly for the White households. The Black households' food insecurity does not differ with SNAP participation. Thus, we highlight that despite the broad consensus that *SNAP matters* (Gundersen et al., 2015) , there exists differential returns to SNAP in reducing food insecurity among Black and White households.

We explore the factors behind the differential experience of race on food insecurity. Black households experience, on average, 11 percentage points higher food insecurity relative to a White household for the period under study (2005-2016). We decompose this mean food insecurity gap into explained and unexplained components using a modified Kitagawa-Oaxaca-Blinder decomposition method. Decomposition methods have been used in various fields from sociology to economics. Kitigawa-Blinder-Oaxaca decomposition method (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) has been used in labor economics to explain the factors that have contributed to the gender (or racial) wage gap (see, Blau and Kahn, 1997; Heckman et al., 2000; Ochsenfeld, 2017; J. P. Smith and Welch, 1989). In the food policy sphere, T. A. Smith et al., 2019 decompose the increase in diet quality over the period of 1994-2010 and the contribution of changes in food choice in explaining the gap. DiNardo et al., 1996 decomposition method (using re-weighted Black households as our counterfactual group) provides evidence that 57.3% of the difference between these two groups is explained by observable household characteristics. Thus, aiding policymakers to target public policies to address part of the food insecurity problem. Furthermore, the detailed decomposition here, too, highlights that differences in SNAP participation rates among the two groups pf households does not contribute to the explained component of the food insecurity gap.

In our final analysis, we move beyond the averages in exploring the heterogeneity in the partial effects of race (here, being black) on the probability of being food insecure. We estimate the average partial effect and sorted partial effect using Chernozhukov et al., 2018 methodology. The average partial effect of being black on food insecurity is 4 percentage points. This tells us that, even after controlling for demographic and household characteristics, Black households are 4 percentage points more likely to experience food insecurity relative to a White household. This singular summary measure masks the heterogeneity in the effect of race on food insecurity. To explore the heterogeneity in the effect of race on food insecurity we employ the *sorted effects* methodology. The *sorted effects* curve graphically depicts the heterogeneity in this summary measure showing that the effects range from 1 to 5 percentage points. Households are, further, classified into having the largest and smallest effects, respectively and the factors that differentiate these two classified households are examined. One of the observable characteristics that make these two households differ is the low home ownership rate among the households that experience higher food insecurity.

This paper is organized as follows. Section 2.2 describes the data and our estimation sample. Section 2.3 explores the differential returns to SNAP on food insecurity among Black and White households using instrumental variables method. Section 2.4 decomposes the mean food insecurity gap into explained and unexplained components using a modified Kitagawa-Oaxaca-Blinder decomposition method. Section 2.5 explores the average and sorted partial effects of race on food insecurity. Section 2.6 discusses and concludes.

2.2 Data Exploration

We use the Current Population Survey - Food Security Supplement (CPS-FSS) data for the period of 2005-2016 (Flood et al., 2020). This section describes the steps involved in our sample creation for replication.

In the CPS-FSS supplement, we keep those households that are below the 185% of the poverty line. These are the group of households representing those that are prone to food hardships. For our analysis of food insecurity responses, we drop those observations for which food insecurity responses are not available. We keep adult civilian population and drop the armed forces population status. Our outcome variable is measured via the food security status for the adults to allow a consistent comparison across different household. Food insecurity is a binary indicator where one indicates that households have responded to 3 or more questions to the survey. We remove missing observations and non-response from the adult food security status. We keep the sample for which the information on SNAP is available. Our householders are all adults ranging from 18 to 70 plus years old. We create a binary SNAP variable with the value of one being of the household received SNAP in December. Food insecurity status is a binary variable with value of one being if CPS-FSS' food security status is '*low*' or '*very low*'. Our sample contains two mutually exclusive household groups - White non-Hispanic and Black non-Hispanic.

Our sample consists of 118,452 person-year observations for whom we have food insecurity responses for the time period 2005 to 2016. We have 96,120 White householders' and 22,332 Black householders' responses. Table 2.1 presents the summary statistics for our sample of two groups of households. All statistics cover the period of 2005-2016 and are weighted using the CPS-FSS sampling weight. Column 4 of table 2.1 conducts a mean comparison test between Black & White households. We find these two groups of households to be statistically different in most of these characteristics (other than *has a job* householder's characteristics).

Table 2.1 show that the probability of being food insecure is 11.4 percentage points higher for black households than for white households. Black householders, relative to White householders, are more likely to be females, less educated, more likely never married, living on the poverty threshold, less likely to own a house, and have about the same age composition of family members. Black householders are relatively more likely to be unemployed and have a higher SNAP participation rates than White householders. Black households reside relatively more in the metro area and in the Southern region of the USA. Black households make up 25% of our sample. More than half our combined sample (59%) are female householders. 21% of the sample report to be on SNAP. Among the labor force indicators , 51% of householders are not in the labor force followed by being at work (42%). About one-third of our sample have householders above the age of 60. Among the marital status categories, one-third householders are married and 28% have never married. More than half of our householders have an educational qualification with a high school diploma or less.

Among the household characteristics, our sample contains 49% households that own a house, of which, 55% of White households own a house. White households on average have a family income above the poverty threshold and Black households are living just on the poverty threshold. Black households are more likely to have children (age 17 and less) living in the house. Black households are more likely residing in the South and living in metro areas. Table 2.2 presents mean food insecurity status by SNAP participation. We see that for those *on SNAP*, 48.49% of the SNAP households are food insecure.

Table 2.1: Descriptive Statistics of Our Black & White CPS-FSM Households for the year 2005-2016

	Full Sample Mean (St. Dev) [1]	Blacks Mean (St. Dev) [2]	Whites Mean (St. Dev) [3]	B-W Difference [p-value] [4]
Food Insecurity And SNAP:				
Food Insecurity Status (Overall)	0.276	0.360	0.248	-0.114***
	(0.447)	(0.480)	(0.432)	[0.000]
On SNAP Indicator	0.212	0.325	0.175	-0.152***
	(0.408)	(0.468)	(0.380)	[0.000]
Householder's Characteristics:				
Black (non-Hispanic)	0.246			
	(0.431)			
Female	0.592	0.655	0.571	-0.097***
	(0.492)	(0.475)	(0.495)	[0.000]
Has A Job	0.424	0.447	0.417	-0.004
	(0.494)	(0.497)	(0.493)	[0.279]
Not in the Labor Force	0.505	0.450	0.523	0.047***
	(0.500)	(0.497)	(0.499)	[0.000]
Unemployed	0.071	0.103	0.060	-0.043***
	(0.256)	(0.305)	(0.238)	[0.000]
Age Between 18 to 21	0.035	0.034	0.036	0.004***
	(0.184)	(0.181)	(0.185)	[0.001]
Age Between 22 to 29	0.145	0.174	0.136	-0.023***
	(0.353)	(0.379)	(0.343)	[0.000]
Age Between 30 to 39	0.157	0.199	0.144	-0.045***
	(0.364)	(0.399)	(0.351)	[0.000]
Age Between 40 to 49	0.153	0.175	0.145	-0.026***
	(0.360)	(0.380)	(0.353)	[0.000]
Age Between 50 to 59	0.157	0.170	0.152	-0.028***
	(0.363)	(0.376)	(0.359)	[0.000]
Age Between 60 to 69	0.144	0.127	0.149	0.010***
	(0.351)	(0.333)	(0.356)	[0.000]
Age 70 plus	0.209	0.121	0.238	0.108***
	(0.407)	(0.326)	(0.426)	[0.000]
Married	0.319	0.214	0.354	0.144***
	(0.466)	(0.410)	(0.478)	[0.000]
Widowed	0.156	0.111	0.171	0.049***
	(0.363)	(0.314)	(0.376)	[0.000]
Separated	0.046	0.079	0.035	-0.047***
	(0.209)	(0.270)	(0.184)	[0.000]
Divorced	0.198	0.155	0.212	0.053***

	(0.398)	(0.362)	(0.409)	[0.000]
Never-married	0.281	0.442	0.228	-0.199***
	(0.449)	(0.497)	(0.420)	[0.000]
Less Than HS	0.190	0.238	0.175	-0.080***
	(0.393)	(0.426)	(0.380)	[0.000]
High School graduate	0.379	0.378	0.380	0.005
	(0.485)	(0.485)	(0.485)	[0.183]
Some College	0.309	0.306	0.310	0.017***
	(0.462)	(0.461)	(0.462)	[0.000]
College Graduate	0.092	0.059	0.102	0.045***
	(0.289)	(0.236)	(0.303)	[0.000]
Advanced Diploma	0.030	0.018	0.034	0.014***
	(0.170)	(0.134)	(0.180)	[0.000]
Own a House	0.488	0.306	0.547	0.228***
	(0.500)	(0.461)	(0.498)	[0.000]
Household Characteristics:				
Family income to poverty ratio	1.184	1.007	1.241	0.243***
	(0.573)	(0.579)	(0.559)	[0.000]
Share of members between age 0 and 5	0.062	0.083	0.055	-0.024***
	(0.147)	(0.170)	(0.138)	[0.000]
Share of members between age 6 and 10	0.050	0.068	0.045	-0.020***
	(0.127)	(0.147)	(0.119)	[0.000]
Share of members between age 11 and 14	0.037	0.049	0.033	-0.016***
	(0.107)	(0.124)	(0.101)	[0.000]
Share of members between age 15 and 17	0.027	0.036	0.024	-0.013***
	(0.093)	(0.108)	(0.087)	[0.000]
Share of members between age 18 and 21	0.051	0.054	0.050	-0.003**
	(0.170)	(0.164)	(0.172)	[0.004]
Share of members between age 22 and 29	0.117	0.129	0.113	-0.008***
	(0.261)	(0.260)	(0.262)	[0.000]
Share of members between age 30 and 39	0.094	0.111	0.088	-0.020***
	(0.212)	(0.229)	(0.206)	[0.000]
Share of members between age 40 and 49	0.104	0.117	0.100	-0.016***
	(0.241)	(0.255)	(0.236)	[0.000]
Share of members between age 50 and 59	0.131	0.135	0.130	-0.012***
	(0.294)	(0.294)	(0.294)	[0.000]
Share of members between age 60 and 69	0.130	0.108	0.137	0.020***
	(0.307)	(0.280)	(0.315)	[0.000]
Share of members between age 70 plus	0.197	0.109	0.226	0.112***
	(0.378)	(0.289)	(0.399)	[0.000]
Living in metro area	0.754	0.851	0.722	-0.172***
	(0.431)	(0.356)	(0.448)	[0.000]

Region Characteristics:				
State unemployment rate:	6.730	6.881	6.681	-0.604***
	(2.169)	(2.144)	(2.175)	[0.000]
North-east	0.156	0.132	0.164	0.080***
	(0.363)	(0.338)	(0.371)	[0.000]
Mid-west	0.260	0.193	0.282	0.109***
	(0.439)	(0.395)	(0.450)	[0.000]
Southern	0.426	0.594	0.371	-0.326***
	(0.494)	(0.491)	(0.483)	[0.000]
Western	0.158	0.082	0.183	0.137***
	(0.365)	(0.274)	(0.386)	[0.000]
Years:				
2005	0.075	0.076	0.075	0.004*
	(0.264)	(0.265)	(0.264)	[0.029]
2006	0.076	0.074	0.076	0.007***
	(0.265)	(0.261)	(0.266)	[0.000]
2007	0.078	0.079	0.077	0.002
	(0.268)	(0.269)	(0.267)	[0.162]
2008	0.091	0.087	0.093	0.010***
	(0.288)	(0.282)	(0.290)	[0.000]
2009	0.089	0.086	0.091	0.004
	(0.285)	(0.280)	(0.287)	[0.086]
2010	0.089	0.087	0.090	0.000
	(0.285)	(0.281)	(0.286)	[0.891]
2011	0.087	0.086	0.088	0.002
	(0.282)	(0.280)	(0.283)	[0.465]
2012	0.085	0.086	0.085	-0.001
	(0.279)	(0.281)	(0.279)	[0.720]
2013	0.081	0.082	0.080	-0.003
	(0.272)	(0.274)	(0.272)	[0.102]
2014	0.088	0.091	0.087	-0.009***
	(0.284)	(0.287)	(0.283)	[0.000]
2015	0.081	0.085	0.080	-0.009***
	(0.273)	(0.279)	(0.271)	[0.000]
2016	0.079	0.083	0.078	-0.008***
	(0.270)	(0.276)	(0.268)	[0.000]
Observations	118,452	22,332	96,120	118,452

Notes: Weighted means and standard deviation (in parentheses) using the CPS-FSS Sampling Weights.
Sample includes 118,452 observations. 96,120 are White householders & 22,332 Black householders.
Data using CPS Food Security Supplement 2005-2016.
Column 4 presents the t-test results from a mean comparison test assuming unequal variance.

The square brackets below the means are the p-values. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2: Food Insecurity By SNAP Status

Food Insecurity Status (Overall)	Not on SNAP	On SNAP (In Percent)	Total
Not Food Insecure	78.01	51.51	72.4
Food Insecure	21.99	48.49	27.6
Total	100	100	100

Source: Authors' calculation using CPS-FSS 2005-2016 and mean calculated using survey weights.

2.2.1 Components Food Insecurity Statistics

In tables 2.3 and 2.4 we explore the components of our food insecurity measure for the Whites & Blacks, respectively. Food insecurity is categorized by the CPS-FSS into four categories: *high food secure* (households had access at all times to enough food for an active, healthy life, i.e. zero affirmative responses); *marginal food secure* (households reported anxiety about food sufficiency or shortage of food, i.e. 1 to 2 affirmative responses); *low food secure* (households reported reduced quality, variety, or desirability of diet, i.e. 3 to 5 affirmative responses); and *very low food secure* (households reported multiple indications of disrupted eating patterns and reduced food intake, i.e. 6 or more affirmative responses).[3]

[3] See Gundersen and Ziliak, 2015 for an overview of the CPS-FSS food security responses and its association with health outcomes.

In both tables 2.3 & 2.4 , the first block provides statistics for the overall food insecurity indicator and its 4 components of food insecurity experience over the past year for the White & Black households, respectively. The second block reports food insecurity experience in the last 30 days of the survey. The third block measures *food severity* (food insecurity measured on the intensive margin) by counting the number of affirmative responses to the 10 food security questionnaire (both for past year and last 30 days measure). The final block reports the SNAP participation rates for each household group.

Overall, Black households are less likely to be *high food secure* whether a 12-month or 30-day measure of food insecurity. Furthermore, *food severity*, also reflects the differential experience between Black and White households suggesting that Black households are more likely to respond affirmatively to more food insecurity questions than White households (2.23 12-month food insecurity responses versus 1.62 responses for Blacks & Whites, respectively).

Table 2.3: Food Insecurity Experience & SNAP Indicator: For Whites

	Mean	SD	Min	Max	Obs.
Food Insecurity Experience Past Year					
Food Insecurity Status (Overall)	0.25	0.43	0	1	96120
High Food Security Status	0.59	0.49	0	1	96120
Marginal Food Security Status	0.16	0.37	0	1	96120
Low Food Security Status	0.13	0.33	0	1	96120
Very Low Food Security Status	0.12	0.33	0	1	96120
30 Day Measure of Food Insecurity					
Food Insecurity Status (30 Days Measure)	0.15	0.35	0	1	96120
High 30 Days Food Security Status	0.59	0.49	0	1	96120
Marginal 30 Days Food Security Status	0.16	0.37	0	1	96120
Low 30 Days Food Security Status	0.13	0.33	0	1	96120
Very Low 30 Days Food Security Status	0.12	0.33	0	1	96120
Food Severity Measure					
Num. of Affirmative Responses to Overall Food Security	1.62	2.58	0	10	96120
Num. of Affirmative Responses to 30 Days Food Security	0.96	2.15	0	10	96120
SNAP Participation					
On SNAP Indicator	0.18	0.38	0	1	96120

Notes: Weighted summary statistics. We use the CPS-FSM sampling person weights. The observations are for our estimation sample for the period of 2005-2016.

Table 2.4: Food Insecurity Experience & SNAP Indicator: For Blacks

	Mean	SD	Min	Max	Obs.
Food Insecurity Experience Past Year					
Food Insecurity Status (Overall)	0.36	0.48	0	1	22332
High Food Security Status	0.43	0.50	0	1	22332
Marginal Food Security Status	0.21	0.40	0	1	22332
Low Food Security Status	0.20	0.40	0	1	22332
Very Low Food Security Status	0.16	0.37	0	1	22332
30 Day Measure of Food Insecurity					
Food Insecurity Status (30 Days Measure)	0.20	0.40	0	1	22332
High 30 Days Food Security Status	0.43	0.50	0	1	22332
Marginal 30 Days Food Security Status	0.21	0.40	0	1	22332
Low 30 Days Food Security Status	0.20	0.40	0	1	22332
Very Low 30 Days Food Security Status	0.16	0.37	0	1	22332
Food Severity Measure					
Num. of Affirmative Responses to Overall Food Security	2.23	2.72	0	10	22332
Num. of Affirmative Responses to 30 Days Food Security	1.28	2.35	0	10	22332
SNAP Participation					
On SNAP Indicator	0.33	0.47	0	1	22332

Notes: Weighted summary statistics. We use the CPS-FSM sampling person weights. The observations are for our estimation sample for the period of 2005-2016.

2.3 Returns to SNAP on Food Insecurity

The structural equation for returns to SNAP participation on food insecurity is given as:

$$FI_i = \beta_0 + \beta_1 SNAP_i + \mathbf{X_i'}\boldsymbol{\beta} + u_i \tag{2.1}$$

where, FI_i is the food insecurity status for household i. $SNAP_i$ is the SNAP participation status of household i. X_i are the vector of controls for household i. u_i is the unobservable random disturbance or error. And, β's are the parameters we would like to estimate. One of the components of u_i could be an omitted variable that is correlated with $SNAP_i$. Thus, making the OLS estimates of $\boldsymbol{\beta}$'s to be biased. Endogeneity in SNAP participation arises as it is a household decision variable that differs across participating and non-participating eligible households based on unobservable characteristic not observable to an econometrician. One of the omitted variable that could be driving SNAP participation and food insecurity is a strong food support system. That is, whether a household has neighbors and family members helping out when food is scarce. Thus, we can view the omitted variable, here, q as,

$$FI = \beta_0 + \beta_1 SNAP + \mathbf{X}'\boldsymbol{\beta} + \gamma q + \nu \tag{2.2}$$

where,

$$u \equiv \gamma q + \nu \tag{2.3}$$

When omitted variable is ignored, OLS omitted variables inconsistency can be characterized using the plims of the OLS estimators as follows,[4]

$$\texttt{plim}\,\hat{\beta}_1 = \beta_1 + \gamma\Big[\frac{Cov(SNAP, q)}{Var(SNAP)}\Big] \tag{2.4}$$

[4] See equation 4.24 in Chapter 4 of Wooldridge, 2010 for details behind the derivation.

This formula helps us infer the sign of the inconsistency in $\hat{\beta}_1$. In our case, $\gamma < 0$ as a strong food support system reduces food insecurity. $SNAP$ and q are negatively correlated as a strong food support system may reduce the need to be on SNAP. Thus, the asymptotic bias is positive. Omitted variable bias as a source of endogeniety can be corrected if we can find a good proxy variable that is correlated with the unobserved variable. However, we will use the instrumental variable (IV) methods to address the endogeneity of SNAP participation. The crux of the application of proxy versus an IV is best captured in Chapter 5 (page 93) of Wooldridge, 2010, "*a proxy variable makes a poor IV and an IV makes a poor proxy variable*". Thus, a good IV will be uncorrelated with our unobserved factor. An IV estimate helps overcome the problem when the bias of the OLS estimate arises from the correlation of the causal variable and the unobservable portion of the disturbance term of our dependent variable (Foster, 2009, page 289). The intuition of the technique using an IV , say Z, is that Z is correlated with both FI and $SNAP$, but only with FI through $SNAP$, and is uncorrelated with the unobservable portion of FI (i.e., strong food support system) (Foster, 2009, page 290). Another reason a candidate for an IV can be a poor IV is when the IV, Z, may belong in the main outcome regression that explain part of the variation in Y that can't be explained by X.

2.3.1 Identification of SNAP Participation via Instrumental Variables

To address SNAP endogeneity (non-random selection into participation), several studies using the IV-2SLS econometric method exploit the variation in a State's SNAP eligibility and benefits policies as a candidate for an IV. SNAP is a federal program with rules set by the federal government. However, since the 1996 welfare reform, State's have the discretion to tighten or loosen policies beyond those set by the federal government.[5] Gregory et al., 2015 provide an in-depth examination of the SNAP program and the returns to SNAP on food insecurity by estimating both association (linear probability model) and causal relationship (instrumental variable) using the CPS-FSS data for 2009 to 2011. The authors use few of the SNAP policies as instruments to identify the SNAP causal parameter. Furthermore, they show how their estimate varies with inclusion of elderly in the household. Their work helps us as we can use it to compare our sample's estimates to theirs as we use 18 to 70 plus year old households.

[5] See, Stacy et al., 2018 for the discussion and application of SNAP policies on State and County level participation. And, see USDA, 2022 for the access to the State's SNAP policy datasets.

The validity of State level variation in SNAP policies over space and time as a valid candidate for an IV for SNAP participation is motivated by not only its usage in prior works on examining returns to SNAP on outcomes such as, food insecurity, mortality, health, education, etc. (See, Gundersen and Kreider, 2008, Kreider et al., 2012, Gundersen et al., 2015, Ziliak, 2015b, Gregory et al., 2015, Schmidt et al., 2016), but also providing our arguments to justify the two properties of a good IV for our study :- i) instrument relevance and ii) instrument exogeneity. Since, *instrument relevance* is a testable property, we will explain that in a while. We begin with providing our argument to a non-testable property of a good IV using the brief explanation provided above for *instrument exogeneity*. Essentially, to satisfy instrument exogeneity property, we have to argue that - 1) an IV, Z, does not belong in the main regression outcome and 2) that it is uncorrelated with the omitted variable, *food support system*. In essence, we argue that *SNAP Policies* (our IV , Z) is correlated with both FI and $SNAP$, but only with FI through SNAP and is uncorrelated with the unobservable portion of our disturbance term, *strong food support system*.

State-level SNAP policies comprise of policies that expand or restrict eligibility, transaction costs and outreach. The SNAP policy index as created by the USDA (see, USDA, 2022) is an overall measure of the accessibility of SNAP using policies like the broad-based eligibility criteria, the adoption of the electronic benefit transfer system, the asset-test eligibility, the outreach program, biometric and fingerprint application process and the availability of online versus paper application.The tightening and loosening of these SNAP policies across States and time has been analyzed by economists to understand how these policies impact household SNAP participation (Dickert-Conlin et al., 2020; Ganong and Liebman, 2013, 2018; Mabli and Ferrerosa, 2010; Ratcliffe et al., 2008; Ribar et al., 2008, 2010; Stacy et al., 2018; Ziliak, 2015a). Dickert-Conlin et al., 2020 examine how monthly variation in each of the SNAP policies among States and across time impact the SNAP caseloads. They highlight that changes in these State SNAP policies occur with the performance of the local economy in aspects like the unemployment rate. They find that changes in policies that target eligibility and transaction costs of participation have a strong impact on the SNAP participation with a moderate effect of policies that target stigma. Ganong and Liebman, 2013, 2018 reflect on how eight SNAP policies impacted the SNAP enrollment. They create a an "omnibus of summary index" that is the sum of all 8 indicators divided by 8. March et al., 2020 analyzes whether SNAP participants pay higher food prices. Thus, they control for endogeneity of SNAP participation by using state SNAP policies for 2012 and 2013.

Our instrument (Z), *SNAP policy index*, is uncorrelated with our unobserved variable in the food insecurity disturbance term, *food support system*, as the SNAP policies are there to make SNAP more accessible and does not impact how strong are households' food assistance support system with neighbors and families. Second, we argue that our instrument is correlated with FI and $SNAP$, but works through moving the needle of SNAP participation. That is, SNAP policy index, does not belong in the main outcome regression as strict or loose SNAP policies are more correlated with political stance of a state. Take the states of Mississippi, Alabama, Louisiana, where the food insecurity rates have been higher than the national average (see, Coleman-Jensen et al., 2021; Coleman-Jensen et al., 2014; Coleman-Jensen et al., 2017, 2018b, 2020, table on the prevalence of food insecurity by the states.). If SNAP policies were linked to the prevalence of high food insecurity rates , then the states above would have a higher SNAP Policy Index. However, despite high food insecurity rates, these states have a stricter SNAP policies than the Blue States with looser SNAP policies.

2.3.2 Results of the IV-2SLS estimation:

We use the overall SNAP Policy Index as constructed by USDA (in prior works, researchers have used specific components of the State's SNAP policies). Stacy et al., 2018 constructed a yearly SNAP policy index using 10 SNAP policies for the years 1996-2016 that allows for a straightforward comparison of the SNAP policies across States. They use the SNAP Policy Database maintained by the Economic Research Services (ERS) at the USDA that contains the monthly record of policies active in each state from 1996-2016 (USDA, 2022). Table 2.5 provides the summary statistic of the SNAP Policy Index for our estimation sample. We can see the mean of the index is about 8 for the period of 2005-2016 with a range of 4 to 10. Here, higher index value signifies more accommodating policies to SNAP participation. Figure 2.2 displays the mean SNAP Policy Index over time for our estimation sample. The box plot summary statistics shows the index varying with time and within each year.

Table 2.5: Summary Statistic of State's SNAP Policy Index, 2005-2016

	mean	s.d.	min	max
SNAP Policy Index	8.41	1.10	4.38	9.79

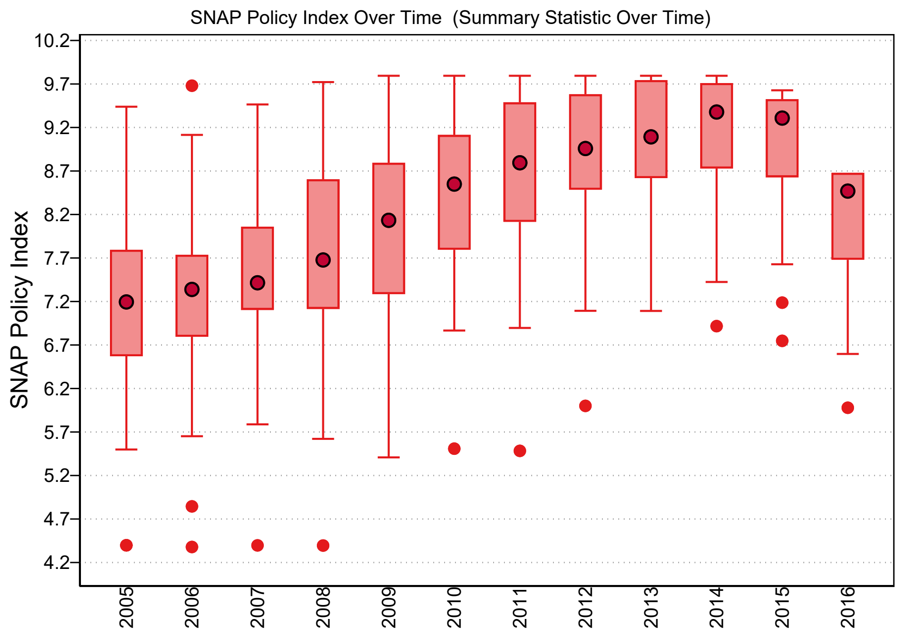

Figure 2.2: SNAP Policy Index (mean) variation across space and time.

To identify our causal parameter of interest, *SNAP participation*, we employ the instrumental variables (IV) econometric method. Our econometric specification for our instrumental variable-two stage least squares (IV-2SLS) is:

$$\mathtt{SNAP}_{it} = \delta_0 + \alpha Z_t + \mathbf{X}_{it}\delta + \nu_{it} \tag{2.5}$$

$$FIS_{it} = \gamma_0 + \beta \widehat{\mathtt{SNAP}}_{it} + \mathbf{X}_{it}\gamma + \epsilon_{it} \tag{2.6}$$

where, FIS_{it} is the food insecure status ($\{0,1\}$) for household *i* at time *t*. $SNAP_{it}$ is the SNAP participation status ($\{0,1\}$) for household *i* at time *t*. Z_t is the SNAP Policy Index, our instrumental variable, for household *i*'s State and at time *t*. X_{it} are the demographic controls as listed in the table 2.1. ν_{it} is the error term for first-stage. ϵ_{it} is the error term for the second-stage. We treat each observation of our CPS-FSS sample as a repeated cross-section such that each cell is a household-year observation.

Table 2.6 displays the IV-2SLS results for our estimation sample.[6]. The first three columns of table 2.6 are the results from estimation of the second stage regression equation 2.6. The causal parameter estimate of SNAP participation tells us that SNAP reduces food insecurity by 29 percentage points for our Black-White pooled sample (first column). This estimate of returns to SNAP participation can be understood by the mean food insecurity rate among SNAP participants in 2.2. Since 48.49% of the SNAP participants experience food insecurity, our returns to SNAP reduces the mean food insecurity rate to 19.59% (a reduction of 59.4%).[7]

[6] Table 2.6 provides a snapshot of the estimates for our variables of interest. The detailed table displaying the full table is available in the appendix/or upon request

[7] This is calculated as follows: $\frac{48.49 - 19.59}{48.49} = \frac{28.9}{48.49} = 0.594$

When we dissect our overall returns to SNAP estimate between Black and White households, we find from columns 2 and 3 that *returns to SNAP participation primarily working through White households*. Black households appear to be indifferent in experiencing the benefit of SNAP participation on reducing food insecurity. Insignificance of returns to SNAP on food insecurity for Black households could be arising from the weakness of the instrument among Black households. Our causal estimates of SNAP effect on food insecurity and the difference in its impact across these two household groups gives credence to the data plotted in figure 2.1 where we observed Black households not only have higher food insecurity rates but have a higher SNAP participation rates relative to a White household.

The strength of the instrument can be seen by the first stage *F-statistic* (second to last row in table 2.6) for the full sample and the sub-samples. Column 1 shows F-statistic to be higher than 100, thus, suggesting a strong instrument. But the instrument strength falls below 10 for the Black households. Column 4, 5, and 6 of table 2.6 provides the results of the first-stage regression results of the equation 2.5. We can see from column 4 to 6 that as SNAP policies become more relaxed it increases SNAP participation for the full sample as well as for White and Black households, separately.

Table 2.6: IV-2SLS Estimation Result: Causal Effect of SNAP Participation on Food Insecurity Status. And First-Stage Results

	(1) Full Sample	(2) Whites Sample	(3) Blacks Sample	(4) First-Stage Full Sample	(5) First-Stage White Sample	(6) First-Stage Black Sample
Causal Variable of Interest						
On SNAP Indicator	-0.289**	-0.294**	-0.452			
	(0.120)	(0.129)	(0.409)			
Race / Ethnicity						
Black (non-hispanic)	0.044***			0.037***		
	(0.006)			(0.004)		
Instrumental Variable						
SnapPolicyIndexT				0.016***	0.016***	0.014***
				(0.002)	(0.002)	(0.004)
Constant	0.050*	0.039	0.234	0.032	-0.004	0.227***
	(0.028)	(0.028)	(0.145)	(0.021)	(0.023)	(0.057)
(Mean) Food Insecurity Rate						
Overall	0.28					
Whites		0.25				
Blacks			0.36			
(Mean) SNAP Participation Rate						
Overall	0.21					
Whites		0.17				
Blacks			0.32			
Exogenous Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Years	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016	2005-2016
Effective F statistic	114.05	103.36	9.95			
Obs.	118452	96120	22332	118452	96120	22332

Note: Weighted regression coefficients. Weights used are the food security supplement weight for the household. Standard errors in parentheses and corrected for heteroscedasticity. Weak exogenous controls contain the inclusion of variables associated with the labor market characteristics of the household head and its family members. ***, **, * indicate statistical significance at 1,5 and 10 percent, respectively.The instrument used to identify the causal impact of SNAP participation is the (unweighted) SNAP policy index for the current year of the survey. *Effective F statistic* is the first stage F-test on the instrument strength.

2.4 Decomposition Analysis Of Food Insecurity Gap

In this section, we decompose the mean food insecurity gap (about 11 percentage points difference) between Black-White households to extract proportion of gap explained by observable demographic characteristics. Thus, we employ a modified Kitagawa-Oaxaca-Blinder (KOB) decomposition method that uses the DiNardo et al., 1996 re-weighting method to construct a counterfactual group to compare with our Black households. KOB decomposes the difference in mean outcomes between two groups into two parts : 1) explained by differences in average characteristics and 2) an unexplained component that measures the differences in returns to these characteristics. (Blinder, 1973; Duncan, 1967; Fortin et al., 2010, 2011; Jann, 2008a; Kitagawa, 1955; Oaxaca, 1973). [8]

The DiNardo et al., 1996 decomposition method is explained below. We assume the following structural equation :

$$\begin{aligned}\mathtt{FIS}_i^{\mathtt{B}} &= m^{\mathtt{B}}(X_i, \varepsilon_i)\\ &= \mathbf{X}\beta^{\textbf{Blacks}} + \varepsilon \quad \texttt{for Blacks}\end{aligned}$$

$$\begin{aligned}\mathtt{FIS}_i^{\mathtt{W}} &= m^{\mathtt{W}}(X_i, \varepsilon_i)\\ &= \mathbf{X}\beta^{\textbf{Whites}} + \varepsilon \quad \texttt{for Whites}\end{aligned}$$

Here, FIS^B is the food insecurity status of Blacks. FIS^W is the food insecurity status of Whites.$\mathbf{X}$ is the vector containing the intercept and the covariates. ε is the error term for each group. Some assumptions behind this structural equations are a) additive linearity (i.e. $m(X,\varepsilon) = X\beta+\varepsilon$), where the observed and unobserved characteristics are additively separable; b) exogeneity or zero conditional mean (i.e. $E(\varepsilon|X, Race) = 0$)

Thus the average difference in outcome can be decomposed as follows. Δv is the difference in mean food insecurity gap between Black (v_B) and White (v_W) households. $\bar{X}^{W'}$ and $\bar{X}^{B'}$ are the vectors of sample means of the controls. v_C is the mean food insecurity of a *counterfactual group*.

[8] The KOB decomposition has been extensively used in economics to explain discrimination in the gender/racial wage gap. See, Fortin et al., 2011 for a great overview. Huber and Solovyeva, 2020 examine the sensitivity of the decomposition method. We use *Stata* statistical software command for KOB decomposition, `oaxaca`, written by Jann, 2008a

$$
\begin{aligned}
\Delta v &= \texttt{FIS}_i^{\texttt{W}} - \texttt{FIS}_i^{\texttt{B}} \\
&= v_W - v_B \\
&= \bar{X}^{W'}\hat{\beta}^W - \bar{X}^{B'}\hat{\beta}^B \\
&= v_w - v_C + v_C - v_B \\
&= \bar{X}^{W'}\hat{\beta}^W - \bar{X}^{C'}\hat{\beta}^C + \bar{X}^{C'}\hat{\beta}^C - \bar{X}^{B'}\hat{\beta}^B \\
&= \left(\bar{X}^C - \bar{X}^B\right)'\hat{\beta}^B + \bar{X}^{B'}\left(\hat{\beta}^C - \hat{\beta}^B\right) \\
&= \Delta v_X + \Delta v_S \\
&= \begin{array}{c}\texttt{Gap attributed}\\ \texttt{to differences in}\\ \texttt{mean characteristics}\end{array} + \begin{array}{c}\texttt{Difference attributed}\\ \texttt{to the returns}\\ \texttt{between FIS \& X}\end{array}
\end{aligned}
\tag{2.7}
$$

We employ the DiNardo et al., 1996 [DFL] re-weighting method to construct our counterfactual group. DFL decomposition incorporates a re-weighting factor for the counterfactual analysis. DFL method is used to construct a counterfactual group and estimate their mean food insecurity ($v_C = \bar{X}^{C'}\hat{\beta}^C$). The method helps to ask: "*What would the mean food insecurity look like if Blacks had the same observable characteristics as Whites?*". The re-weighting factor is calculated using the inverse propensity score ($\Psi(h)$) method and is calculated as follows:

$$\Psi(h) = \frac{Pr(t_h = W|h)}{Pr(t_h = B|h)} \cdot \frac{Pr(t_h = B)}{Pr(t_h = W)}$$

where $\frac{Pr(t_h=W|h)}{Pr(t_h=B|h)}$ is the ratio of the conditional probability of being White (or Black) given demographics. And $\frac{Pr(t_h=B)}{Pr(t_h=W)}$ is the ratio of sample of Whites (and Blacks).[9] The DFL weights are calculated using age, education, marital status and home ownership, family composition as our (plausibly) exogenous demographics to condition the probability of belonging to a group.[10]

Table 2.7 presents the aggregate results of KOB-DFL decomposition method.[11] The counterfactual group is created such that the Blacks are re-weighted to have the same distribution of covariates as the Whites household. In Table 2.7, in the first three rows, we provide the mean of households that experience food insecurity for each group. *Group 1 : Whites* gives the mean food insecurity of 24.9 % for the White households. *Group 2 : Blacks* gives the mean food insecurity of 36.1 % for the Black households. *Counterfactual Group* is the group of black households that have been re-weighted to have the same distribution of characteristics as the Whites. This groups mean food insecurity rate is 29.7%. The counterfactual group, by construction, has a food insecurity mean closer to the Whites (about 30% of the counterfactual group experience food insecurity.).

[9] Given that our data has survey sampling weights, we can readjust our weighting factor by multiplying the two weights, $\omega_i = \theta_i \hat{\Psi}_i(h)$. Here ω_i is the new weight that multiplies our estimate of DFL re-weighting $\hat{\Psi}_i(h)$ with the sampling weights, θ_i.

[10] Additionally, Firpo et al., 2018 provides us with further components to Δv that adds estimates of reweighting error and specification error. That is: $\Delta v = \Delta v_X + \Delta v_X^e + \Delta v_S + \Delta v_S^e$. Reweighting error (Δv_S^e) is used to assess the quality of the re-weighting strategy. Specification error (Δv_X^e) assesses the quality of model specification. If everything is specified well, we would expect these errors go to zero. A large values of these errors indicate re-examination of our model. See, Firpo et al., 2018 and Rios-Avila, 2020 for extensive discussion.

The middle row of the table , *Difference in Food Insecurity Between Blacks and Whites (Group 1 minus Group 2)*, gives the raw difference of 11.2 percentage points in the mean food insecurity rates between the White households (24.9%) and Black households (36.1%). The following two rows present the results of the re-weighted counterfactual OB decomposition of the gap in food insecurity. We can see that 57.32% of the gap is explained by the difference in the mean characteristics between the two groups. The remainder of the gap, 42.59 %, is *unexplained*. That is, arising due to the differences in the returns to these characteristics (or, put simply differences in the coefficients).

The detailed results of our decomposition are given in table 2.8. We observe that difference in differences in mean SNAP participation between the Blacks and the counterfactual group does not add to the explained component.[12] This is another suggestive evidence that *returns to SNAP is ineffective in explaining Black households' food insecurity*. The factors that add to the explained portion are : education, home ownership, poverty, composition of family members.

[11] The software implementation of the Firpo et al., 2018 methodology is created by Fernando Rios-Avila and available in Stata (See, Rios-Avila, 2020 for the `oaxaca_rif` command for the implementation. `oaxaca_rif` is a wrapper around Jann, 2008b's `oaxaca` and adds to it the FFL methodology to allow standard OB decomposition or the re-weighted decomposition. And its application in our study can be found in the supplementary data and code repository.)

[12] We employ the control function approach to address SNAP endogeneity and estimate our KOB-DFL decomposition.

Table 2.7: Summary of the KOB Decomposition With DiNardo Re-Weighting Counterfactual Analysis.

	Decomposition With Re-Weighting		
	coefficient	std. err.	95% CI
Overall:			
Group 1 : Whites	0.249***	0.002	[0.246,0.252]
Counterfactual Group	0.297***	0.006	[0.286,0.308]
Group 2 : Blacks	0.361***	0.004	[0.354,0.368]
Difference in Food Insecurity Between Blacks and Whites (Group 1 minus Group 2)	-0.112***	0.004	[-0.120,-0.104]
Explained Component	-0.0642***	0.004	[-0.073,-0.056]
[57.32% Explained]			
Unexplained Component	-0.0477***	0.006	[-0.059,-0.036]
[42.59% Unexplained]			

Notes: Standard errors obtained using Bootstrap with 500 replication (using parallelization with 8 CPU cores that took about 85 minutes). Above OB-Decomposition uses sampling weights and corrects for SNAP endogeneity using the Control function Approach & Re-weighting Counterfactual Analysis. The counterfactual group is constructed such that Blacks look like Whites in their respective demographic characteristics.

Thus, we can conclude from the table 2.7, that more than half of the food insecurity gap we observe between the Black and White households can be explained by differences in their observable characteristics. Policymakers can target public programs that address some these differences in characteristics, like education, home ownership, unemployment rate, to name a few. These targets can address a part of the food insecurity problem causing differential experience between to groups of households.

Table 2.8: Detailed KOB with DiNardo Re-weighting Decomposition Results

OB Decomposition With Re-Weighting Counterfactual Analysis			
	Decomposition With Re-Weighting		
	coefficient	std. err.	95% CI
Overall:			
Group 1 : Whites	0.249***	0.002	[0.246,0.252]
Counterfactual Group	0.297***	0.006	[0.286,0.308]
Group 2 : Blacks	0.361***	0.004	[0.354,0.368]
Difference in Food Insecurity Between Blacks and Whites (Group 1 minus Group 2)	-0.112***	0.004	[-0.120,-0.104]
Explained Component	-0.0642***	0.004	[-0.073,-0.056]
	[57.32% Explained]		
Unexplained Component	-0.0477***	0.006	[-0.059,-0.036]
	[42.59% Unexplained]		
Explained			
Total	-0.0642***	0.004	[-0.073,-0.056]
Pure_explained	-0.0644***	0.004	[-0.072,-0.057]
Specif_err	0.000224	0.002	[-0.004,0.005]
Pure- Explained			
On SNAP Indicator	0.0448	0.036	[-0.027,0.116]
SNAP Residual [First-Stage]	-0.00371	0.003	[-0.009,0.002]
Work Status	0.000197	0.001	[-0.002,0.003]
Female	-0.00267	0.002	[-0.006,0.001]
Age Categories	-0.000484	0.004	[-0.008,0.007]
Marital Status Categories	-0.00775	0.005	[-0.017,0.001]
Educational Status Categories	-0.0101**	0.004	[-0.017,-0.003]

continued

Table 2.8: Detailed KOB with DiNardo Re-weighting Decomposition Results

OB Decomposition With Re-Weighting Counterfactual Analysis			
	Decomposition With Re-Weighting		
	coefficient	std. err.	95% CI
Own a House	-0.0243**	0.008	[-0.039,-0.010]
Family Income To Poverty Ratio	-0.0376**	0.013	[-0.064,-0.011]
Composition of Family Members	-0.0206*	0.009	[-0.038,-0.003]
Living in Metro Area	-0.00201*	0.001	[-0.004,-0.000]
State Unemployment Rate (BLS)	-0.000296	0	[-0.001,0.000]
Regional Fixed Effetcs	0.00107	0.002	[-0.003,0.005]
Year Fixed Effects	-0.00101	0.001	[-0.002,0.000]
	Specification-Error		
On SNAP Indicator	0.000933	0.083	[-0.162,0.164]
SNAP Residual [First-Stage]	0.0000155	0.003	[-0.006,0.006]
workstat	-0.00706	0.005	[-0.017,0.003]
Female	0.0137	0.009	[-0.005,0.032]
agecat	-0.0041	0.008	[-0.020,0.012]
maritalstat	0.00145	0.004	[-0.007,0.010]
educstat	-0.00822	0.008	[-0.023,0.006]
Own a House	-0.00198	0.023	[-0.046,0.042]
Family Income To Poverty Ratio	-0.0172	0.083	[-0.179,0.145]
Composition of Family Members	-0.017	0.065	[-0.144,0.110]
Living in Metro Area	-0.0122	0.011	[-0.033,0.009]
unemployment rate (BLS)	0.0291	0.023	[-0.016,0.074]
regionfe	-0.00274	0.002	[-0.007,0.001]
yearfe	0.00089	0.001	[-0.000,0.002]
Constant	0.0247	0.115	[-0.201,0.251]
	Unexplained		
Total	-0.0477***	0.006	[-0.059,-0.036]
Reweight-err	0.0097	0.017	[-0.024,0.044]
Pure-Unexplained	-0.0574**	0.018	[-0.092,-0.023]
	Pure-Unexplained		
On SNAP Indicator	0.0177	0.087	[-0.152,0.188]
SNAP Residual [First-Stage]	-4.75E-13	0	[-0.000,0.000]
workstat	0.00324	0.007	[-0.011,0.017]

continued

Table 2.8: Detailed KOB with DiNardo Re-weighting Decomposition Results

OB Decomposition With Re-Weighting Counterfactual Analysis			
	Decomposition With Re-Weighting		
	coefficient	std. err.	95% CI
Female	-0.0016	0.012	[-0.026,0.022]
agecat	-0.00378	0.011	[-0.025,0.018]
maritalstat	-0.00154	0.006	[-0.014,0.011]
educstat	0.018	0.011	[-0.004,0.040]
Own a House	-0.00717	0.029	[-0.063,0.049]
Family Income To Poverty Ratio	0.0494	0.104	[-0.154,0.252]
family-members	0.0313	0.078	[-0.122,0.184]
Living in Metro Area	-0.0083	0.013	[-0.033,0.016]
unemployment rate (BLS)	-0.0214	0.029	[-0.078,0.035]
regionfe	0.00083	0.002	[-0.004,0.005]
yearfe	0.00111	0.001	[-0.001,0.003]
Constant	-0.135	0.143	[-0.415,0.145]
	Reweight-Error		
On SNAP Indicator	0.0141	0.018	[-0.021,0.049]
SNAP Residual [First-Stage]	0.00369	0.004	[-0.004,0.012]
workstat	-0.00063	0.001	[-0.003,0.001]
Female	0.00112*	0.001	[0.000,0.002]
agecat	0.0000955	0	[-0.001,0.001]
maritalstat	-0.00123*	0.001	[-0.002,-0.000]
educstat	0.000828	0.001	[-0.002,0.003]
Own a House	-0.000424	0.001	[-0.001,0.001]
Family Income To Poverty Ratio	0.00138	0.001	[-0.001,0.004]
familymembers	-0.00765	0.008	[-0.023,0.008]
Living in Metro Area	-0.000899	0.001	[-0.003,0.001]
unemployment rate (BLS)	-0.00068	0	[-0.002,0.000]
regionfe	0.000947	0.001	[-0.001,0.003]
yearfe	-0.000924	0.001	[-0.003,0.001]
Observations	118452		

Notes: Standard errors obtained using Bootstrap with 500 replication using parallelization with 8 cores . Took about 83 minutes. Above OB-Decomposition uses sampling weights and corrects for SNAP endogeneity using the Control function Approach. And Re-weighting Counterfactual Analysis.

2.5 Exploring the Effect of Race on Food Insecurity

The goal of the study is to explore factors behind the differential experience in food insecurity between Black & White households. In this section, we examine the effect of race (here, being Black) on food insecurity. We explore how strong is the association of race with food insecurity. We continue with our estimation sample and examine the overall effect of race (here, being Black) on food insecurity after conditioning on observable characteristics. We further examine the heterogeneity in the effect of race (being Black) on food insecurity gap and examine the differences in household characteristics that contribute to the differential experience.

2.5.1 Overview of Average Partial Effects

We start with a brief summary of the basics of partial effects, beginning with the *average partial effect* (**APE**) (Chapter 2 of Wooldridge, 2010 provides a great overview of the concept for further details and for the discussion for calculations of *partial effects at the means* versus *average partial effects*). When we are dealing with an econometric specification that is either nonlinear in variables or nonlinear in parameters (or a combination of both), the partial (marginal) effects returned are not just simply the coefficient of interests given by the derivative (say, $\frac{\partial y}{\partial x} \neq \beta_1$, where y is an outcome (continuous), x is the co-variate and β_1 is the parameter associated with the co-variate). The partial effects are conditional on values of all or certain covariates. In nonlinear regression models (nonlinear in parameters), such as the logit model applied in our analysis of the effect of race on our binary outcome of food insecurity, the partial effects (or predictive effects) are more complicated: they are usually nonlinear combinations of all covariates and regression coefficients of the model. The best way to analyze and interpret the effects from the coefficients is to compute "*the partial effects for each individual in the sample and averaging of these effects*". Accordinging to Greene, 2008 (Greene (2008, 775)), this is a more preferred method than just computing the effect at means. Furthermore , to explore the heterogeneity that makes up the summary measure of APE, "*a more complete description of the sample distribution of the estimated effects (versus just reporting the average) would be to report quantiles or to graph the distribution of the effects.*" And, that is the idea behind the analysis in this section.

2.5.2 Concept

Let y be an outcome (continuous or discrete) variable and $\mathbf{x}$ be a vector of controls. A conditional expectation (CE) equation is written as:

$$E[y|\mathbf{x}] = \mu(\mathbf{x})$$

$\mu(\mathbf{x})$ is the functional form taking $\mathbf{x}$ as input. We often encounter conditional expectation models where the model is non-linear in parameters. Example:

$$E(y|x_1, x_2) = exp(\beta_0 + \beta_1 log(x_1) + \beta_2 x_2)$$

Non-linearity in the parameters has implication for estimating the parameters, β_j. We are often interested in how y changes when some components of $\mathbf{x}$ change. We can define the partial effects of x_j on the conditional expectation $E[y|\mathbf{x}]$ as :

$$\Delta E[y|\mathbf{x}] \approx \frac{\partial \mu(\mathbf{x})}{\partial x_j} \cdot \Delta x_j \quad \text{holding } x_1,\ldots,x_{j-1}, x_{j+1},\ldots,x_K \text{ fixed}$$

In our example above, for non-linear in parameters CE model, the partial effect of a change in x on y, is given by:

$$\frac{\partial E[y|\mathbf{x}]}{\partial x_1} = exp(\cdot)(\frac{\beta_1}{x_1})$$

$$\frac{\partial E[y|\mathbf{x}]}{\partial x_2} = exp(\cdot)\beta_2$$

In this case, the partial effects of x_1 and x_2 both depend on $\mathbf{x} = (x_1, x_2)$

2.5.3 Moving Beyond Averages: Sorted Effects

The following section applies the Chernozhukov et al., 2018 method to explore the heterogeneity in the partial effects of race (here, being Black) on food insecurity in addition to the average partial effect (APE is commonly employed when dealing with non-linear models). Note, that we do not make any causal statements about being Black on food insecurity. That is, we do not make statements such as, "*being Black* ***causes*** *food insecurity*". Such causal analysis is not possible in quasi-experimental studies without a well-defined structural model or examining causal inference in economics of discrimination studies done through either a correspondence or an audit study. Also, racial classifications are societal constructs and are immutable characteristics for whom a counterfactual analysis is difficult to estimate (See, Greiner and Rubin, 2011 for discussion on dealing with immutable characteristics as how a racial group is perceived). We are examining households for whom being Black is strongly associated with being food insecure. That is, households for whom race is a strong predictor of being food insecure. This helps us in answering the question "*what type of households experience higher food insecurity for being Black?*"

The method proposed by Chernozhukov et al., 2018 extends the estimation of average partial effects (APE, see Chapter 2 of Wooldridge, 2010) to calculate partial effects that go beyond the mean. The method, called the Sorted Partial Effects (SPE) calculates the range of heterogeneous partial effects of race on food insecurity for each household and sorts and bins them on a percentile index ranging from those least affected to the most affected by race on food insecurity.[13] Briefly, the Chernozhukov et al., 2018 method can be understood as follows. Let Y be our binary outcome of interest of food insecurity & $\mathbf{X} = (B, \mathbf{C})$ be a matrix of our covariates where B is our variable of interest, an indicator of being Black. And $\mathbf{C}$ is the vector of other control variables. In our model estimation, Y and X are linked through a logit function. So, $Y = G(X\beta)$ becomes,

$$Y = \Lambda(B\beta_1 + C\beta') + \varepsilon, \tag{2.8}$$

where Λ is the CDF of a logistic function. The partial (or, marginal) effect is :

$$\Delta(x) = \Lambda(B\beta_1 + C\beta')\beta_1 \tag{2.9}$$

where $\Delta(x)$ is equivalent to $\dfrac{\partial y}{\partial x}$ for continuous outcome and change in probability of outcome ($Pr(y = 1|\mathbf{x}) - Pr(y = 0|\mathbf{x})$) for discrete outcomes.

[13] See Chen et al., 2019, 2020 for the software program accompanying Chernozhukov et al., 2018 method

In equation 2.9, we see that the partial effects depend on the value of our covariates C. Since individuals in our data have different values for their demographic characteristic, $\Delta(x)$ captures the heterogeneity that is masked in the calculation of the average partial effects. We use our sample to give an empirical estimate of $\Delta(x)$ and provide inference by quantifying the uncertainty associated with our empirical estimate of $\Delta(x)$. Chernozhukov et al., 2018 method helps in graphically displaying the SPE and its associated confidence bands. Their method uses the SPE and further develop a *classification analysis* where we group households into 10% least and 10% most affected by race on food insecurity. And we conclude by testing whether the demographic characteristics of these two classified groups are statistically different.[14]

[14] We use 10% as our threshold, but any other threshold can also be examined.

We estimate a binary response model where the outcome variable Y is an indicator of food insecurity status (where one indicates food insecurity and zero, otherwise). The key covariate B is an indicator for Black household, and the control variables C include observable household characteristics: SNAP participation indicator; age categories, five marital status indicators (widowed, divorced, separated, never married, and married); a female indicator; composition of family members; income-to-poverty ratio; five educational attainment indicators (less than high school graduate, high school graduate, some college, college graduate, and advanced degree); home ownership indicator; employment status; four region indicators (Midwest, South, West, and Northeast); state unemployment rate. All calculations use the CPS sampling weights to account for non-random sampling in the December CPS.[15]

[15] We follow the same process as in our KOB-DFL decomposition to address SNAP endogeneity. We adjust the Chernozhukov et al., 2018 SPE method with a control function approach to correct for SNAP endogeneity.

2.5.4 Sorted Partial Effects: Evidence of Heterogeneity in Food Insecurity Gap

Chernozhukov et al., 2018 provide a useful visual display of the APE and the SPE curve that displays the heterogeneity of race on food insecurity for our sample of Black-White households. Figure 2.3 and 2.4 plot the APE and SPE estimates and 90% confidence bands for our Black & White pooled households and separately for the estimates among Black sub-sample of households, respectively. The partial effects are obtained estimating a logit model in the pooled Black-White sample. The SPEs show significant amount of heterogeneity in the effect of race, with partial effects ranging from 1 to 5 percentage points. Table 2.9 summarizes the APE estimates for the full sample and the Black households, for both weighted (using CPS-FSS sampling weights) and unweighted (without CPS-FSS sampling weights) estimates.

Figure 2.3 plots estimates and 90% confidence bands of the population APE and SPE-function of being black on food insecurity. The PEs are obtained using a logit model $P(X) = X = (T, W)$ and $\hat{\mu}$ equal to the empirical distribution of X in the whole sample. The confidence bands are constructed using the algorithm in Chernozhukov et al., 2018 using at least 500 weighted bootstrap draws[16] and are uniform across the SPE function spread over the percentile grid of $\{0.02, 0.03, \ldots, 0.98\}$. After controlling for household characteristics, the Black-White food insecurity gap remains at 3.7%. More importantly, the SPE-function shows significant heterogeneity, with the PE ranging between 1% to 5%. Thus, there exists a subgroup of households that is 5% more likely to experience food insecurity if they were black versus a subgroup that is marginally affected by the effect of race on food insecurity.

[16] Chernozhukov et al., 2018 recommend bootstrap draws of more than 500.

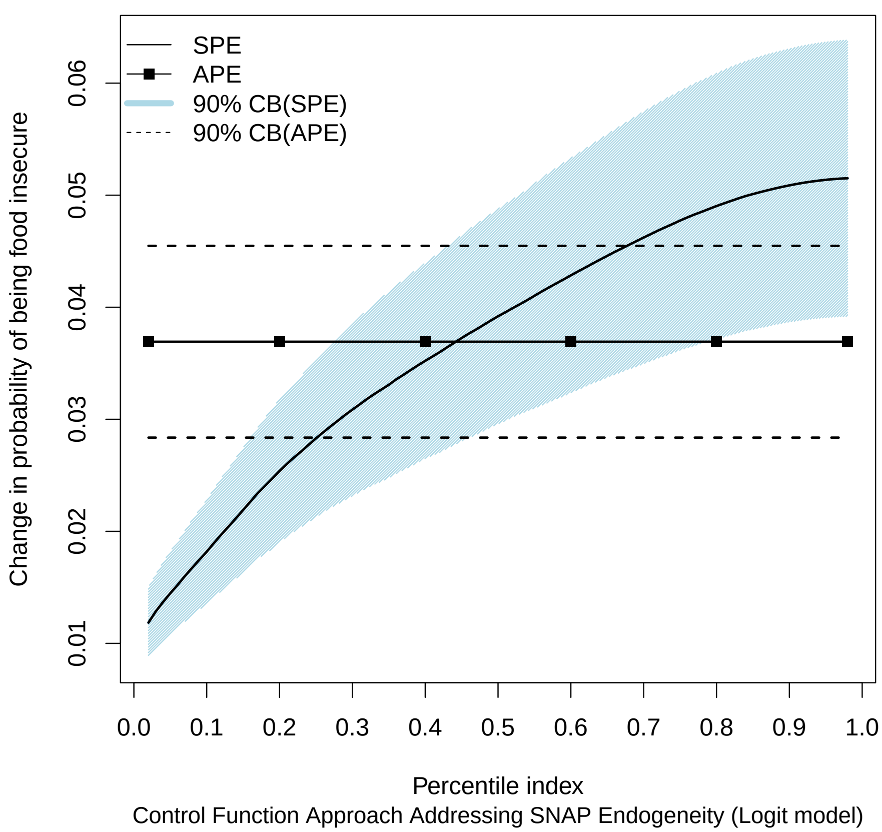

Figure 2.3: Average and Sorted Partial Effects Curve for Full Sample Exploring The Heterogeneity in the Effect of Race on Food Insecurity

Figure 2.4 displays the APE and SPE curve for the Black household sample. The effect of race on black households food insecurity is 4.1%, given the distribution of characteristics for the full sample.

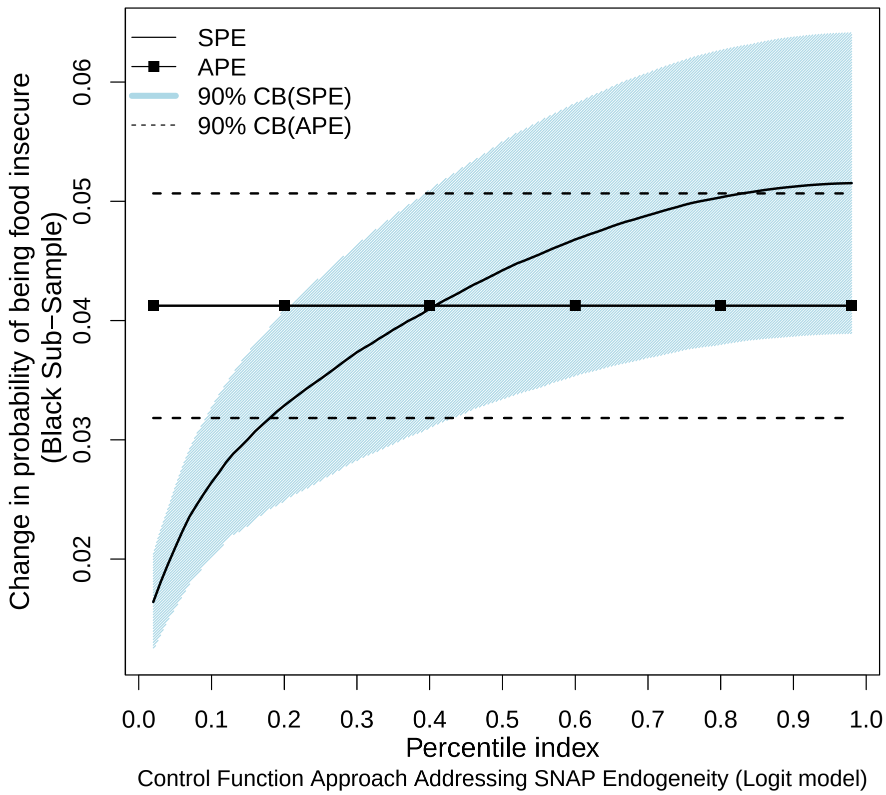

Figure 2.4: Average and Sorted Partial Effects Curve For Black Sub-Sample: Exploring The Heterogeneity in the Effect of Race on Food Insecurity

Table 2.9: Average Partial Effect of Change in Probability of Being Food Insecure For Being Black (Un-weighted and Weighted)

	APE	Std. Dev.	Min	Max
Un-Weighted Estimates:				
Full Sample	0.0362	0.0122	0.0040	0.0515
Black Sub Sample	0.0411	0.0101	0.0064	0.0515
White Sub Sample	0.0351	0.0123	0.0040	0.0515
Weighted Estimates:				
Full Sample	0.0369	0.0119		
Black Sub Sample	0.0412	0.0098		
White Sub Sample	0.0355	0.0122		

2.5.5 Classification Analysis

Table 2.10 shows the results of the classification analysis, answering the question "who is affected the most and who the least?". The first four columns present the characteristics among the full sample of households. The latter 4 columns are the characteristics associated with the Black households. The 10% of households most affected by race are more likely to have the following characteristics: a household head who is black, female, unemployed, age less than 60, either separated, divorced or never married and without a high school degree. On the other hand, the household characteristics that define the 10% most affected by race are more likely to be on SNAP, less likely to own a house, living two-thirds below the poverty guideline, have more members living in the house, living in the metro areas, living in states with high unemployment rates and live in the South.

Among the Black households, the most affected by race are more likely to be on SNAP, household head who is a female, unemployed, working-age, divorced or never married. These households are less likely to own a house, have other working age household members in the house and live in states with higher unemployment rates.

Table 2.11 tests if the differences found in Table 2.10 are statistically significant. The p-values reported are associated with the test of equality of means for most and least affected households [17]. The p-values show that most of the differences observed in Table 2.10 are statistically significant at conventional levels after controlling for simultaneous inference. Among the Black households, they most versus least are not statistically different in the region of the US.

[17] Chernozhukov et al., 2018 provide two types of p-values for inference. The PW p-value accounts for simultaneous inference on all variables within a given category. The JP p-values accounts for the simultaneous inference of all the differences displayed in the table. Refer to their paper for further details on the algorithm

Table 2.10: Characteristics of 10% most and least affected

	Full Sample				Black Sub-Sample			
	10% Most		10% Least		10% Most		10% Least	
	Mean.	S.Err.	Mean	S.Err.	Mean	S.Err.	Mean	S.E.
Food Insecure Status	0.490	0.005	0.053	0.002	0.476	0.013	0.183	0.009
Household Head Characteristics								
Blacks	0.361	0.007	0.077	0.005	1.000	0.000	1.000	0.000
SNAP Participation Status	0.697	0.016	0.001	0.000	0.783	0.018	0.007	0.002
Female	0.674	0.007	0.549	0.011	0.748	0.011	0.556	0.015
At Work	0.294	0.010	0.128	0.008	0.313	0.015	0.299	0.017
Unemployed	0.171	0.005	0.002	0.001	0.186	0.011	0.005	0.002
Not In Labor Force	0.535	0.008	0.870	0.008	0.501	0.014	0.696	0.017
Age Between 18 to 21	0.019	0.003	0.002	0.001	0.029	0.005	0.022	0.006
Age Between 22 to 29	0.148	0.008	0.012	0.003	0.194	0.015	0.084	0.011
Age Between 30 to 39	0.225	0.006	0.011	0.003	0.241	0.012	0.064	0.008
Age Between 40 to 49	0.231	0.006	0.005	0.002	0.206	0.010	0.040	0.007
Age Between 50 to 59	0.241	0.007	0.003	0.001	0.199	0.011	0.032	0.005
Age Between 60 to 69	0.129	0.005	0.028	0.005	0.123	0.008	0.088	0.009
Age 70 plus	0.007	0.002	0.938	0.010	0.009	0.004	0.670	0.019
Divorced	0.306	0.007	0.054	0.005	0.163	0.009	0.089	0.008
Married	0.180	0.006	0.429	0.012	0.122	0.009	0.342	0.014
Never Married	0.364	0.009	0.062	0.004	0.550	0.013	0.191	0.013

Separated	0.091	0.004	0.003	0.001	0.106	0.008	0.026	0.004
Widowed	0.059	0.003	0.451	0.015	0.059	0.006	0.352	0.015
Less Than High School	0.265	0.006	0.158	0.008	0.286	0.012	0.276	0.012
High School Graduate	0.382	0.007	0.447	0.010	0.390	0.012	0.331	0.013
Some College	0.320	0.007	0.194	0.007	0.308	0.012	0.180	0.010
College Graduate	0.026	0.003	0.131	0.008	0.014	0.004	0.140	0.012
Advanced Diploma	0.006	0.001	0.070	0.006	0.003	0.002	0.073	0.008
Household Characteristics & Composition								
Own House	0.201	0.008	0.929	0.006	0.109	0.010	0.750	0.016
Income To Poverty Ratio	0.757	0.011	1.591	0.009	0.676	0.013	1.392	0.016
Share of members between age 0 and 5	0.088	0.004	0.009	0.002	0.116	0.006	0.044	0.005
Share of members between age 6 and 10	0.079	0.002	0.003	0.001	0.099	0.005	0.026	0.003
Share of members between age 11 and 14	0.053	0.002	0.001	0.000	0.064	0.004	0.015	0.002
Share of members between age 15 and 17	0.037	0.001	0.001	0.000	0.042	0.003	0.010	0.002
Share of members between age 18 and 21	0.042	0.002	0.002	0.001	0.055	0.004	0.027	0.005
Share of members between age 22 and 29	0.100	0.004	0.009	0.002	0.118	0.008	0.068	0.008
Share of members between age 30 and 39	0.121	0.003	0.006	0.001	0.112	0.006	0.031	0.003
Share of members between age 40 and 49	0.162	0.005	0.004	0.001	0.132	0.007	0.025	0.003
Share of members between age 50 and 59	0.198	0.006	0.006	0.001	0.154	0.009	0.032	0.003
Share of members between age 60 and 69	0.113	0.003	0.035	0.004	0.101	0.007	0.077	0.007
Share of members age 70 plus	0.006	0.001	0.923	0.010	0.007	0.001	0.645	0.019
Living In Metro	0.773	0.006	0.699	0.010	0.852	0.009	0.833	0.010
State Unemployment Rate	7.084	0.029	6.380	0.040	7.150	0.060	6.572	0.061

Midwest	0.260	0.006	0.277	0.009	0.216	0.011	0.179	0.010
Northeast	0.150	0.005	0.204	0.008	0.152	0.011	0.151	0.012
Southern	0.438	0.007	0.375	0.010	0.546	0.015	0.596	0.015
Western	0.152	0.005	0.144	0.007	0.086	0.008	0.073	0.007
Year Sample								
2005	0.058	0.004	0.111	0.006	0.067	0.006	0.117	0.009
2006	0.054	0.003	0.124	0.006	0.067	0.007	0.120	0.010
2007	0.044	0.003	0.075	0.005	0.049	0.006	0.078	0.008
2008	0.085	0.004	0.096	0.006	0.080	0.009	0.087	0.008
2009	0.093	0.004	0.077	0.005	0.090	0.008	0.079	0.007
2010	0.097	0.004	0.090	0.005	0.101	0.008	0.080	0.008
2011	0.104	0.004	0.075	0.005	0.105	0.008	0.075	0.007
2012	0.103	0.004	0.067	0.005	0.096	0.008	0.066	0.008
2013	0.097	0.004	0.059	0.005	0.089	0.008	0.059	0.006
2014	0.101	0.004	0.075	0.005	0.087	0.007	0.075	0.007
2015	0.083	0.004	0.073	0.005	0.086	0.007	0.086	0.008
2016	0.082	0.004	0.079	0.005	0.083	0.008	0.079	0.007

Table 2.11: Differences in the Average Characteristics of 10% most and least affected

	Full Sample				Black Sub-Sample			
	Est.	Std.Err.	P-value	Joint P-val.	Est	Std.Err.	P-value	Joint P-val
Food Insecure Status	0.437	0.006	0.000	0.000	0.293	0.015	0.000	0.000
Household Head Characteristics								
Blacks	0.284	0.010	0.000	0.000	0.000	0.000		
SNAP Participation Status	0.697	0.016	0.000	0.000	0.776	0.018	0.000	0.000
Female	0.125	0.015	0.000	0.000	0.192	0.020	0.000	0.000
At Work	0.166	0.015	0.000	0.000	0.014	0.023	0.804	1.000
Unemployed	0.169	0.005	0.000	0.000	0.181	0.011	0.000	0.000
Not In Labor Force	-0.335	0.013	0.000	0.000	-0.195	0.023	0.000	0.000
agecat_1	0.017	0.003	0.000	0.000	0.007	0.008	0.934	1.000
agecat_2	0.136	0.009	0.000	0.000	0.110	0.022	0.000	0.000
agecat_3	0.213	0.008	0.000	0.000	0.177	0.016	0.000	0.000
agecat_4	0.226	0.007	0.000	0.000	0.167	0.012	0.000	0.000
agecat_5	0.238	0.007	0.000	0.000	0.167	0.013	0.000	0.000
agecat_6	0.101	0.008	0.000	0.000	0.034	0.014	0.150	0.604
agecat_7	-0.931	0.011	0.000	0.000	-0.661	0.021	0.000	0.000
Divorced	0.251	0.010	0.000	0.000	0.074	0.013	0.000	0.000
Married	-0.248	0.015	0.000	0.000	-0.220	0.019	0.000	0.000
Nevermarried	0.302	0.010	0.000	0.000	0.358	0.022	0.000	0.000
MS_separated	0.087	0.004	0.000	0.000	0.080	0.010	0.000	0.000

MS_widowed	-0.392	0.017	0.000	0.000	-0.293	0.017	0.000	0.000
E_lhs	0.108	0.013	0.000	0.000	0.010	0.018	0.980	1.000
E_hsg	-0.065	0.015	0.000	0.002	0.059	0.022	0.046	0.360
E_sc	0.127	0.012	0.000	0.000	0.128	0.017	0.000	0.000
E_cg	-0.105	0.010	0.000	0.000	-0.127	0.014	0.000	0.000
E_ad	-0.064	0.007	0.000	0.000	-0.070	0.009	0.000	0.000
Household Characteristics & Composition								
ownhouse	-0.727	0.013	0.000	0.000	-0.641	0.022	0.000	0.000
pctpov	-0.833	0.016	0.000	0.000	-0.717	0.021	0.000	0.000
countmembers0share	0.079	0.005	0.000	0.000	0.071	0.010	0.000	0.000
countmembers6share	0.076	0.003	0.000	0.000	0.073	0.007	0.000	0.000
countmembers11share	0.052	0.002	0.000	0.000	0.049	0.004	0.000	0.000
countmembers15share	0.036	0.002	0.000	0.000	0.032	0.004	0.000	0.000
countmembers18share	0.040	0.002	0.000	0.000	0.028	0.007	0.004	0.010
countmembers22share	0.091	0.004	0.000	0.000	0.050	0.012	0.000	0.000
countmembers30share	0.115	0.004	0.000	0.000	0.081	0.008	0.000	0.000
countmembers40share	0.158	0.005	0.000	0.000	0.106	0.008	0.000	0.000
countmembers50share	0.192	0.007	0.000	0.000	0.122	0.009	0.000	0.000
countmembers60share	0.078	0.007	0.000	0.000	0.024	0.010	0.252	0.710
countmembers70share	-0.917	0.010	0.000	0.000	-0.639	0.019	0.000	0.000
livinginmetro	0.075	0.014	0.000	0.000	0.019	0.014	0.172	0.998
unemploymentrate	0.703	0.062	0.000	0.000	0.577	0.087	0.000	0.000
R_midwest	-0.017	0.013	0.498	1.000	0.036	0.016	0.056	0.700

R_northeast	-0.054	0.011	0.000	0.000	0.001	0.017	1.000	1.000
R_southern	0.063	0.015	0.000	0.002	-0.050	0.022	0.060	0.718
R_western	0.008	0.011	0.900	1.000	0.013	0.012	0.670	1.000
Year Sample								
yrnum1	-0.053	0.009	0.000	0.000	-0.050	0.012	0.000	0.000
yrnum2	-0.069	0.008	0.000	0.000	-0.053	0.014	0.010	0.022
yrnum3	-0.031	0.007	0.000	0.002	-0.030	0.011	0.116	0.346
yrnum4	-0.011	0.009	0.958	1.000	-0.007	0.013	1.000	1.000
yrnum5	0.016	0.009	0.518	0.920	0.011	0.012	0.998	1.000
yrnum6	0.007	0.009	0.998	1.000	0.021	0.012	0.648	0.972
yrnum7	0.029	0.008	0.002	0.022	0.030	0.011	0.112	0.338
yrnum8	0.036	0.009	0.000	0.002	0.030	0.011	0.132	0.372
yrnum9	0.039	0.007	0.000	0.000	0.030	0.010	0.056	0.160
yrnum10	0.026	0.008	0.032	0.148	0.012	0.010	0.970	1.000
yrnum11	0.009	0.008	0.958	1.000	0.001	0.011	1.000	1.000
yrnum12	0.003	0.007	1.000	1.000	0.004	0.012	1.000	1.000

2.5.6 Black-White SNAP Participation Gap

Here, we use the above methodology to explore the effects of black-white SNAP Participation gap. In the Table 2.1 shows that the black households are more likely to participate in SNAP than white households. The unconditional mean black-white gap is 15%. In this section we estimate the average predictive effects of being black on SNAP participation after conditioning on observable characteristics. Then, we explore the heterogeneity in households for whom black matters for SNAP participation.

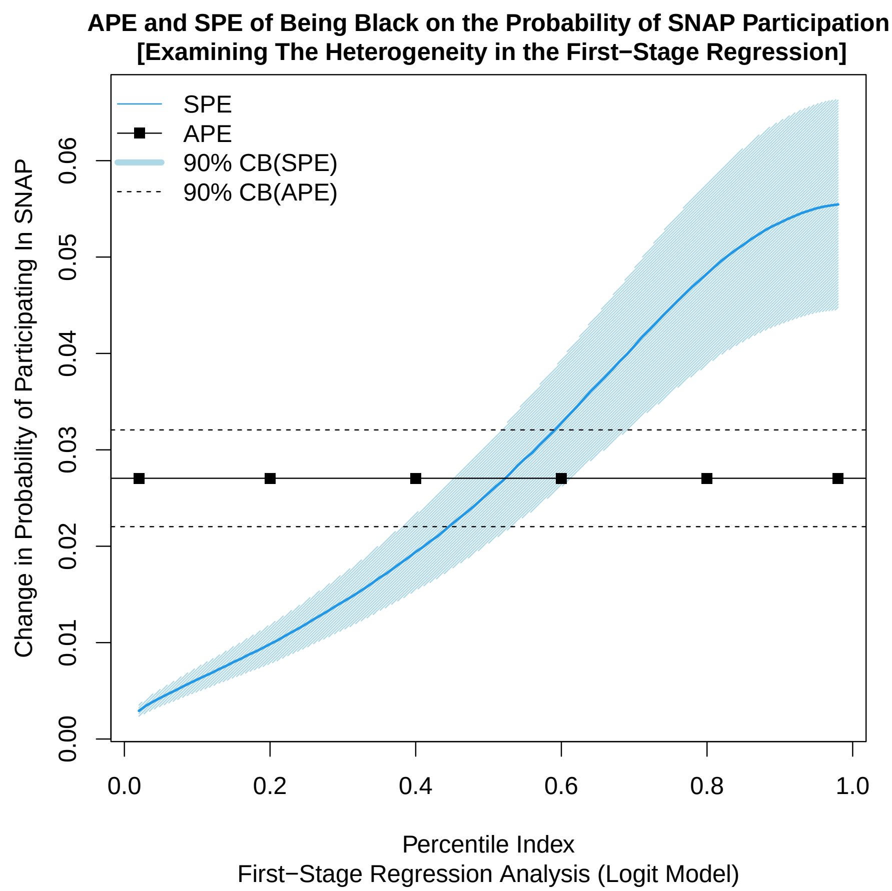

Figure 2.5

In the Figure 2.5 we see that the snap participation gap between blacks and white, after condition on demographics, falls to about 3%. Yet, blacks households are 3% ore likely to participate in SNAP than white households. The SPE curve explores the heterogeneity in households for whom being black matters for SNAP participation. At the lower end of the percentile index, there exists households for whom race doesn't change their probability in participating in

SNAP. And at the other end of the percentile index, there are households for whom being increases their participation in SNAP by about 6%. Appendix Table A.1 provides the detailed estimates of each percentile index for the SPE and the point estimates with confidence interval.

The Table 2.12 answers the question who are the households on the distribution at the tails of the SPE curve in Figure 2.5. And Table 2.13 provides the estimates of difference in means between the 10% most and 10% least impacted by the black-white SNAP participation gap as seen in Table 2.12.

Table 2.12: Classification Analysis Table Exploring Heterogeneity in Black-White SNAP Participation Gap : 10% Most Affected by Being Black and 10% Least Afftected By Being Black

	10% Most		10% Least			10% Most		10% Least	
	Est.	S.E.	Est.	S.E.		Est.	S.E.	Est.	S.E.
foodinsecure	0.439	0.005	0.106	0.003	countmembers50share	0.199	0.004	0.081	0.004
snap_dummy	0.502	0.005	0.014	0.001	countmembers60share	0.134	0.005	0.119	0.005
blackrace	0.376	0.005	0.115	0.004	countmembers70share	0.036	0.003	0.367	0.012
female	0.694	0.006	0.404	0.008	atwork	0.257	0.005	0.641	0.013
agecat_1	0.018	0.002	0.055	0.004	nilf	0.632	0.007	0.348	0.013
agecat_2	0.145	0.004	0.176	0.008	unemployed	0.111	0.004	0.012	0.001
agecat_3	0.208	0.005	0.079	0.004	shareoffemales	0.585	0.005	0.482	0.005
agecat_4	0.190	0.005	0.096	0.006	shareofHSLessEduc	0.803	0.005	0.385	0.008
agecat_5	0.237	0.005	0.098	0.005	inperson	0.462	0.006	0.306	0.007
agecat_6	0.154	0.005	0.126	0.005	livinginmetro	0.746	0.005	0.805	0.005
agecat_7	0.047	0.003	0.371	0.013	unemploymentrate	6.386	0.028	6.133	0.037
MS_married	0.164	0.005	0.513	0.010	R_northeast	0.187	0.005	0.104	0.005
MS_widowed	0.076	0.004	0.164	0.008	R_midwest	0.271	0.006	0.217	0.008
MS_separated	0.085	0.003	0.010	0.001	R_southern	0.423	0.006	0.453	0.009
MS_divorced	0.292	0.005	0.069	0.003	R_western	0.119	0.005	0.227	0.006
MS_nevermarried	0.382	0.006	0.244	0.010	yrnum1	0.049	0.002	0.079	0.005
E_lhs	0.277	0.006	0.047	0.003	yrnum2	0.044	0.002	0.108	0.005
E_hsg	0.409	0.006	0.287	0.007	yrnum3	0.031	0.002	0.089	0.005
E_sc	0.283	0.006	0.303	0.009	yrnum4	0.058	0.002	0.140	0.006
E_cg	0.025	0.003	0.250	0.010	yrnum5	0.067	0.002	0.101	0.005
E_ad	0.006	0.001	0.113	0.007	yrnum6	0.078	0.003	0.065	0.004
ownhouse	0.151	0.006	0.693	0.010	yrnum7	0.079	0.003	0.062	0.004
pctpov	0.662	0.006	1.831	0.004	yrnum8	0.081	0.003	0.046	0.004
countmembers0share	0.093	0.002	0.011	0.001	yrnum9	0.080	0.003	0.040	0.003
countmembers6share	0.077	0.002	0.013	0.001	yrnum10	0.081	0.003	0.056	0.003
countmembers11share	0.052	0.002	0.015	0.001	yrnum11	0.077	0.003	0.048	0.003
countmembers15share	0.035	0.001	0.014	0.001	yrnum12	0.073	0.003	0.051	0.004
countmembers18share	0.033	0.002	0.072	0.004	yrnum13	0.071	0.003	0.035	0.003
countmembers22share	0.090	0.003	0.186	0.008	yrnum14	0.065	0.003	0.035	0.003
countmembers30share	0.114	0.003	0.061	0.004	yrnum15	0.066	0.004	0.047	0.004
countmembers40share	0.137	0.004	0.061	0.004					

Table 2.13: Classification Analysis Table Estimates of Difference In Meands between 10% Most Affected by Being Black and 10% Least Afftected By Being Black

	Estimate	S.E.	JP-vals	PW P-vals		Estimate	S.E.	JP-vals	PW P-vals
foodinsecure	0.332	0.006	0.000	0.000	countmembers50share	0.118	0.007	0.000	0.000
snap_dummy	0.488	0.005	0.000	0.000	countmembers60share	0.015	0.009	1.000	0.052
blackrace	0.262	0.008	0.000	0.000	countmembers70share	-0.331	0.015	0.000	0.000
female	0.291	0.011	0.000	0.000	atwork	-0.384	0.017	0.000	0.000
agecat_1	-0.036	0.005	0.000	0.000	nilf	0.284	0.017	0.000	0.000
agecat_2	-0.031	0.010	0.110	0.001	unemployed	0.100	0.004	0.000	0.000
agecat_3	0.129	0.007	0.000	0.000	shareoffemales	0.103	0.008	0.000	0.000
agecat_4	0.094	0.009	0.000	0.000	shareofHSLessEduc	0.417	0.012	0.000	0.000
agecat_5	0.139	0.009	0.000	0.000	inperson	0.157	0.012	0.000	0.000
agecat_6	0.029	0.009	0.110	0.001	livinginmetro	-0.059	0.010	0.000	0.000
agecat_7	-0.324	0.015	0.000	0.000	unemploymentrate	0.252	0.053	0.000	0.000
MS_married	-0.350	0.014	0.000	0.000	R_northeast	0.083	0.008	0.000	0.000
MS_widowed	-0.088	0.011	0.000	0.000	R_midwest	0.054	0.011	0.000	0.000
MS_separated	0.075	0.003	0.000	0.000	R_southern	-0.029	0.012	0.440	0.005
MS_divorced	0.223	0.007	0.000	0.000	R_western	-0.108	0.009	0.000	0.000
MS_nevermarried	0.139	0.013	0.000	0.000	yrnum1	-0.031	0.005	0.000	0.000
E_lhs	0.230	0.009	0.000	0.000	yrnum2	-0.064	0.006	0.000	0.000
E_hsg	0.122	0.013	0.000	0.000	yrnum3	-0.058	0.005	0.000	0.000
E_sc	-0.020	0.012	1.000	0.044	yrnum4	-0.082	0.006	0.000	0.000
E_cg	-0.225	0.012	0.000	0.000	yrnum5	-0.034	0.006	0.000	0.000
E_ad	-0.107	0.008	0.000	0.000	yrnum6	0.013	0.005	0.320	0.003
ownhouse	-0.542	0.015	0.000	0.000	yrnum7	0.017	0.007	0.490	0.006
pctpov	-1.169	0.008	0.000	0.000	yrnum8	0.036	0.006	0.000	0.000
countmembers0share	0.082	0.002	0.000	0.000	yrnum9	0.040	0.005	0.000	0.000
countmembers6share	0.064	0.002	0.000	0.000	yrnum10	0.025	0.005	0.000	0.000
countmembers11share	0.036	0.002	0.000	0.000	yrnum11	0.029	0.005	0.000	0.000
countmembers15share	0.021	0.002	0.000	0.000	yrnum12	0.023	0.007	0.060	0.000
countmembers18share	-0.039	0.005	0.000	0.000	yrnum13	0.036	0.006	0.000	0.000
countmembers22share	-0.096	0.009	0.000	0.000	yrnum14	0.031	0.005	0.000	0.000
countmembers30share	0.053	0.007	0.000	0.000	yrnum15	0.020	0.007	0.370	0.004
countmembers40share	0.076	0.005	0.000	0.000					

2.6 Discussion & Conclusion

We explore the factors behind the differential experience in food insecurity between Black & White households. Black households experience, on average, 11 percentage points higher food insecurity relative to a White household for the period under study (2005-2016). Our IV-2SLS results highlight that food stamps reduces food insecurity more for White households than Black households. We employ the Kitagawa-Oaxaca-Blinder decomposition with the updated method using DiNardo et al., 1996 re-weighting factor. Decomposition results provide evidence that 57.3% of the difference between these two groups is explained by differences in mean observable household characteristics. Thus, aiding policymakers to target public policies to address part of the food insecurity problem. Next, we move beyond the averages in exploring the heterogeneity in the partial effects of being black on the probability of being food insecure. We estimate the average partial effect and sorted partial effect using Chernozhukov et al., 2018 methodology on the Food Security Module of the Current Population Survey data covering 2005-2016. The average partial effect of being black on food insecurity is 4 percentage points. The *sorted effects* curve graphically depicts the heterogeneity in this summary measure showing that the effects range from 1 to 6 percentage points. Households are classified into having the largest and smallest effects, respectively. One of the observable characteristics that make these two households differ is the low home ownership rate among the households that experience higher food insecurity.

This study provides an estimate of the racial disparity between Black and White households on food insecurity experience. We estimate the average partial effect of being black on the probability of being food insecure and explore the heterogeneous effects in this regard by using the Chernozhukov et al., 2018 *sorted effects* methodology. The methodology explores the factors that contribute to the racial disparity in food insecurity experience between Black & White households. Over the years of the study 2005-2016, Black households experience higher food insecurity relative to a White households (an unconditional mean of 11 percentage points higher). This gap persists even after controlling for demographic characteristics (approximately, 4 percentage points higher). This paper explores the heterogeneity among Black & White households' experiencing food insecurity. The paper provides evidence of the gap in food insecurity between the two racial groups and show that Black's have consistently experienced higher food insecurity relative to a White household throughout the period under study (2005-2016). Decomposition analysis found that differences in observable household characteristics explains 57.3% of the food insecurity gap between a Black and White household. The remaining 43% accounts for the 'unexplained', driven by differences in returns to these characteristics.

Chapter 3

Food Insecurity And Unemployment

3.1 Introduction

Unemployment and job instability has been a huge macro and micro-economic shock as a result of the global pandemic. Economically vulnerable households, as a result, have been distressed in many aspects of daily life and loss of a job / paycheck has been at the center (Kalil et al., 2020). We explore the causal impact of unemployment on food insecurity and severity. Food insecurity is a major health concern in the USA. A recent report by the United States Department of Agriculture (USDA) by Coleman-Jensen et al., 2018a states that in the year 2017, 11.8% of households were food insecure at least some time during that year. Although a decrease from 2016 , when the number was 12.3%, the percentage of food insecure households is still large. By the definition of *food insecurity*, this indicates that there were households that at some point in the year had limited access to food owing to lack of money or other resources to obtain food. On the other hand, many regions of the United States suffer from low levels of labor force participation. Recent studies have begun to show a link between economic distress (e.g. unemployment) and health outcomes (see Betz and Jones, 2018). However, there still remains a question as to what extent unemployment affects a household's food insecurity status. The connection between job-loss and the resulting socio-economic outcomes is well hypothesized by Wilson, 2011 that declining job prospects have a wider impact on social outcomes like marriage, single parenthood, crime, drug use and health. We posit that *food insecurity* be also considered as a dimension of socio-economic outcomes an economically vulnerable household faces. The task of the researcher is to uncover the mechanisms that drive this causal relationship.

Figure 3.1 displays the relationship between unemployment and mean food insecurity rates over the years for our sample households in the Current Population Survey's December Food Security Supplement (CPS-FSS). Food insecurity is a binary indicator, with an average of 52% for our entire sample. Figure 3.2 displays the between unemployment and mean food severity. Food severity is measured via the count of affirmative responses to the 18 item CPS-FSS food security questionnaire (on average 3.5 affirmative responses). In both figures, the x-axis are the years (2001-2020) and the left y-axis measures the mean food insecurity (or severity) rates (plotted using solid red lines) and the right y-axis measures the unemployment rate (plotted using blue dashed line). From both figures, we can see in certain periods food insecurity/severity tracks unemployment. However, during the US post-Great recession economic recovery period (2013 onwards), we see unemployment falling but food insecurity rates being high. This highlights the objective our study to examine the causal impact of unemployment on household's food insecurity (and severity).

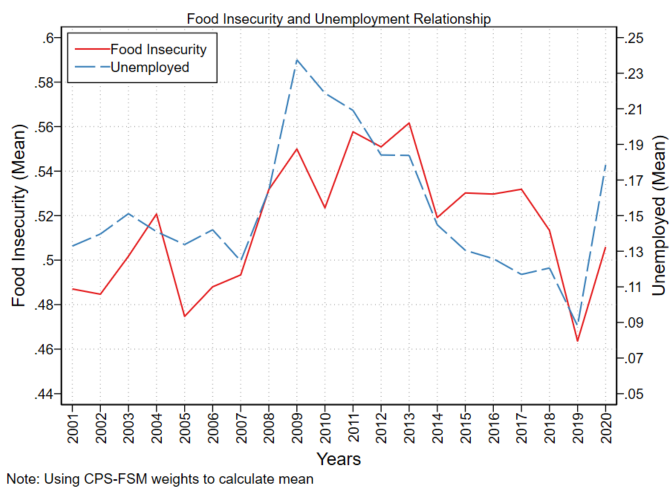

Figure 3.1: Food insecurity and unemployment over the years for our CPS-FSS sample

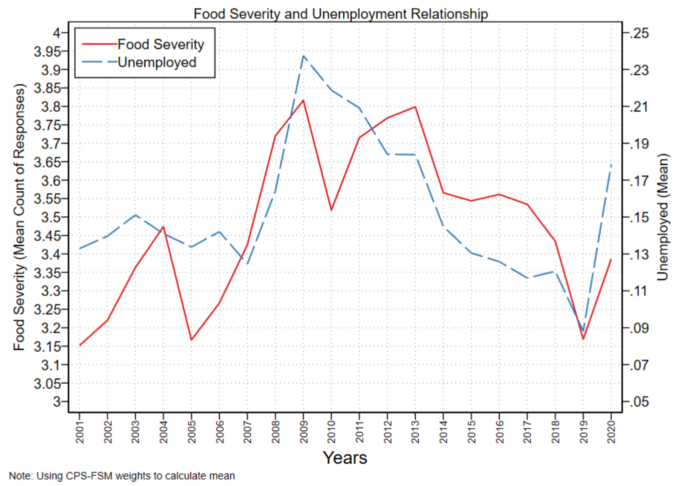

Figure 3.2: Food severity and unemployment over the years for our CPS-FSS sample

This paper studies how unemployment affects and exacerbates food insecurity among low-income individuals. Intuitively, unemployment leads to loss of a paycheck and this directly would affect an individual's basket of food making an individual feel less food secure. Nord et al., 2014 observe that household food insecurity and unemployment rate has been moving in tandem upto a few years since the financial crisis of 2008 but since 2010 even though unemployment rate has shown modest improvement food insecurity has remained high. Anderson et al., 2016 in examining very low food security status of low-income households with children, find that labour force patterns among potential workers in a household matters. That is, children in households where the adult works a larger fraction of the year are less likely to have a very low food secure (VLFS) status. This causal relationship between unemployment and food insecurity matters as can be motivated by an aggregated state level analysis of unemployment rate and state food insecurity status by Gundersen et al., 2017 that finds the elasticity of food insecurity rate with respect to the unemployment rate is greater and statistically significant than poverty rate. This highlights the importance of examining unemployment status and its impact on the incidence and severity of food insecurity.

It has been well documented in the food policy literature on the role of education and household income as determinants of household food insecurity. Bartfeld et al., 2006 have shown correlation between household-level characteristics as well as macroeconomic conditions on the household's food insecurity status. The household level determinants examined are income, education , race, number of children , employment status of the adult, household member with disability, etc. . The state-level characteristics examined are unemployment rate , SNAP participation rate, cost of rental housing, average wages, etc. Despite these descriptive associations the direction of causality is not yet well understood. In this paper, we aim to explore the negative causal relationship between unemployment status and food insecurity.

Local Economic Condition on SNAP & Disability take up: Studies have shown how a decline in labor demand in counties impact the take-up rates of SNAP and Disability Benefits. The negative income shock affects the probability of leaving labor force by increasing it by 30% post-displacement (Huttunen et al., 2011). This brings about a rise in disability benefits use by 24% (Rege et al., 2009).

Job Displacement on Labor Market Outcomes: A large literature on job displacement has examined the labor market outcomes of displaced workers. Such workers owing to either mass layoff or plant closures experience long-term losses in earnings, reduced job stability, lower employment rates and earlier retirement. On earnings, Jacobson et al., 1993 found huge earnings losses of about 25% after displacement for the Pennsylvania workers. Since this study a consensus has built on the negative impact on earnings. However the magnitude varies across countries. Workers displaced during mass layoffs experience large losses in annual earnings lasting over 15-20 years (Couch and Placzek, 2010; Jacobson et al., 1993). Earning losses after displacement have an important cyclical component where recession exacerbates the impact by doubling it relative to displacement during boom periods (Farber, 2017). Recently, Lachowska et al., 2018 using administrative data from the state of Washington show workers displaced during the Great Recession experienced persistent wage losses if lost a job at a high-paying firm. (Schmieder et al., 2018) addresses the question of sources of earning losses and their cyclicality. Losses in annual earnings in Germany after displacement are large, persistent, and highly cyclical, nearly doubling in size during economic downturn. Part of these losses and their cyclicality is driven by unemployment. Longer-term loss in earnings and their cyclicality driven by decline in wages (because of changes in employer characteristics).

Furthermore, job displacement literature has expanded to observe the impact of economic shock on health outcomes. Studies on Sweden and Denmark show smaller effect of job displacement on mortality (Browning and Heinesen, 2012; Eliason and Storrie, 2009). Sullivan and von Wachter, 2009 show hat displaced workers can also experience higher rates of mortality. They use unemployment insurance administrative data on quarterly earnings and employment histories of male workers from Pennsylvania in the 1970s and 1980s as well as death records from the Social Security Administration from 1980-2006 anywhere in the US. Sullivan and von Wachter, 2009 find that high-tenured male workers displaced experienced a significant increase in mortality rates of 50-100% increase in the immediate period and that converges to 10-15% increase in the hazard rate. This implies a decline in life-expectancy of 1.0-1.5 years for displaced workers in middle age.

Job Displacement on Health Outcomes (Physical And Mental health Outcomes) :It has been well documented the negative association between unemployment and health. However, the direction of causality needs to be explored. Job displacement affects health through various mechanisms. Firstly, a negative income shock affects consumption and exercise Second, job displacement increases stress known to have negative effects on cardiovascular health. Bergemann et al., 2011 show that job displacement on diabetes incidence increased in Sweden for single men and women with children. A recent study by Black et al., 2015 use a rich detailed health survey form Norway matched with administrative register data from 1986-1999. Their sample consists of of men and women in their early 40s and compare displaced and non-displaced workers' health from 5years before to 7 years after displacement. The health outcomes the authors observe are cholesterol, blood pressure, smoking and an index of risk of heart disease. Black et al., 2015 find that the exact nature of displacement matters for health - downsizing versus plant closure - and find that the effect of plant closure on smoking dominate downsizing with differences large for women.

This paper addresses the issue using two measures of food-related hardships (Flores-Lagunes et al., 2018b). We examine the *incidence*, captured by the binary indicator of household's food insecurity status; and *severity*, captured by the count of the affirmative responses in the food security module. The official statistics of food (in)security in the United States are based on a Food Security Supplement to the Current Population Survey (CPS-FSS). Our sample covers respondents of the CPS-FSS who pass the common screening questions an report some level of food hardships over the two waves of the survey. The individuals are of working age (18 - 64 years old) and in the labor force (i.e. currently working or actively searching for a job when unemployed). The sample consists of 60,292 person-year observations for the period of 2000-2020. We also, measure unemployment either via the unemployment status of the householder or share of unemployed family members (conditional on being in the labor force). The latter definition of unemployment attempts to address the stress a family as a whole undergoes with a loss of a paycheck.

We address the identification issue arising from the endogeneity of unemployment status (possibly, simultaneity bias arising from the relationship between food insecurity and unemployment) to identify the causal relationship by using a recently proposed method, the *front-door criterion*, by Bellemare et al., 2021. We use *resource deficiency* as the mechanism (a mediator) that translates unemployment into food insecurity. We find that householder's unemployment increases the probability of being food insecure by one percentage points. And the impact increases to 1.6 percentage points if all family members in the labor force are employed. On *food severity*, measured by the count of responses to the food security questions, we find that both householder's and family members' unemployment status increases the responses to the food insecurity experiences. The analysis of the paper could suggest to policymakers the need to strengthen the local labor market to address a part of the food insecurity problem.

In terms of policy, Gundersen et al., 2011 and Gundersen and Ribar, 2011 point out that food insecurity and income is not a clear relationship. There are households who are above the poverty line and are yet food insecure. Therefore, as we examine the unemployment status as a causal impact on food insecurity, this could provide policy makers to address the labour market structure through re-examining work-incentivising programs such as the Earned Income Tax Credit or tax incentives for the entrepreneurial sector in helping create jobs or work incentives within the food-stamp program. Proceeding forward, the goal of our study is to measure the causal impact that unemployment has on the intensive and extensive margin of food insecurity.

Section 3.2 describes the data, measurement of food insecurity, measurement of unemployment and the creation of our estimation sample. Section 3.3 uses linear regression to explore the association between householder's unemployment status and food insecurity. In this section, we further explore how householder's unemployment status is associated with three primary food insecurity questions and how the relationship between unemployment and food insecurity varies with householder's sex and age of the householder. Section 3.4 uses the front-door criterion estimation to provide the estimates of the indirect effect of unemployment on food insecurity using resource deficiency as the mediator. The argument in this section relies on our position that the total effect of unemployment on food insecurity is completely mediated via the fall in monetary resources. Section 3.5 measures the effect of unemployment on food severity, an intensive margin measure of food insecurity using the count of affirmative responses to the CPS-FSS questionnaire. Section 3.6 uses an alternative definition of measuring household unemployment status. We use the share of unemployed family members (conditional on being in the labor force) as our variable of interest and examine its effect on food insecurity (and severity). Section 3.7 ends with our discussion and conclusion.

3.2 Data

Table 3.1 present the summary statistics of our outcome variable, causal variable and other covariates. We use the December Current Population Survey - Food Security Supplement (CPS-FSS) where each observation corresponds to the householder's response to the FSM questionnaire. These householder's adult civilian members that are considered vulnerable households by passing the FSM screening procedure. We exclude observations that haven't passed the food security screen and are above the 185% poverty threshold. We drop any food security non-response and keep working adults 18 to 64 year old. Our sample covers the time period of 2001 to 2020.[18]

To measure unemployment in the household, we keep household that are in the labor force (i.e. currently working or actively searching for jobs when unemployed) and create a binary indicator of householder's unemployment status. Furthermore, we also measure household unemployment by calculating the fraction of family members in the labor force that are unemployed. Our outcome variable measures household's food insecurity status and is created as a binary indicator using the categorical definition of food security as defined by the ERS-USDA: high food secure, marginal food secure, low food secure and very low food secure. Households that experience low and very low food insecurity are classified as being food insecure.[19]

Respondents demographic characteristics include race/ethnicity (Black non-Hispanic, White non-Hispanic, other non-Hispanics and Hispanics), age of the respondent, high school diploma or less indicator, ever married marital status indicator, female householder indicator and family income measured as a ratio of the poverty guideline threshold. To account for household members' composition we construct the share of family members in the house for each age bracket: 0 to 5 year old, 6 to 11, 12 to 19, 20 to 29, 30 to 39, 40 to 49, 50 to 59 and 60 and above year old. Additionally, we control for year , region (north-east, south, mid-west and west) and CPS wave rotation number the respondent is observed.

The total number of person-year observations are 60,292 with 9,051 observations being unemployed householders. Since this CPS-FSS survey is conducted every December, we have households who might be surveyed twice in a CPS rotation. So, 60,292 observations contain 52,470 unique households and 52,591 unique persons. But for our analysis we consider each observation as unique. Our observations are for persons we have complete data on all our variables. We use the food security supplement person weight to weight our statistics and estimation results.

[18] Our full sample covers the time period of 2001 to 2020. However, home ownership is only available until December 2016 CPS-FSM. Similarly, the disability measure is available only from year 2008. Hence, we examine our research question with these variables as additional robustness results and have them excluded from our baseline.

[19] We use the detailed food security status measure constructed by the CPS-FSM survey as it covers our entire period of 2001-2020. In previous studies, economists have used the adult responses measure of the food security. However, this measure is available only 2005 onwards.

Table 3.1: Summary Statistics

	Full Sample	Employed	Unemployed	
	Mean	Mean	Mean	Difference
	(St. Dev)	(St. Dev)	(St. Dev)	[p-value]
Food Insecurity Status:				
Household food insecurity status	0.519	0.500	0.617	-0.120***
	(0.500)	(0.500)	(0.486)	[0.000]
Resource Deficiency:				
relative amount of money	2.259	2.242	2.354	-0.126***
needed to meet needs	(0.701)	(0.703)	(0.682)	[0.000]
Unemployment Measure:				
Indicator For Being Unemployed	0.158			
	(0.365)			
Share of Labor Force Members	0.105	0.025	0.534	-0.517***
That Are Unemployed	(0.237)	(0.090)	(0.310)	[0.000]
Householder's Characteristics:				
Household head is female	0.558	0.563	0.534	0.035***
	(0.497)	(0.496)	(0.499)	[0.000]
Age	38.703	38.666	38.901	-0.386**
	(11.462)	(11.401)	(11.783)	[0.004]
Married at present or ever	0.659	0.671	0.594	0.077***
	(0.474)	(0.470)	(0.491)	[0.000]
White non-hispanic	0.481	0.487	0.448	0.058***
	(0.500)	(0.500)	(0.497)	[0.000]
Black non-hispanic	0.213	0.201	0.277	-0.075***
	(0.410)	(0.401)	(0.448)	[0.000]
Other races non-hispanic	0.053	0.053	0.052	-0.002
	(0.224)	(0.224)	(0.222)	[0.556]
Hispanic ethicity only	0.253	0.259	0.223	0.019***
	(0.435)	(0.438)	(0.416)	[0.000]
High school diploma or less	0.568	0.561	0.604	-0.057***
	(0.495)	(0.496)	(0.489)	[0.000]
Household Characteristics:				
Income to poverty ratio	1.169	1.223	0.882	0.346***
	(0.565)	(0.548)	(0.571)	[0.000]
Share of members between age 0 and 5	0.107	0.108	0.105	0.006**
	(0.177)	(0.177)	(0.180)	[0.005]

continued

Table 3.1: Summary Statistics

	Full Sample	Employed	Unemployed	
	Mean	Mean	Mean	Difference
	(St. Dev)	(St. Dev)	(St. Dev)	[p-value]
Share of members between age 6 and 11	0.113	0.116	0.098	0.017***
	(0.177)	(0.178)	(0.170)	[0.000]
Share of members between age 12 and 19	0.130	0.132	0.117	0.015***
	(0.205)	(0.206)	(0.199)	[0.000]
Share of members between age 20 and 29	0.193	0.195	0.180	0.019***
	(0.302)	(0.304)	(0.290)	[0.000]
Share of members between age 30 and 39	0.155	0.155	0.154	0.001
	(0.247)	(0.244)	(0.261)	[0.766]
Share of members between age 40 and 49	0.141	0.138	0.162	-0.027***
	(0.260)	(0.253)	(0.293)	[0.000]
Share of members between age 50 and 59	0.114	0.111	0.129	-0.020***
	(0.270)	(0.266)	(0.289)	[0.000]
Share of members between age 60 plus	0.047	0.045	0.055	-0.011***
	(0.179)	(0.175)	(0.197)	[0.000]
Mid-west region	0.224	0.224	0.222	0.016**
	(0.417)	(0.417)	(0.416)	[0.001]
North-East region	0.128	0.126	0.136	-0.009*
	(0.334)	(0.332)	(0.343)	[0.029]
South region	0.415	0.418	0.398	-0.006
	(0.493)	(0.493)	(0.489)	[0.295]
West region	0.234	0.232	0.244	-0.001
	(0.423)	(0.422)	(0.430)	[0.820]
Year Sample:				
2001	0.044	0.046	0.037	0.010***
	(0.206)	(0.209)	(0.190)	[0.000]
2002	0.047	0.048	0.042	0.009***
	(0.212)	(0.214)	(0.200)	[0.001]
2003	0.047	0.048	0.045	0.005
	(0.213)	(0.213)	(0.208)	[0.074]
2004	0.049	0.050	0.044	0.007**
	(0.216)	(0.218)	(0.205)	[0.003]
2005	0.046	0.047	0.039	0.012***
	(0.209)	(0.212)	(0.193)	[0.000]

continued

Table 3.1: Summary Statistics

	Full Sample	Employed	Unemployed	
	Mean	Mean	Mean	Difference
	(St. Dev)	(St. Dev)	(St. Dev)	[p-value]
2006	0.045	0.045	0.040	0.006**
	(0.206)	(0.208)	(0.196)	[0.008]
2007	0.048	0.050	0.038	0.011***
	(0.214)	(0.218)	(0.191)	[0.000]
2008	0.062	0.062	0.065	-0.003
	(0.241)	(0.240)	(0.246)	[0.337]
2009	0.063	0.057	0.095	-0.040***
	(0.243)	(0.232)	(0.293)	[0.000]
2010	0.064	0.059	0.088	-0.034***
	(0.244)	(0.236)	(0.284)	[0.000]
2011	0.060	0.057	0.080	-0.023***
	(0.238)	(0.231)	(0.271)	[0.000]
2012	0.058	0.056	0.067	-0.013***
	(0.233)	(0.230)	(0.250)	[0.000]
2013	0.053	0.051	0.061	-0.008**
	(0.223)	(0.220)	(0.240)	[0.002]
2014	0.058	0.059	0.053	0.007**
	(0.234)	(0.236)	(0.225)	[0.005]
2015	0.048	0.050	0.040	0.009***
	(0.215)	(0.218)	(0.196)	[0.000]
2016	0.046	0.048	0.037	0.012***
	(0.210)	(0.214)	(0.188)	[0.000]
2017	0.043	0.045	0.032	0.012***
	(0.203)	(0.208)	(0.176)	[0.000]
2018	0.039	0.040	0.030	0.011***
	(0.193)	(0.197)	(0.170)	[0.000]
2019	0.040	0.043	0.022	0.014***
	(0.195)	(0.203)	(0.147)	[0.000]
2020	0.040	0.039	0.045	-0.004*
	(0.195)	(0.193)	(0.207)	[0.028]
Observations	60292	51241	9051	60292

continued

Table 3.1: Summary Statistics

	Full Sample	Employed	Unemployed	
	Mean	Mean	Mean	Difference
	(St. Dev)	(St. Dev)	(St. Dev)	[p-value]

Notes: CPS-FSS 2001-2020 data. Weighted summary statistics. Weights used are the food security supplement weight for the person. The parentheses below the mean is the standard deviation. The square brackets below the difference value are the p-values from a t-test (*** 1%, ** 5%, *1%). Resource deficiency takes discrete values of 1(less), 2(same) and 3(more).

3.3 Relationship Between Food Insecurity & Unemployment

Here we look at the association between a householder's unemployment status and their food insecurity status. The structural equation describing the relationship is given in equation 3.1, below:

$$\text{Food Insecurity}_i = \alpha + \beta\,\text{Unemployed}_i + \boldsymbol{X}_i'\gamma + \varepsilon_i \tag{3.1}$$

where `Food Insecurity`$_i$ is the binary indicator of household (i) experiencing food insecurity sometime in the past year.[20] `Unemployed`$_i$ is our variable of interest measured as a binary indicator of the unemployment status of the householder. $\boldsymbol{X}$ is a vector of controls measuring household demographics and characteristics as described in the summary statistics table 3.1 . The parameter of interest is β provides an estimate of the association between unemployment and the probability of being food insecure. α is the intercept coefficient, γ is the vector of parameters associated with our controls and ε is the unobserved disturbance or error.

[20] Note, that we use the 12-month measure of food insecurity rather than past 30-days experience of food insecurity

Table 3.2 displays the results using ordinary least squares (OLS) method to explore the relation given in equation 3.1. Column 1 of table 3.2 displays the relation between householder's unemployment status and food insecurity without any additional demographic and household characteristics. We see, from column 1, that unemployed households experience 11.2 percentage points higher probability of being food insecure. Column 3 of table 3.2 adds in all the controls. Column 3 of table 3.2 tells us that even after controlling for demographic and household characteristics an unemployed household experiences 7.2 percentage points higher probability of being food insecure than an employed household.

This suggests that with the addition of controls we still observe a strong positive relationship between unemployed householder and food insecurity (going from 11.2 percentage points to 7.2 percentage points). Moving forward in the paper, columns 3 of table 3.2 will be our preferred baseline specification for further analysis.[21]

[21] Column 2 and column 4 are discussed in section 3.6 since it utilizes an alternative broader definition of unemployment, *share of unemployed family members*.

Table 3.2: Estimation Results: Relationship between unemployment and food insecurity

	Unemployed Household Head Coeff./S.err.	Unemployed Members Share Coeff./S.err.	Unemployed With Demographics Coeff./S.err.	Unemployed Share With Demographics Coeff./S.err.
Indicator For Being Unemployed	0.112***		0.077***	
	(0.007)		(0.007)	
Share of Labor Force Members That Are Unemployed		0.165***		0.134***
		(0.010)		(0.010)
Household head is female			0.054***	0.054***
			(0.005)	(0.005)
Married at present or ever			-0.008	-0.007
			(0.006)	(0.006)
White non-hispanic			-0.032***	-0.033***
			(0.011)	(0.011)
Black non-hispanic			0.019	0.018
			(0.012)	(0.012)
Hispanic ethicity only			-0.001	-0.002
			(0.012)	(0.012)
High school diploma or less			0.019***	0.020***
			(0.005)	(0.005)
Age of the respondent			0.009***	0.009***
			(0.002)	(0.002)
Age of the respondent (squared)			-0.000***	-0.000***
			(0.000)	(0.000)
Share of members between age 0 and 5			-0.007	0.009
			(0.025)	(0.025)
Share of members between age 6 and 11			0.068***	0.083***
			(0.025)	(0.025)
Share of members between age 12 and 19			0.055**	0.063***
			(0.022)	(0.022)
Share of members between age 20 and 29			0.013	0.008
			(0.022)	(0.022)
Share of members between age 30 and 39			0.037	0.030
			(0.024)	(0.024)
Share of members between age 40 and 49			0.046**	0.038*
			(0.022)	(0.022)
Share of members between age 50 and 59			0.043**	0.039**
			(0.017)	(0.017)
Share of members between age 60 plus			0.000	0.000
			(.)	(.)
Income to poverty ratio			-0.100***	-0.099***
			(0.005)	(0.005)
Constant	0.488***	0.490***	0.406***	0.400***
	(0.013)	(0.013)	(0.044)	(0.044)
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Survey wave effect	Yes	Yes	Yes	Yes
R-squared	0.011	0.010	0.035	0.036
Observations	60292	60292	60292	60292
Food Insecure Mean	0.519			

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

3.3.1 Relationship Between Type of Food Insecurity & Unemployment

In Table 3.3 we take column 3 of table 3.2 and add it to column 1 of table 3.3 and examine our relationship of interest on 4 different categories of food security. Food insecurity status, our binary indicator, is constructed using four levels of food security- high food secure, marginal food secure, low food secure and very low food secure. CPS-FSS and other economists classify households as food insecure if they are low and very low food secure. So, in table 3.3, we explore the relationship between householder's unemployment on each of the food security categories: high food secure (column 2, where 1 indicates being high food secure), marginal food secure (column 3, where 1 indicates being marginally food secure), low food secure (column 4, where 1 indicates being low food secure), and very low food secure (column 5,, where 1 indicates as being very low food secure). Our evidence shows, that high, marginal and very low categories exhibit the strongest relationship. Householder's unemployment is associated with 5.4 percentage points less likely to be *high food secure*, as shown in column 2. Whereas, householder's unemployment is associated with 2 percentage point reduction in being *marginal food secure* and 6.3 percentage points more likely to be *very low food secure*.

Table 3.3: Estimation Results: Relationship between household head's unemployment status and the levels of food insecurity

	Overall Food Insecurity Coeff./S.err.	High Food Security Coeff./S.err.	Marginal Food Security Coeff./S.err.	Low Food Security Coeff./S.err.	Very Low Food Security Coeff./S.err.
Indicator For Being Unemployed	0.077***	-0.058***	-0.019***	0.011*	0.065***
	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)
Household head is female	0.054***	-0.042***	-0.012***	0.022***	0.032***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Married at present or ever	-0.008	0.006	0.002	-0.002	-0.006
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
White non-hispanic	-0.032***	0.034***	-0.002	-0.040***	0.008
	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)
Black non-hispanic	0.019	-0.028***	0.008	0.005	0.014
	(0.012)	(0.010)	(0.011)	(0.012)	(0.010)
Hispanic ethicity only	-0.001	-0.006	0.007	0.024**	-0.025***
	(0.012)	(0.010)	(0.010)	(0.011)	(0.009)
High school diploma or less	0.019***	-0.027***	0.007*	0.021***	-0.002
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Age of the respondent	0.009***	-0.007***	-0.002	0.007***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000***	0.000***	0.000	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	-0.007	-0.045**	0.051**	0.175***	-0.182***
	(0.025)	(0.022)	(0.022)	(0.023)	(0.020)
Share of members between age 6 and 11	0.068***	-0.072***	0.005	0.168***	-0.101***
	(0.025)	(0.021)	(0.022)	(0.023)	(0.020)
Share of members between age 12 and 19	0.055**	-0.069***	0.014	0.106***	-0.051***
	(0.022)	(0.019)	(0.019)	(0.020)	(0.018)
Share of members between age 20 and 29	0.013	-0.024	0.011	0.015	-0.001
	(0.022)	(0.020)	(0.019)	(0.020)	(0.018)
Share of members between age 30 and 39	0.037	-0.020	-0.017	-0.010	0.047**
	(0.024)	(0.021)	(0.021)	(0.022)	(0.020)
Share of members between age 40 and 49	0.046**	-0.019	-0.026	-0.017	0.063***
	(0.022)	(0.019)	(0.019)	(0.020)	(0.018)
Share of members between age 50 and 59	0.043**	-0.022	-0.021	-0.018	0.061***
	(0.017)	(0.015)	(0.015)	(0.015)	(0.014)
Income measured relative to poverty threshold	-0.100***	0.073***	0.026***	-0.029***	-0.071***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.406***	0.367***	0.227***	0.187***	0.219***
	(0.044)	(0.038)	(0.038)	(0.041)	(0.035)
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes	Yes	Yes
Mean of Outcome	0.519	0.235	0.246	0.326	0.193
R-squared	0.035	0.034	0.004	0.022	0.035
Observations	60292	60292	60292	60292	60292

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

3.3.2 Relationship to Three Primary Questions of Food Insecurity

In table 3.4 we again dissect our baseline specifications in column 3 of 3.2 by looking at our relationship of interest to three of the primary food insecurity questions:

- Q1: Whether worried food would run out?
- Q2: Household ran out of food
- Q3: Whether household did not have enough money for a balanced meal?

The results show that householder's unemployment, increases the likelihood of any of the three food insecurity scenarios for a household.

Table 3.4: Estimation Results: Relationship between unemployment and food insecurity among the 3 primary food insecurity question

	Overall Food Insecurity Coeff./S.err.	Q1:Worried Food Run Out Coeff./S.err.	Q2: Ran Out of Food Coeff./S.err.	Q3: Not Enough Balanced meals Coeff./S.err.
Indicator For Being Unemployed	0.077***	0.075***	0.078***	0.045***
	(0.007)	(0.006)	(0.007)	(0.007)
Household head is female	0.054***	0.057***	0.052***	0.044***
	(0.005)	(0.005)	(0.005)	(0.005)
Married at present or ever	-0.008	0.007	0.001	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
White non-hispanic	-0.032***	-0.037***	-0.045***	-0.029***
	(0.011)	(0.011)	(0.011)	(0.011)
Black non-hispanic	0.019	0.052***	0.054***	-0.016
	(0.012)	(0.012)	(0.012)	(0.013)
Hispanic ethicity only	-0.001	0.011	0.015	0.011
	(0.012)	(0.011)	(0.012)	(0.012)
High school diploma or less	0.019***	0.039***	0.042***	0.023***
	(0.005)	(0.005)	(0.005)	(0.005)
Age of the respondent	0.009***	0.008***	0.007***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	-0.007	0.041*	-0.048*	-0.190***
	(0.025)	(0.024)	(0.025)	(0.025)
Share of members between age 6 and 11	0.068***	0.045*	-0.026	-0.138***
	(0.025)	(0.024)	(0.025)	(0.025)
Share of members between age 12 and 19	0.055**	0.052**	0.008	-0.090***
	(0.022)	(0.021)	(0.022)	(0.022)
Share of members between age 20 and 29	0.013	0.005	0.005	0.007
	(0.022)	(0.022)	(0.022)	(0.022)
Share of members between age 30 and 39	0.037	0.016	0.027	0.043*
	(0.024)	(0.023)	(0.024)	(0.024)
Share of members between age 40 and 49	0.046**	0.033	0.043**	0.054**
	(0.022)	(0.021)	(0.022)	(0.022)
Share of members between age 50 and 59	0.043**	0.027*	0.042**	0.049***
	(0.017)	(0.017)	(0.017)	(0.017)
Income to poverty ratio	-0.100***	-0.092***	-0.109***	-0.073***
	(0.005)	(0.004)	(0.005)	(0.005)
Constant	0.406***	0.545***	0.483***	0.499***
	(0.044)	(0.042)	(0.044)	(0.044)
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes	Yes
Mean of Outcome	0.519	0.654	0.533	0.479
R-squared	0.035	0.045	0.043	0.027
Observations	60292	60255	60198	59337

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

3.3.3 Unemployment & Food Insecurity By Householder's Sex

Table 3.5 presents the heterogeneity in our baseline specification by sex of the householder's sub-sample. Column 1 and column 3 of the table 3.5 are results when we have a *male householder*. Column 2 and column 4 of the table 3.5 are results when we have a *female householder*.

Comparing column 1 and column 2 of table 3.5 we can see that food insecurity increases more when male householder is unemployed. Comparing column 3 and column 4 of table 3.5 we can see when there is a male householder, food insecurity increases marginally more (about 7 percentage points difference between the two columns) when all members are unemployed.

Table 3.5: Heterogeneity in the unemployment-food insecurity relationship by gender of household head

	Male Household Head Coeff./S.err.	Female Household Head Coeff./S.err.	Unemployed Share Male Head Coeff./S.err.	Unemployed Share Female Head Coeff./S.err.
Indicator For Being Unemployed	0.093***	0.062***		
	(0.010)	(0.009)		
Share of Labor Force Members			0.136***	0.128***
That Are Unemployed			(0.015)	(0.015)
Household head is female				
Married at present or ever	0.014	-0.020***	0.015	-0.020***
	(0.010)	(0.008)	(0.010)	(0.008)
White non-hispanic	-0.046***	-0.021	-0.047***	-0.022
	(0.016)	(0.016)	(0.016)	(0.016)
Black non-hispanic	0.040**	0.005	0.040**	0.004
	(0.019)	(0.017)	(0.019)	(0.017)
Hispanic ethicity only	0.001	-0.006	-0.000	-0.006
	(0.017)	(0.017)	(0.017)	(0.017)
High school diploma or less	0.035***	0.010	0.036***	0.010
	(0.008)	(0.007)	(0.008)	(0.007)
Age of the respondent	0.001	0.014***	0.001	0.014***
	(0.004)	(0.003)	(0.004)	(0.003)
Age squared	-0.000	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	-0.116***	0.108***	-0.100**	0.120***
	(0.040)	(0.033)	(0.040)	(0.033)
Share of members between age 6 and 11	-0.010	0.156***	0.006	0.168***
	(0.040)	(0.033)	(0.040)	(0.033)
Share of members between age 12 and 19	-0.072**	0.154***	-0.063*	0.159***
	(0.035)	(0.029)	(0.035)	(0.029)
Share of members between age 20 and 29	-0.074**	0.092***	-0.076**	0.085***
	(0.034)	(0.029)	(0.034)	(0.029)
Share of members between age 30 and 39	-0.012	0.085***	-0.017	0.076**
	(0.037)	(0.032)	(0.037)	(0.032)
Share of members between age 40 and 49	0.018	0.076***	0.012	0.066**
	(0.033)	(0.029)	(0.033)	(0.029)
Share of members between age 50 and 59	0.024	0.060***	0.020	0.056**
	(0.027)	(0.022)	(0.027)	(0.022)
Share of members between age 60 plus	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Income to poverty ratio	-0.110***	-0.089***	-0.111***	-0.088***
	(0.007)	(0.006)	(0.007)	(0.006)
Constant	0.649***	0.281***	0.645***	0.274***
	(0.068)	(0.058)	(0.068)	(0.058)
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Survey wave effect	Yes	Yes	Yes	Yes
R-squared	0.043	0.029	0.043	0.030
Observations	26074	34218	26074	34218
Test Unemployed coefficients pvalue (Col 1 vs. Col 2)		0.029		
Test Unemp-Share coefficients pvalue (Col 3 vs. Col 4)				0.748

The sample covers CPS-FSM respondents fro the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

3.3.4 Unemployment & Food Insecurity By Age of Householder

In figure 3.3 we explore the heterogeneity in our relationship of interest by age of the householder. Either measure of unemployment exhibits an increasing relationship between age of householder and food insecurity. So, growing older and being unemployed exhibits a strong relationship.

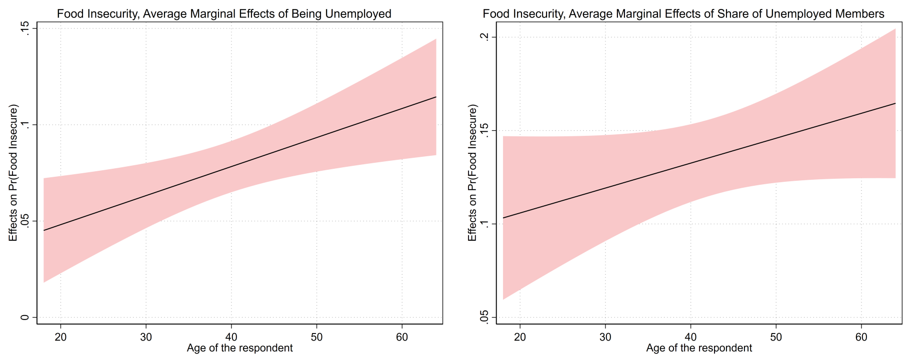

Figure 3.3: Average marginal effect of being unemployed on probability of being food insecure. Relationship showing variation over age of the householder. Left figure is when householder is unemployed and right figure is when family members are unemployed

3.3.5 Robustness: Sub-samples with Home Ownership Information

Home ownership is not available for all the years we want to examine in our causal analysis. In table 3.6 we take the sub-sample of households from 2001-2016 and re-examine our results from table 3.2. Thus, we can see that our relationship remains stable with or without inclusion of home ownership. Hence, we use 2001-2020 and exclude home ownership.

Table 3.6: Estimation Results: Relationship between unemployment and food insecurity using sub-sample of observations with home ownership information for the period of 2001-2016

	Unemployed Household Head Coeff./S.err.	Unemployed Members Share Coeff./S.err.	Unemployed With Demographics Coeff./S.err.	Unemployed Share With Demographics Coeff./S.err.
Indicator For Being Unemployed	0.115***		0.078***	
	(0.007)		(0.007)	
Share of Labor Force Members		0.173***		0.145***
That Are Unemployed		(0.010)		(0.011)
own-house			-0.077***	-0.077***
			(0.006)	(0.006)
Household head is female			0.045***	0.045***
			(0.005)	(0.005)
Married at present or ever			0.005	0.006
			(0.007)	(0.007)
White non-hispanic			-0.027**	-0.027**
			(0.012)	(0.012)
Black non-hispanic			0.012	0.011
			(0.013)	(0.013)
Hispanic ethicity only			0.007	0.006
			(0.013)	(0.013)
High school diploma or less			0.020***	0.020***
			(0.005)	(0.005)
Age of the respondent			0.012***	0.012***
			(0.002)	(0.002)
Age (squared)			-0.000***	-0.000***
			(0.000)	(0.000)
Share of members between age 0 and 5			-0.000	0.017
			(0.027)	(0.027)
Share of members between age 6 and 11			0.079***	0.096***
			(0.027)	(0.027)
Share of members between age 12 and 19			0.072***	0.081***
			(0.024)	(0.024)
Share of members between age 20 and 29			0.003	-0.002
			(0.024)	(0.024)
Share of members between age 30 and 39			0.026	0.018
			(0.026)	(0.026)
Share of members between age 40 and 49			0.033	0.024
			(0.024)	(0.024)
Share of members between age 50 and 59			0.044**	0.039**
			(0.019)	(0.019)
Share of members between age 60 plus			0.000	0.000
			(.)	(.)
Income to poverty ratio			-0.092***	-0.091***
			(0.005)	(0.005)
Constant	0.488***	0.490***	0.350***	0.341***
	(0.013)	(0.013)	(0.047)	(0.047)
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Survey wave effect	Yes	Yes	Yes	Yes
R-squared	0.011	0.010	0.041	0.042
Observations	52287	52287	52287	52287
Food Insecure Mean	0.522			

This sub-sample covers CPS-FSM respondents for the period of 2001-2016. This is because home ownership information is available only till December of 2016. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

3.4 Causal exploration: front-door criterion

We attempt to explore a causal relation between unemployment and food insecurity. Equation 3.2 gives the structural regression equation to be estimated. Our parameter of interest β measures the marginal increase in food insecurity for being unemployed (in other words, average treatment effect (ATE)). **Z** is a vector of demographic characteristics (alongwith their respective parameters γ) as mentioned in the earlier sections. The causal relation is confounded by unobservables that impact both unemployment status and food insecurity. Figure 3.4 shows that the causal path from unemployment to food insecurity is complicated by unobservables driving both variables. Thus, making unemployment status endogenous to food insecurity response because being unemployed is not a random outcome.

$$Y_i = \alpha + \beta \, \text{Unemployment}_i + \mathbf{Z}_i^{'} \gamma + \varepsilon_i \tag{3.2}$$

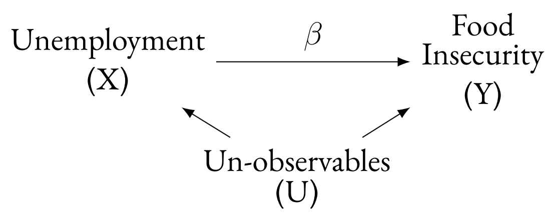

Figure 3.4: Causal relation between unemployment & food insecurity confounded by unobservables

We argue that the total effect of unemployment on food insecurity is mediated by the effect of unemployment on resource deficiency and resource deficiency's effect on the outcome, food insecurity. The mediation analysis graph below depicts the argument. Figure 3.5 depicts the relationship between unemployment and food insecurity (or severity) with the inclusion of a mediator, *resource deficiency*. And, further, we posit that the total effect is completely mediated by resource deficiency using Pearl, 1995, 2009's front-door criterion (as seen in causal diagram figure 3.6).

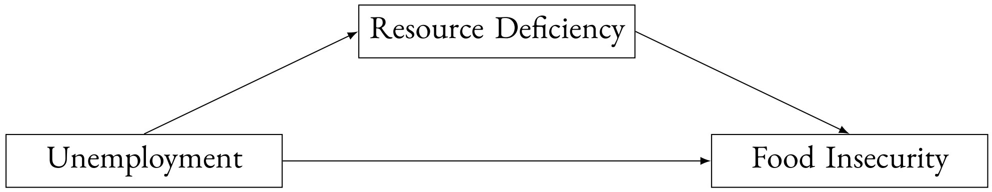

Figure 3.5: Diagrammatic exposition of the relationship between unemployment and food insecurity using the mediation analysis concept. Resource deficiency is our mediator of interest.

In this paper, we try to uncover causality by estimating the average treatment effect via the front-door criterion as developed by Pearl, 1995, 2009 and with a recent economic application in Bellemare et al., 2021. The front-door mediator/mechanism we explore is the resource (monetary) deficiency mechanism. Figure 3.6 shows how the front-door criterion works. However, a front-door mediator has to satisfy certain criterion for it to be effective. Just like in the instrumental variable econometric methodology, a front-door mediator must satisfy the following assumptions:

1. All causal paths from unemployment (X) to food insecurity (Y) only go through the mediator (M), i.e. resource deficiency.

2. There is no backdoor entry going from unemployment (X) to resource deficiency (M).

3. There is no backdoor entry going from resource deficiency (M) to food insecurity (Y).

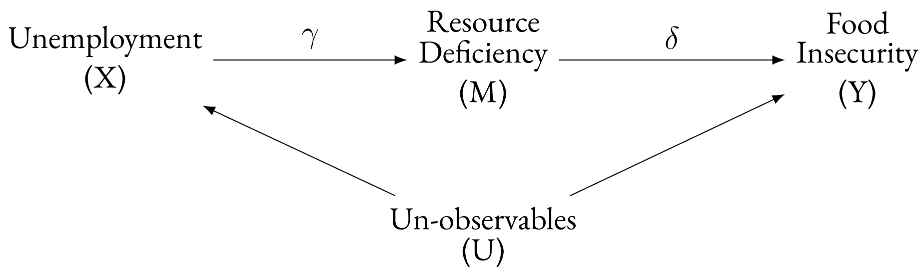

Figure 3.6: Causal relation between unemployment & food insecurity via the front-door criterion. Unemployment (X), Food Insecurity (Y) and Resource Deficiency (M) are all observed, but the unknown component (U) is an unobserved common cause of both Unemployment and Food Insecurity. The back-door path, given by $X \leftarrow U \rightarrow Z$, is the confounding effect of Unemployment on Food Insecurity with their common cause. However, we propose that, all of the effects of unemployment on food insecurity is mediated through unemployment's effect on resource deficiency (M). This opens a back-door path in the causal path of resource deficiency effect's on food insecurity, given by $M \leftarrow X \leftarrow U \rightarrow Z$. But this path is blocked by X. Thus, we use a back-door adjustment to estimate $Pr(Y|(M = m))$ and directly estimate $Pr(M|(X = x))$ and with the two estimates together we can obtain $Pr(Y|(X = x))$

Thus, we argue that since food insecurity is measured with questions that center around lack of monetary resources to access food, th etotal effect of unemployment is completely mediated by fall in resources that impacts food insecurity experiences. The second and third properties of a valid mediator/mechanism is satisfied using plausibly exogenous controls that aim to close off the back-doors from unemployment to resource deficiency and resource deficiency to food insecurity. Following Bellemare et al., 2021 we estimate our causal relation assuming a linear relationship and estimate the regression specification given in 3.3. Tables 3.7 and 3.14 we present the estimation results of the front-door estimation given in equation 3.3

$$\begin{aligned} M_i &= \alpha_0 + \gamma U_i + \nu_i, \\ Y_i &= \alpha_1 + \delta M_i + \zeta U_i + \varepsilon_i, \\ \text{Where the ATE,} \quad \beta &= \gamma \cdot \delta \end{aligned} \tag{3.3}$$

The results, *estimated FDC Average Treatment Effect*(FDC ATE), from table 3.7 are that , unemployed householder (mediated by resource deficiency) increases food insecurity by 1.1 percentage points, relative to an employed householder.

Table 3.7: Estimation Results: Estimation results exploring causality between unemployment status on food insecurity using the front-door criterion.

		Front Door Estimation	
		First-step estimation	Second step estimation
Outcome: Food Insecurity Status	Regular OLS Estimation Coeff./S.err.	Resource Deficiency Coeff./S.err.	Food Insecurity Coeff./S.err.
Indicator For Being Unemployed	0.077***	0.057***	0.066***
	(0.007)	(0.009)	(0.007)
Mediator: Resource Deficiency			0.186***
			(0.003)
Estimated FDC ATE		0.011***	
		(0.001)	
Household head is female	0.054***	0.052***	0.044***
	(0.005)	(0.007)	(0.005)
Married at present or ever	-0.008	0.014	-0.010*
	(0.006)	(0.009)	(0.006)
White non-hispanic	-0.032***	-0.078***	-0.017
	(0.011)	(0.016)	(0.011)
Black non-hispanic	0.019	0.148***	-0.008
	(0.012)	(0.018)	(0.012)
Hispanic ethicity only	-0.001	0.047***	-0.010
	(0.012)	(0.017)	(0.012)
High school diploma or less	0.019***	0.071***	0.006
	(0.005)	(0.007)	(0.005)
Age of the respondent	0.009***	0.021***	0.005**
	(0.002)	(0.003)	(0.002)
Age squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	-0.007	0.027	-0.012
	(0.025)	(0.034)	(0.024)
Share of members between age 6 and 11	0.068***	0.020	0.064***
	(0.025)	(0.034)	(0.024)
Share of members between age 12 and 19	0.055**	0.023	0.051**
	(0.022)	(0.030)	(0.022)
Share of members between age 20 and 29	0.013	-0.103***	0.033
	(0.022)	(0.030)	(0.021)
Share of members between age 30 and 39	0.037	-0.072**	0.051**
	(0.024)	(0.033)	(0.023)
Share of members between age 40 and 49	0.046**	-0.034	0.052**
	(0.022)	(0.030)	(0.021)
Share of members between age 50 and 59	0.043**	0.005	0.042**
	(0.017)	(0.023)	(0.016)
Income measured relative to poverty threshold	-0.100***	-0.113***	-0.079***
	(0.005)	(0.006)	(0.004)
Constant	0.406***	1.819***	0.067
	(0.044)	(0.061)	(0.043)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes
R-squared	0.035	0.053	0.100
Observations	60292	60292	60292

This sub-sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. The estimated standard errors for the FDC ATE is calculated using the delta method. Stars indicate: *** 1%, ** 5% , * 10%.

3.5 Food Severity: Measuring Food Insecurity at the Intensive Margin

We re-examine the causal relationship between food insecurity and unemployment by re-defining our response variable to reflect the intensive margin of food insecurity, we call this the food severity measure. We do this by taking the number of CPS-FSS questions responded. The histogram in the figure 3.7 shows the distribution of the observations by the number of questions with affirmative responses. The range of count of responses from 0 to 18, reflect the level of food insecurity going from high food secure at 0 to very low food secure at 10 or more. Figure 3.7 plots the mean count of responses (the solid reference line on the x-axis) of 3.5. 3.8, explores how the food severity differs among the unemployed and employed. We see in figure 3.8 that those employed are more likely to respond to fewer food security questions versus the unemployed that are more likely to respond 3 or more. Each panel of figure 3.8 also displays the mean responses for each group of individual. The employed have on average 3.35 questions responded versus 4.28 questions responded by employed. Thus, even with our food severity measure, we observe unemployed experiencing greater food insecurity at the intensive margins.

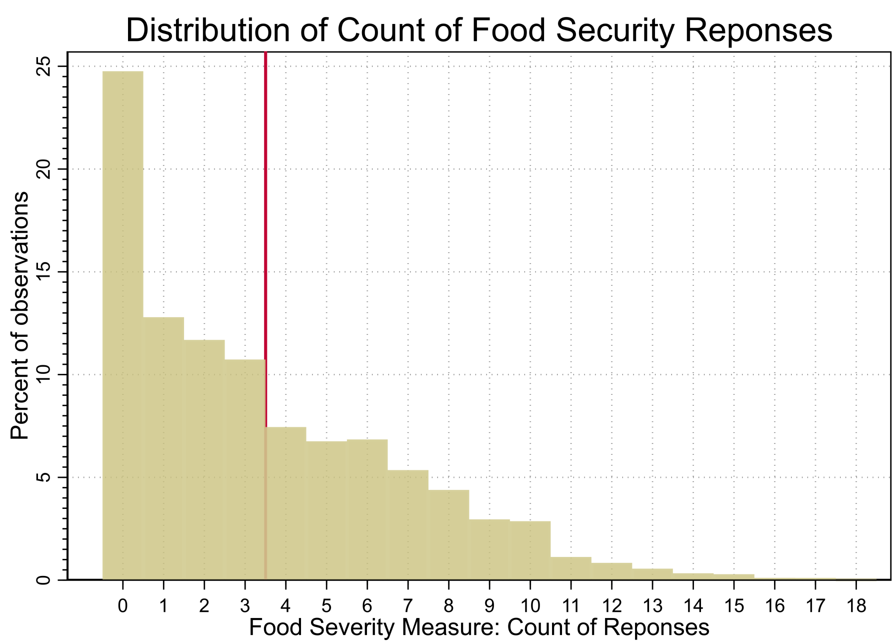

Figure 3.7: Distribution of the food severity measure defined as the count of affirmative responses to the CPS-FSM questionnaire

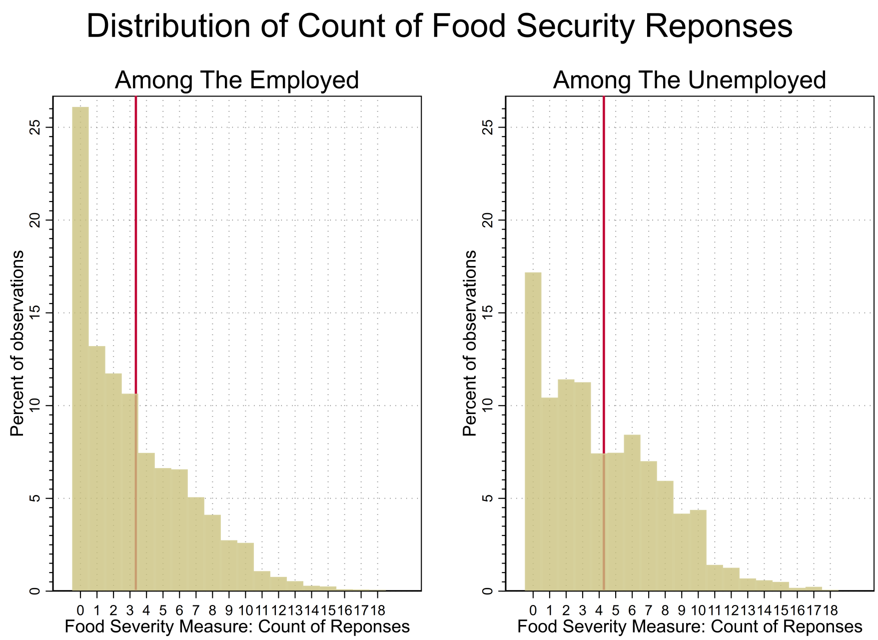

Figure 3.8: Distribution of the food severity measure by unemployment status

Figure 3.9 displays graphically the estimates exploring the association between household head's unemployment status and food severity. We use OLS to model the count of responses and present the marginal effects in figure 3.9.Figure 3.9 shows that unemployed household head increases the severity of food insecurity by 0.62 responses. We can interpret this using the mean responses we saw displayed in the histogram of figure 3.7. Thus, being unemployed increases mean responses from 3.5 to 4.12.

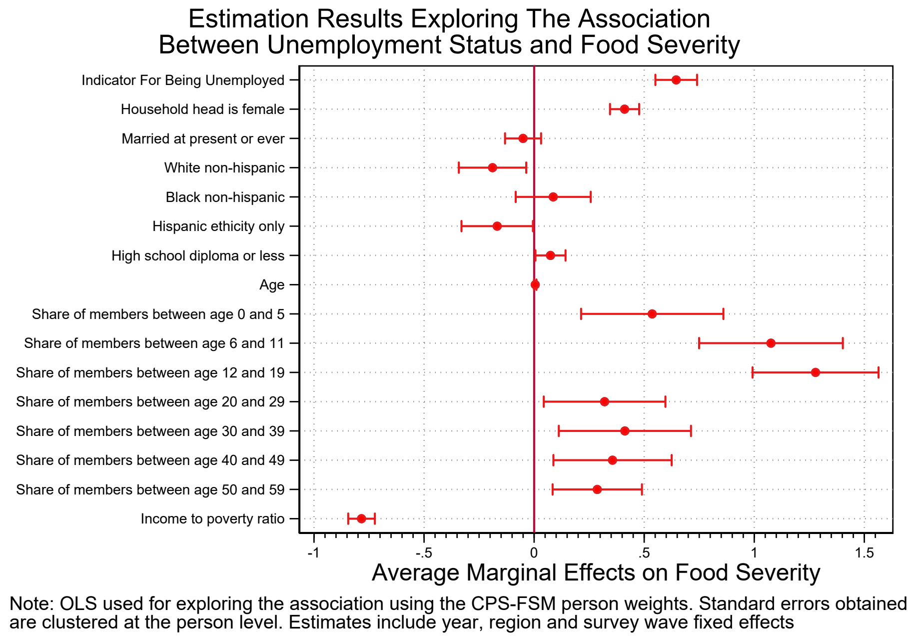

Figure 3.9: Food Severity and Unemployment Status: Marginal Effects of an OLS Model exploring the association of unemployment status and food severity.

Next, we move from association to causal by exploring the front-door criterion on the food severity measure. For this analysis, we modify our casual path diagram in figure 3.10 by now examining the causal path of unemployment status on the intensive margin of food insecurity. Our regression specification remains the same as in 3.3 with the only difference that we model the food severity measure as our response. We employ linear regression specification to model the count of responses to estimate the front-door criterion average treatment effect (i.e., $\beta = \gamma \cdot \delta$). Table 3.8 present the snapshot of the FDC ATE estimation (and Table 3.9 and 3.10 present the full results with covariates.).

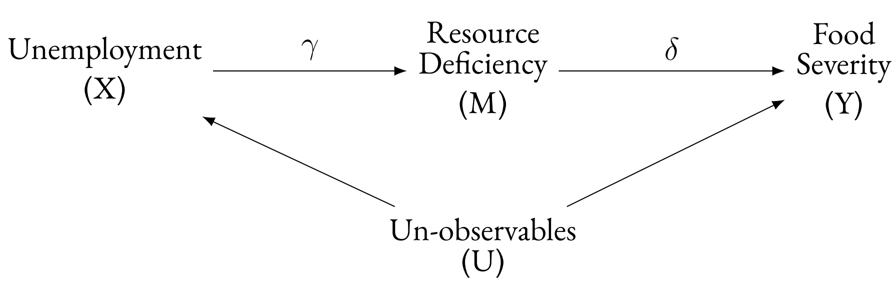

Figure 3.10: Causal relation between unemployment & food severity via the front-door criterion

The results from table 3.8 help us conclude that being unemployed causes food severity to increase by 0.073 responses and 0.124 responses when the householder is unemployed and when all family members are unemployed, respectively

Table 3.8: Estimation Results: Summary results of the front door criterrion exploring the causality between unemployment and food severity.

		Front Door Estimation	
		First-step estimation	Second step estimation
Outcome: Food Severity (Count of Responses)	Naive Relationship Coeff./S.err.	Resource Deficiency Coeff./S.err.	Food Severity Coeff./S.err.
Model 1: Unemployment Status Of The Household Head			
Indicator For Being Unemployed	0.645***	0.057***	0.566***
	(0.048)	(0.009)	(0.047)
Mediator: Resource Deficiency			1.400***
			(0.023)
Estimated FDC ATE		0.080***	
		(0.011)	
Model 2: Share of Members Unemployed In The House			
Share of Labor Force Members	1.051***	0.096***	0.917***
That Are Unemployed	(0.071)	(0.015)	(0.068)
Mediator: Resource Deficiency			1.399***
			(0.023)
Estimated FDC ATE		0.134***	
		(0.017)	

This sub-sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. The estimated standard errors for the FDC ATE is calculated using the delta method. Stars indicate: *** 1%, ** 5% , * 10%.

Table 3.9: Estimation Results: Causality between unemployment status on Food Severity using the front-door criterion.

		Front Door Estimation	
		First-step estimation	Second step estimation
	Regular OLS Estimation	Resource Deficiency	Food Severity
Outcome: Food Severity (Count of Responses)	Coeff./S.err.	Coeff./S.err.	Coeff./S.err.
Indicator For Being Unemployed	0.645***	0.057***	0.566***
	(0.048)	(0.009)	(0.047)
Mediator: Resource Deficiency			1.400***
			(0.023)
Estimated FDC ATE		0.080***	
		(0.011)	
Household head is female	0.411***	0.052***	0.338***
	(0.034)	(0.007)	(0.032)
Married at present or ever	-0.050	0.014	-0.069*
	(0.042)	(0.009)	(0.040)
White non-hispanic	-0.189**	-0.078***	-0.080
	(0.078)	(0.016)	(0.075)
Black non-hispanic	0.087	0.148***	-0.120
	(0.087)	(0.018)	(0.084)
Hispanic ethicity only	-0.168**	0.047***	-0.234***
	(0.083)	(0.017)	(0.080)
High school diploma or less	0.074**	0.071***	-0.025
	(0.035)	(0.007)	(0.033)
Age	0.090***	0.021***	0.061***
	(0.015)	(0.003)	(0.014)
Age squared	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	0.537***	0.027	0.498***
	(0.165)	(0.034)	(0.158)
Share of members between age 6 and 11	1.076***	0.020	1.048***
	(0.167)	(0.034)	(0.160)
Share of members between age 12 and 19	1.279***	0.023	1.246***
	(0.146)	(0.030)	(0.140)
Share of members between age 20 and 29	0.320**	-0.103***	0.465***
	(0.141)	(0.030)	(0.135)
Share of members between age 30 and 39	0.412***	-0.072**	0.514***
	(0.153)	(0.033)	(0.146)
Share of members between age 40 and 49	0.356***	-0.034	0.404***
	(0.137)	(0.030)	(0.131)
Share of members between age 50 and 59	0.287***	0.005	0.279***
	(0.104)	(0.023)	(0.099)
Income to poverty ratio	-0.784***	-0.113***	-0.626***
	(0.031)	(0.006)	(0.030)
Constant	1.788***	1.819***	-0.758***
	(0.289)	(0.061)	(0.278)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes
R-squared	0.051	0.053	0.132
Observations	60292	60292	60292

This sub-sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. The estimated standard errors for the FDC ATE is calculated using the delta method. Stars indicate: *** 1%, ** 5% , * 10%.

Table 3.10: Estimation Results: Causality between share of unemployed members in the household on Food Severity using the front-door criterion.

		Front Door Estimation	
		First-step estimation	Second step estimation
	Regular OLS Estimation	Resource Deficiency	Food Severity
Outcome: Food Severity (Count of Responses)	Coeff./S.err.	Coeff./S.err.	Coeff./S.err.
Share of Labor Force Members	1.051***	0.096***	0.917***
That Are Unemployed	(0.071)	(0.015)	(0.068)
Mediator: Resource Deficiency			1.399***
			(0.023)
Estimated FDC ATE		0.134***	
		(0.017)	
Household head is female	0.409***	0.052***	0.336***
	(0.034)	(0.007)	(0.032)
Married at present or ever	-0.046	0.014	-0.066
	(0.042)	(0.009)	(0.040)
White non-hispanic	-0.195**	-0.078***	-0.086
	(0.078)	(0.016)	(0.075)
Black non-hispanic	0.081	0.147***	-0.125
	(0.087)	(0.018)	(0.084)
Hispanic ethicity only	-0.171**	0.047***	-0.237***
	(0.083)	(0.017)	(0.080)
High school diploma or less	0.079**	0.071***	-0.021
	(0.035)	(0.007)	(0.033)
Age	0.092***	0.021***	0.062***
	(0.015)	(0.003)	(0.014)
Age squared	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	0.653***	0.038	0.600***
	(0.165)	(0.034)	(0.158)
Share of members between age 6 and 11	1.189***	0.031	1.146***
	(0.167)	(0.034)	(0.160)
Share of members between age 12 and 19	1.331***	0.028	1.292***
	(0.146)	(0.030)	(0.140)
Share of members between age 20 and 29	0.274*	-0.107***	0.424***
	(0.141)	(0.030)	(0.135)
Share of members between age 30 and 39	0.352**	-0.078**	0.460***
	(0.153)	(0.033)	(0.146)
Share of members between age 40 and 49	0.295**	-0.040	0.350***
	(0.137)	(0.030)	(0.131)
Share of members between age 50 and 59	0.253**	0.002	0.250**
	(0.103)	(0.023)	(0.099)
Income to poverty ratio	-0.786***	-0.113***	-0.628***
	(0.031)	(0.006)	(0.030)
Constant	1.768***	1.816***	-0.772***
	(0.289)	(0.061)	(0.278)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes
R-squared	0.052	0.053	0.132
Observations	60292	60292	60292

This sub-sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. The estimated standard errors for the FDC ATE is calculated using the delta method. Stars indicate: *** 1%, ** 5% , * 10%.

3.6 Exploring the Share of Unemployed Family Members

In this section, we explore the relationship between unemployment and food hardships (measured as food insecurity and food severity) using an alternative measure of unemployment. Unemployed, here, goes beyond just the unemployment status of the householder. Rather, we measure the share of adult family members unemployed conditional ob being in the labor force.

Equation 3.4, below, describes the structural equation exploring the relationship between household's *food insecurity* (or severity) status and the share of unemployed family members, conditional on being in the labor force (given as *unemployed share* in the equation). $\boldsymbol{X}$ is a vector of controls containing demographic and household characteristics.

$$\text{Food Insecurity}_i = \alpha + \beta \text{ Unemployed Share}_i + \boldsymbol{X}_i^{'}\gamma + \epsilon_i \tag{3.4}$$

Again, we argue that the total effect of share of unemployed family members on food insecurity/severity is mediated by the effect of unemployment on resource deficiency and resource deficiency's effect on the outcome, food insecurity/severity. The mediation analysis graph below depicts the argument. Figure 3.11 depicts the relationship between the share of family members unemployed and food insecurity (or severity) with the inclusion of a mediator, *resource deficiency*.

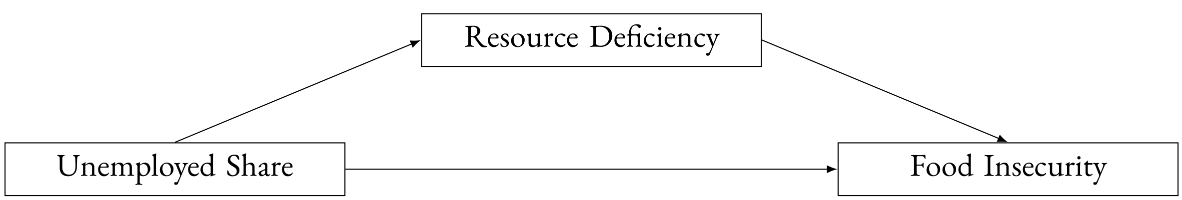

Figure 3.11: Diagrammatic exposition of the relationship between unemployed share and food insecurity using the mediation analysis concept. Resource deficiency is our mediator of interest.

Column 2 of table 3.11 displays the relation between share of unemployed family members and food insecurity , without any controls. From column 2, we see that if all members are unemployed, they experience 16.5 percentage points higher in food insecurity. Column 4 of table 3.2 shows that with addition of controls, *ceteris paribus*, all family members being unemployed increases probability of being food insecure by 12.8 percentage points (going from 16.5 percentage points in column 2 to 12.8 percentage points in column 4).[22] Moving forward in the paper, columns 4 of table 3.2 will be our baseline specification for further analysis.

[22] The mean food insecurity of households when all members are unemployed is 0.647 (There are 2,568 observations with all members unemployed).

Table 3.11: Estimation Results: Relationship Between Share of Unemployed Family Members and Food Insecurity

	Unemployed Household Head Coeff./S.err.	Unemployed Members Share Coeff./S.err.	Unemployed With Demographics Coeff./S.err.	Unemployed Share With Demographics Coeff./S.err.
Indicator For Being Unemployed	0.112***		0.077***	
	(0.007)		(0.007)	
Share of Labor Force Members That Are Unemployed		0.165***		0.134***
		(0.010)		(0.010)
Household head is female			0.054***	0.054***
			(0.005)	(0.005)
Married at present or ever			-0.008	-0.007
			(0.006)	(0.006)
White non-hispanic			-0.032***	-0.033***
			(0.011)	(0.011)
Black non-hispanic			0.019	0.018
			(0.012)	(0.012)
Hispanic ethicity only			-0.001	-0.002
			(0.012)	(0.012)
High school diploma or less			0.019***	0.020***
			(0.005)	(0.005)
Age of the respondent			0.009***	0.009***
			(0.002)	(0.002)
Age of the respondent (squared)			-0.000***	-0.000***
			(0.000)	(0.000)
Share of members between age 0 and 5			-0.007	0.009
			(0.025)	(0.025)
Share of members between age 6 and 11			0.068***	0.083***
			(0.025)	(0.025)
Share of members between age 12 and 19			0.055**	0.063***
			(0.022)	(0.022)
Share of members between age 20 and 29			0.013	0.008
			(0.022)	(0.022)
Share of members between age 30 and 39			0.037	0.030
			(0.024)	(0.024)
Share of members between age 40 and 49			0.046**	0.038*
			(0.022)	(0.022)
Share of members between age 50 and 59			0.043**	0.039**
			(0.017)	(0.017)
Share of members between age 60 plus			0.000	0.000
			(.)	(.)
Income to poverty ratio			-0.100***	-0.099***
			(0.005)	(0.005)
Constant	0.488***	0.490***	0.406***	0.400***
	(0.013)	(0.013)	(0.044)	(0.044)
Year fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Survey wave effect	Yes	Yes	Yes	Yes
R-squared	0.011	0.010	0.035	0.036
Observations	60292	60292	60292	60292
Food Insecure Mean	0.519			

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

In table 3.12, we examine the association of share of unemployed family members on the 4 categories of food security given by CPS-FSS: high, marginal, low and very low food secure. When all family members are unemployed, we observe 9 and 4 percentage points reduction in the probability of being *high* and *marginal food secure*, respectively. Whereas, all family members being unemployed, makes it 12.4 percentage points more likely to exhibit very low food secure.

Table 3.12: Estimation Results: Relationship between share of unemployed members and the levels of food insecurity

	Overall Food Insecurity Coeff./S.err.	High Food Security Coeff./S.err.	Marginal Food Security Coeff./S.err.	Low Food Security Coeff./S.err.	Very Low Food Security Coeff./S.err.
Share of Labor Force Members That Are Unemployed	0.134***	-0.096***	-0.039***	0.007	0.127***
	(0.010)	(0.008)	(0.009)	(0.010)	(0.010)
Household head is female	0.054***	-0.042***	-0.012***	0.022***	0.032***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Married at present or ever	-0.007	0.006	0.001	-0.002	-0.005
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
White non-hispanic	-0.033***	0.035***	-0.002	-0.040***	0.007
	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)
Black non-hispanic	0.018	-0.027***	0.009	0.005	0.013
	(0.012)	(0.010)	(0.011)	(0.012)	(0.010)
Hispanic ethicity only	-0.002	-0.005	0.007	0.024**	-0.025***
	(0.012)	(0.010)	(0.010)	(0.011)	(0.009)
High school diploma or less	0.020***	-0.027***	0.007	0.022***	-0.002
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Age of the respondent	0.009***	-0.007***	-0.002	0.007***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000***	0.000***	0.000	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	0.009	-0.055**	0.046**	0.175***	-0.166***
	(0.025)	(0.022)	(0.022)	(0.023)	(0.020)
Share of members between age 6 and 11	0.083***	-0.083***	0.000	0.168***	-0.085***
	(0.025)	(0.021)	(0.022)	(0.023)	(0.020)
Share of members between age 12 and 19	0.063***	-0.074***	0.011	0.105***	-0.043**
	(0.022)	(0.020)	(0.019)	(0.020)	(0.018)
Share of members between age 20 and 29	0.008	-0.020	0.012	0.014	-0.005
	(0.022)	(0.020)	(0.019)	(0.020)	(0.018)
Share of members between age 30 and 39	0.030	-0.015	-0.015	-0.011	0.040**
	(0.024)	(0.021)	(0.021)	(0.022)	(0.020)
Share of members between age 40 and 49	0.038*	-0.014	-0.024	-0.018	0.055***
	(0.022)	(0.019)	(0.019)	(0.020)	(0.018)
Share of members between age 50 and 59	0.039**	-0.019	-0.020	-0.018	0.057***
	(0.017)	(0.015)	(0.015)	(0.015)	(0.014)
Income measured relative to poverty threshold	-0.099***	0.073***	0.026***	-0.030***	-0.069***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.400***	0.369***	0.231***	0.191***	0.210***
	(0.044)	(0.038)	(0.038)	(0.041)	(0.035)
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes	Yes	Yes
Mean of Outcome	0.519	0.235	0.246	0.326	0.193
R-squared	0.036	0.035	0.004	0.022	0.037
Observations	60292	60292	60292	60292	60292

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

In table 3.13 we again dissect our baseline specifications in column 4 of 3.11 by looking at our relationship of interest to three of the primary food insecurity questions:

- Q1: Whether worried food would run out?
- Q2: Household ran out of food
- Q3: Whether household did not have enough money for a balanced meal?

The results show that higher share of family members being unemployed, increases the likelihood of any of the three food insecurity scenarios for a household.

Table 3.13: Estimation Results: Relationship between share of unemployed members and food insecurity among the 3 primary food insecurity question

	Overall Food Insecurity	Q1:Worried Food Run Out	Q2: Ran Out of Food	Q3: Not Enough Balanced eals
	Coeff./S.err.	Coeff./S.err.	Coeff./S.err.	Coeff./S.err.
Share of Labor Force Members That Are Unemployed	0.134***	0.125***	0.124***	0.084***
	(0.010)	(0.010)	(0.010)	(0.011)
Household head is female	0.054***	0.057***	0.052***	0.044***
	(0.005)	(0.005)	(0.005)	(0.005)
Married at present or ever	-0.007	0.007	0.001	-0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
White non-hispanic	-0.033***	-0.038***	-0.045***	-0.030***
	(0.011)	(0.011)	(0.011)	(0.011)
Black non-hispanic	0.018	0.051***	0.053***	-0.017
	(0.012)	(0.012)	(0.012)	(0.013)
Hispanic ethicity only	-0.002	0.011	0.015	0.011
	(0.012)	(0.011)	(0.012)	(0.012)
High school diploma or less	0.020***	0.040***	0.043***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)
Age of the respondent	0.009***	0.008***	0.007***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	0.009	0.055**	-0.034	-0.180***
	(0.025)	(0.024)	(0.025)	(0.025)
Share of members between age 6 and 11	0.083***	0.059**	-0.013	-0.128***
	(0.025)	(0.024)	(0.025)	(0.025)
Share of members between age 12 and 19	0.063***	0.059***	0.014	-0.085***
	(0.022)	(0.021)	(0.022)	(0.023)
Share of members between age 20 and 29	0.008	-0.000	-0.001	0.004
	(0.022)	(0.022)	(0.022)	(0.022)
Share of members between age 30 and 39	0.030	0.009	0.020	0.039
	(0.024)	(0.023)	(0.024)	(0.024)
Share of members between age 40 and 49	0.038*	0.025	0.036*	0.049**
	(0.022)	(0.021)	(0.022)	(0.022)
Share of members between age 50 and 59	0.039**	0.023	0.038**	0.047***
	(0.017)	(0.017)	(0.017)	(0.017)
Income to poverty ratio	-0.099***	-0.092***	-0.109***	-0.072***
	(0.005)	(0.004)	(0.005)	(0.005)
Constant	0.400***	0.542***	0.482***	0.494***
	(0.044)	(0.042)	(0.044)	(0.044)
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes	Yes
Mean of Outcome	0.519	0.654	0.533	0.479
R-squared	0.037	0.046	0.045	0.029
Observations	60292	60255	60198	59337

The sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. Stars indicate: *** 1%, ** 5% , * 10%.

Table 3.14, presents the results of the front-door criterion estimation using share of unemployed family members as our causal variable of interest. The *estimated FDC ATE* of all members being unemployed increases food insecurity by 1.6 percentage points.

Table 3.14: Estimation Results: Estimation results exploring causality between unemployed household share on food insecurity using the front-door criterion.

		Front Door Estimation	
		First-step estimation	Second step estimation
	Regular OLS Estimation	Resource Deficiency	Food Insecurity
Outcome: Food Insecurity Status	Coeff./S.err.	Coeff./S.err.	Coeff./S.err.
Share of Labor Force Members	0.134***	0.096***	0.117***
That Are Unemployed	(0.010)	(0.015)	(0.010)
Mediator: Resource Deficiency			0.186***
			(0.003)
Estimated FDC ATE		0.018***	
		(0.002)	
Household head is female	0.054***	0.052***	0.044***
	(0.005)	(0.007)	(0.005)
Married at present or ever	-0.007	0.014	-0.010*
	(0.006)	(0.009)	(0.006)
White non-hispanic	-0.033***	-0.078***	-0.018*
	(0.011)	(0.016)	(0.011)
Black non-hispanic	0.018	0.147***	-0.009
	(0.012)	(0.018)	(0.012)
Hispanic ethicity only	-0.002	0.047***	-0.010
	(0.012)	(0.017)	(0.012)
High school diploma or less	0.020***	0.071***	0.007
	(0.005)	(0.007)	(0.005)
Age of the respondent	0.009***	0.021***	0.005**
	(0.002)	(0.003)	(0.002)
Age squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Share of members between age 0 and 5	0.009	0.038	0.002
	(0.025)	(0.034)	(0.024)
Share of members between age 6 and 11	0.083***	0.031	0.077***
	(0.025)	(0.034)	(0.024)
Share of members between age 12 and 19	0.063***	0.028	0.057***
	(0.022)	(0.030)	(0.022)
Share of members between age 20 and 29	0.008	-0.107***	0.028
	(0.022)	(0.030)	(0.021)
Share of members between age 30 and 39	0.030	-0.078**	0.044*
	(0.024)	(0.033)	(0.023)
Share of members between age 40 and 49	0.038*	-0.040	0.045**
	(0.022)	(0.030)	(0.021)
Share of members between age 50 and 59	0.039**	0.002	0.038**
	(0.017)	(0.023)	(0.016)
Income measured relative to poverty threshold	-0.099***	-0.113***	-0.078***
	(0.005)	(0.006)	(0.004)
Constant	0.400***	1.816***	0.062
	(0.044)	(0.061)	(0.043)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Survey Wave Month	Yes	Yes	Yes
R-squared	0.037	0.054	0.101
Observations	60292	60292	60292

This sub-sample covers CPS-FSM respondents for the period of 2001-2020. The regression estimation uses the linear probability model. Weighted estimation results. Weights used are the food security supplement weight for the household respondent. The parentheses present the standard errors. Standard errors are clustered at the person level. The estimated standard errors for the FDC ATE is calculated using the delta method. Stars indicate: *** 1%, ** 5% , * 10%.

Figure 3.12 below shows the relationship between food severity and our measure of share of unemployed family members. The figure plots the mean count of affirmative responses by share of unemployed family members. We see that as more adult family members (conditional on being in the labor force) are unemployed higher is the food severity faced by households.

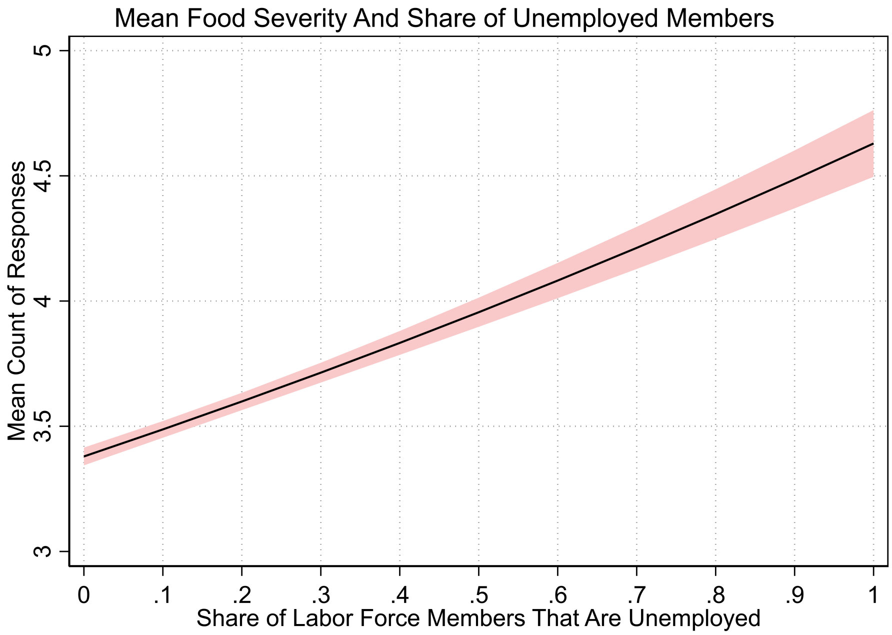

Figure 3.12: Mean Food Severity and Share of Unemployed Family Members.

Figure 3.13 explores food severity using the share of members unemployed in the household. We see that food severity increases by approximately 1 additional response when all members in the household are unemployed. Thus, mean response to food insecurity would increase from 3.5 to 4.5 when all members in the household are unemployed.

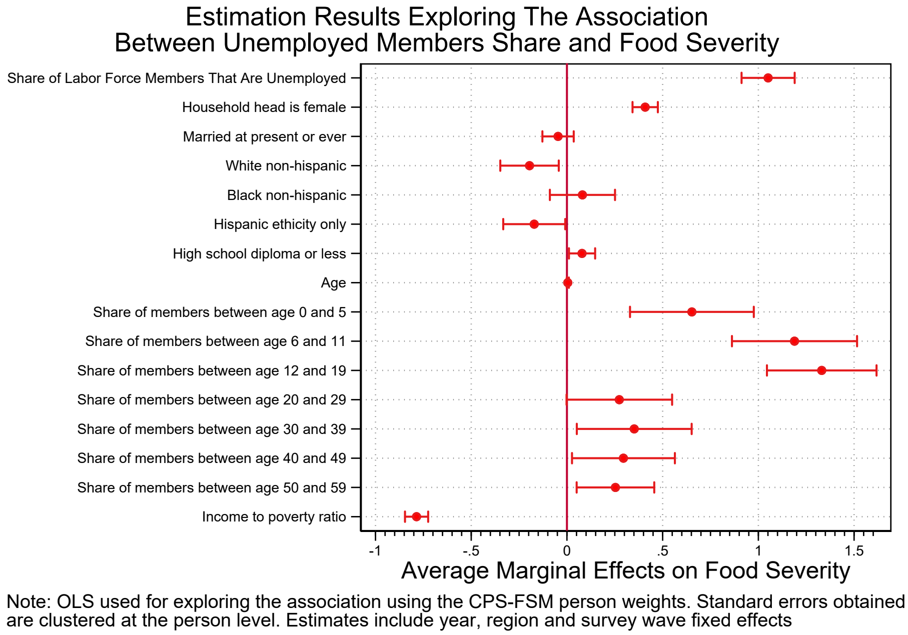

Figure 3.13: Food Severity and Unemployed Members Share: Marginal Effects of a Poisson Model exploring the association of share of unemployed members and food severity.

3.7 Discussion & Conclusion

This paper addresses the relationship between food hardships and being unemployed using food insecurity and food severity as our measures of food-related hardships. We examine the *food insecurity incidence*, captured by the binary indicator of household's food insecurity status; and *food severity*, captured by the count of the affirmative responses in the food security module. The official statistics of food security in the United States are based on a Food Security Supplement to the Current Population Survey (CPS-FSS). Our sample covers respondents of the CPS-FSS who pass the common screening questions an report some level of food hardships over the two waves of the survey. The individuals are of working age (18 - 64 years old) and in the labor force (i.e. currently working or actively searching for a job when unemployed). The sample consists of 60,292 person-year observations for the period of 2001-2020. We also, measure unemployment either via the unemployment status of the householder or share of unemployed family members (conditional on being in the labor force). The latter definition of unemployment attempts to address the stress a family as a whole undergoes with a loss of a paycheck.

We address the identification issue arising from the endogeneity of unemployment status (possibly, simultaneity bias arising from the relationship between food insecurity and unemployment) to identify the causal relationship by using Pearl, 1995, 2009 's *front-door criterion* (and with a recent economic application by Bellemare et al., 2021). We use *resource (monetary) deficiency* as the mechanism (a mediator) that translates unemployment into food insecurity. We argue that the total effect of unemployment on food insecurity is completely mediated by lack of (monetary) resources and this resource deficiency impacts food insecurity (and severity). We find that a householder being unemployed increases the probability of being food insecure by 1.1 percentage points. And the impact increases to 1.8 percentage points if all family members in the labor force are employed. On *food severity*, measured by the count of responses to the food security questions, we find that both householder's and family members' unemployment status increases the responses to the food insecurity experiences. The analysis of the paper could suggest to policymakers the need to strengthen the local labor market to address a part of the food insecurity problem.

Chapter 4

Conclusion

In the first study, *Empirical Analysis of The Black-White Food Insecurity Ga*, we explore the factors behind the differential experience in food insecurity between Black & White households. Black households experience, on average, 11 percentage points higher food insecurity relative to a White household for the period under study (2005-2016). Our IV-2SLS results highlight that food stamps reduces food insecurity more for White households than Black households. We employ the Kitagawa-Oaxaca-Blinder decomposition with the updated method using DiNardo et al., 1996 re-weighting factor. Decomposition results provide evidence that 57.3% of the difference between these two groups is explained by differences in mean observable household characteristics. Thus, aiding policymakers to target public policies to address part of the food insecurity problem. Next, we move beyond the averages in exploring the heterogeneity in the partial effects of being black on the probability of being food insecure. We estimate the average partial effect and sorted partial effect using Chernozhukov et al., 2018 methodology on the Food Security Module of the Current Population Survey data covering 2005-2016. The average partial effect of being black on food insecurity is 4 percentage points. The *sorted effects* curve graphically depicts the heterogeneity in this summary measure showing that the effects range from 1 to 6 percentage points. Households are classified into having the largest and smallest effects, respectively. One of the observable characteristics that make these two households differ is the low home ownership rate among the households that experience higher food insecurity.

This study provides an estimate of the racial disparity between Black and White households on food insecurity experience. We estimate the average partial effect of being black on the probability of being food insecure and explore the heterogeneous effects in this regard by using the Chernozhukov et al., 2018 *sorted effects* methodology. The methodology explores the factors that contribute to the racial disparity in food insecurity experience between Black & White households. Over the years of the study 2005-2016, Black households experience higher food insecurity relative to a White households (an unconditional mean of 11 percentage points higher). This gap persists even after controlling for demographic characteristics (approximately, 4 percentage points higher). This paper explores the heterogeneity among Black & White households' experiencing food insecurity. The paper provides evidence of the gap in food insecurity between the two racial groups and show that Black's have consistently experienced higher food insecurity relative to a White household throughout the period under study (2005-2016). Decomposition analysis found that differences in observable household characteristics explains 57.3% of the food insecurity gap between a Black and White household. The remaining 43% accounts for the 'unexplained', driven by differences in returns to these characteristics.

The second study, *Food Insecurity and Unemployment*, addresses the relationship between food hardships and being unemployed using food insecurity and food severity as our measures of food-related hardships. We examine the *food insecurity incidence*, captured by the binary indicator of household's food insecurity status; and *food severity*, captured by the count of the affirmative responses in the food security module. The official statistics of food security in the United States are based on a Food Security Supplement to the Current Population Survey (CPS-FSS). Our sample covers respondents of the CPS-FSS who pass the common screening questions an report some level of food hardships over the two waves of the survey. The individuals are of working age (18 - 64 years old) and in the labor force (i.e. currently working or actively searching for a job when unemployed). The sample consists of 60,292 person-year observations for the period of 2001-2020. We also, measure unemployment either via the unemployment status of the householder or share of unemployed family members (conditional on being in the labor force). The latter definition of unemployment attempts to address the stress a family as a whole undergoes with a loss of a paycheck.

We address the identification issue arising from the endogeneity of unemployment status (possibly, simultaneity bias arising from the relationship between food insecurity and unemployment) to identify the causal relationship by using Pearl, 1995, 2009 's *front-door criterion* (and with a recent economic application by Bellemare et al., 2021). We use *resource (monetary) deficiency* as the mechanism (a mediator) that translates unemployment into food insecurity. We argue that the total effect of unemployment on food insecurity is completely mediated by lack of (monetary) resources and this resource deficiency impacts food insecurity (and severity). We find that a householder being unemployed increases the probability of being food insecure by 1.1 percentage points. And the impact increases to 1.8 percentage points if all family members in the labor force are employed. On *food severity*, measured by the count of responses to the food security questions, we find that both householder's and family members' unemployment status increases the responses to the food insecurity experiences. The analysis of the paper could suggest to policymakers the need to strengthen the local labor market to address a part of the food insecurity problem.

Bibliography

Anderson, P. M., Butcher, K. F., Hoynes, H. W., & Whitmore Schanzenbach, D. (2016). Beyond income: What else predicts very low food security among children? *Southern Economic Journal*, *82*(4), 1078–1105.

Aussenberg, R. A. (2018a). *Farm Bill Primer: SNAP and Other Nutrition Title Programs.* Congressional Research Service. IF10663. https://crsreports.congress.gov/product/pdf/IF/IF10663

Aussenberg, R. A. (2018b). *Supplemental Nutrition Assistance Program (SNAP): A Primer on Eligibility and Benefits.* [Updated April 11, 2018]. Congressional Research Service. R42505. https://crsreports.congress.gov/product/pdf/R/R42505

Aussenberg, R. A., & Billings, K. C. (2018). *2018 Farm Bill Primer : SNAP and Nutrition Title Programs.* Congressional Research Service. IF11087. https://crsreports.congress.gov/product/pdf/IF/IF11087

Aussenberg, R. A., Colello, K. J., & Billings, K. C. (2019). Domestic food assistance: Summary of programs. r42353.version 26.updated [Updated August 27, 2019]. *Congressional Research Service: Report*, 1–19. https://crsreports.congress.gov/product/pdf/R/R42353

Bartfeld, J., Dunifon, R., Nord, M., & Carlson, S. (2006). What Factors Account for State-to-State Differences in Food Security? *Economic Information Bulletin*, *20*(1476-2016-121049), 16. http://ageconsearch.umn.edu/record/7086

Bellemare, M. F., Bloem, J. R., & Wexler, N. (2021). *The Paper of How: Estimating Treatment Effects Using the Front-Door Criterion* (Working Paper) [Latest working paper available on November 2021]. Available at : http://marcfbellemare.com/wordpress/research. Minnesota.

Bergemann, A., Grönqvist, E., & Gudbjörnsdottir, S. (2011). The Effects of Job Displacement on the Onset and Progression of Diabetes. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1810556

Betz, M. R., & Jones, L. E. (2018). Wage and Employment Growth in America's Drug Epidemic: Is All Growth Created Equal? *American Journal of*

Agricultural Economics, *100*(5), 1357–1374. https://doi.org/10.1093/ajae/aay069

Black, S. E., Devereux, P. J., & Salvanes, K. G. (2015). Losing Heart? The Effect of Job Displacement on Health. *ILR Review*, *68*(4), 833–861. https://doi.org/10.1177/0019793915586381

Blau, F. D., & Kahn, L. M. (1997). Swimming Upstream: Trends in the Gender Wage Differential in the 1980s. *Journal of Labor Economics*, *15*(1, Part 1), 1–42. https://doi.org/10.1086/209845

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436. https://doi.org/10.2307/144855

Browning, M., & Heinesen, E. (2012). Effect of job loss due to plant closure on mortality and hospitalization. *Journal of Health Economics*, *31*(4), 599–616. https://doi.org/10.1016/j.jhealeco.2012.03.001

Cassidy-Vu, L., Way, V., & Spangler, J. (2022). The correlation between food insecurity and infant mortality in north carolina. *Public Health Nutrition*, 1–7.

Chen, S., Chernozhukov, V., Fernández-Val, I., & Luo, Y. (2019). Sortedeffects: Sorted causal effects in r.

Chen, S., Chernozhukov, V., Fernández-Val, I., & Luo, Y. (2020). SortedEffects: Sorted Causal Effects in R. *The R Journal*, *12*(1), 131. https://doi.org/10.32614/rj-2020-006

Chernozhukov, V., Fernández-Val, I., & Luo, Y. (2018). The Sorted Effects Method: Discovering Heterogeneous Effects Beyond Their Averages. *Econometrica*, *86*(6), 1911–1938. https://doi.org/10.3982/ecta14415

Coleman-Jensen, A., Gregory, C., Anita, S., & Rabbitt, M. (2021). Household food security in the united states in 2020, , err-298. *U.S. Department of Agriculture, Economic Research Service*.

Coleman-Jensen, A., Gregory, C., & Singh, A. (2014). Household food security in the united states in 2013, err-173. *USDA-ERS Economic Research Report*.

Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., & Singh, A. (2017). Household food security in the united states in 2016, err-237. *US Department of Agriculture, Economic Research Service*.

Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., & Singh, A. (2018a). *Household Food Security in the United States in 2017* (research rep. ERR-256). U.S. Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/webdocs/publications/90023/err-256.pdf?v=0

Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., & Singh, A. (2018b). Household food security in the united states in 2017, err-256. *U.S. Department of Agriculture, Economic Research Service*.

Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., & Singh, A. (2020). Household Food Security in the United States in 2019, ERR-275. *U.S. Department of Agriculture, Economic Research Service*.

Couch, K. A., & Placzek, D. W. (2010). Earnings Losses of Displaced Workers Revisited. *American Economic Review*, *100*(1), 572–589. https://doi.org/10.1257/aer.100.1.572

Dickert-Conlin, S., Fitzpatrick, K., Stacy, B., & Tiehen, L. (2020). The Downs and Ups of the SNAP Caseload: What Matters? *Applied Economic Perspectives and Policy*. https://doi.org/https://doi.org/10.1002/aepp.13076

DiNardo, J., Fortin, N. M., & Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, *64*(5), 1001. https://doi.org/10.2307/2171954

Duncan, O. D. (1967). Discrimination against negroes. *The Annals of the American Academy of Political and Social Science*, *371*(1), 85–103.

Eliason, M., & Storrie, D. (2009). Does Job Loss Shorten Life? *Journal of Human Resources*, *44*(2), 277–302. https://doi.org/10.3368/jhr.44.2.277

Farber, H. S. (2017). Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey. *Journal of Labor Economics*, *35*(S1), S235–S272. https://doi.org/10.1086/692353

Firpo, S. P., Fortin, N. M., & Lemieux, T. (2018). Decomposing Wage Distributions Using Recentered Influence Function Regressions. *Econometrics*, *6*(2). https://doi.org/10.3390/econometrics6020028

USDA. (2022). Snap policy database, snap policy data sets [dataset last updated in August of 2019, https://www.ers.usda.gov/data-products/snap-policy-data-sets/].

Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. (2020). Integrated public use microdata series, current population survey: Version 7.0 [dataset]. minneapolis, mn: Ipums. https://doi.org/https://doi.org/10.18128/D030.V7.0

Flores-Lagunes, A., Jales, H. B., Liu, J., & Wilson, N. L. (2018a). The differential incidence and severity of food insecurity by racial, ethnic, and immigrant groups over the great recession in the united states. *AEA Papers and Proceedings*, *108*, 379–383.

Flores-Lagunes, A., Jales, H. B., Liu, J., & Wilson, N. L. (2018b). The Differential Incidence and Severity of Food Insecurity by Racial, Ethnic, and Immigrant Groups over the Great Recession in the United States. *AEA Papers and Proceedings*, *108*, 379–83. https://doi.org/10.1257/pandp.20181106

Fortin, N., Lemieux, T., & Firpo, S. (2010). Decomposition Methods in Economics [NBER Working Paper No. 16045]. *National Bureau of Economic Research*. https://doi.org/10.3386/w16045

Fortin, N., Lemieux, T., & Firpo, S. (2011). Decomposition Methods in Economics. *Handbook of labor economics* (pp. 1–102). Elsevier. https://doi.org/10.1016/s0169-7218(11)00407-2

Foster, G. (2009). A diagrammatic exposition of regression and instrumental variables for the beginning student. *The Journal of Economic Education*, *40*(3), 278–296. Retrieved April 7, 2022, from http://www.jstor.org/stable/25766013

Furman, J., Munoz, C., & Black, S. (2015). Long-term benefits of the supplemental nutrition assistance program. *Washington, DC: Council of Economic Advisors*. https://obamawhitehouse.archives.gov/sites/obamawhitehouse.archives.gov/files/documents/SNAP_report_final_nonembargo.pdf

Ganong, P., & Liebman, J. B. (2013). *The Decline, Rebound, and Further Rise in SNAP Enrollment: Disentangling Business Cycle Fluctuations and Policy Changes* (Working Paper No. 19363). National Bureau of Economic Research. https://doi.org/10.3386/w19363

Ganong, P., & Liebman, J. B. (2018). The Decline, Rebound, and Further Rise in SNAP Enrollment: Disentangling Business Cycle Fluctuations and Policy Changes. *American Economic Journal: Economic Policy*, *10*(4), 153–76. https://doi.org/10.1257/pol.20140016

Greene, W. H. (2008). *Econometric analysis*. Prentice Hall. https://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,shib&db=cat06564a&AN=uga.9933413533902959&site=eds-live&custid=uga1

Gregory, C., Rabbitt, M. P., & Ribar, D. C. (2015). The supplemental nutrition assistance program and food insecurity. *SNAP Matters: How Food Stamps Affect Health and Well-Being*, 74.

Greiner, D. J., & Rubin, D. B. (2011). Causal effects of perceived immutable characteristics. *Review of Economics and Statistics*, *93*(3), 775–785.

Gundersen, C., Kreider, B., & Pepper, J. (2011). The Economics of Food Insecurity in the United States. *Applied Economic Perspectives and Policy*, *33*(3), 281–303. https://doi.org/10.1093/aepp/ppr022

Gundersen, C., Dewey, A., Crumbaugh, A. S., Kato, M., & Engelhard, E. (2017). Map the Meal Gap 2017: Technical Brief. *Feeding America*.

Gundersen, C., & Kreider, B. (2008). Food stamps and food insecurity what can be learned in the presence of nonclassical measurement error? *Journal of Human Resources*, *43*(2), 352–382.

Gundersen, C., & Ribar, D. (2011). Food Insecurity and Insufficiency at Low Levels of Food Expenditures. *Review of Income and Wealth*, *57*(4), 704–726. https://doi.org/10.1111/j.1475-4991.2011.00471.x

Gundersen, C., Smeeding, T., Bartfeld, J., & Ziliak, J. P. (2015). *SNAP Matters: How Food Stamps Affect Health and Well-Being*. Stanford University Press. http://www.sup.org/books/title/?id=24621

Gundersen, C., & Ziliak, J. P. (2015). Food insecurity and health outcomes. *Health affairs*, *34*(11), 1830–1839.

Gundersen, C., & Ziliak, J. P. (2018). Food insecurity research in the united states: Where we have been and where we need to go. *Applied Economic Perspectives & Policy*, *40*(1), 119. https://doi.org/10.1093/aepp/ppx058

Gupta, P., Gonzalez, D., & Waxman, E. (2020). Forty Percent of Black and Hispanic Parents of School-Age Children Are Food Insecure [Accessed on January 4, 2021]. https://www.urban.org/research/publication/forty-percent-black-and-hispanic-parents-school-age-children-are-food-insecure

Heckman, J. J., Lyons, T. M., & Todd, P. E. (2000). Understanding Black–White Wage Differentials: 1960–1990. *American Economic Review*, *90*(2), 344–349. https://doi.org/10.1257/aer.90.2.344

Huber, M., & Solovyeva, A. (2020). On the Sensitivity of Wage Gap Decompositions. *Journal of Labor Research*, *41*(1-2), 1–33. https://doi.org/10.1007/s12122-020-09302-7

Huttunen, K., Møen, J., & Salvanes, K. G. (2011). HOW DESTRUCTIVE IS CREATIVE DESTRUCTION? EFFECTS OF JOB LOSS ON JOB MOBILITY, WITHDRAWAL AND INCOME. *Journal of the European Economic Association*, *9*(5), 840–870. https://doi.org/10.1111/j.1542-4774.2011.01027.x

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings Losses of Displaced Workers. *The American Economic Review*, *83*(4), 685–709. http://www.jstor.org/stable/2117574

Jann, B. (2008a). The Blinder–Oaxaca Decomposition for Linear Regression Models. *The Stata Journal: Promoting communications on statistics and Stata*, *8*(4), 453–479. https://doi.org/10.1177/1536867x0800800401

Jann, B. (2008b). The Blinder–Oaxaca Decomposition for Linear Regression Models. *The Stata Journal*, *8*(4), 453–479. https://doi.org/10.1177/1536867X0800800401

Kalil, A., Mayer, S., & Shah, R. (2020). Impact of the COVID-19 crisis on family dynamics in economically vulnerable households. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3706339

Kitagawa, E. M. (1955). Components of a Difference Between Two Rates*. *Journal of the American Statistical Association*, *50*(272), 1168–1194. https://doi.org/10.1080/01621459.1955.10501299

Kreider, B., Pepper, J. V., Gundersen, C., & Jolliffe, D. (2012). Identifying the effects of snap (food stamps) on child health outcomes when participation is endogenous and misreported. *Journal of the American Statistical Association*, *107*(499), 958–975.

Lachowska, M., Mas, A., & Woodbury, S. (2018). *Sources of Displaced Workers' Long-Term Earnings Losses* (tech. rep.). NBER. National Bureau of Economic Research. https://doi.org/10.3386/w24217

Liese, A. D., Davis, R. E., Diaz, D., Stucker, J., Reid, L. A., Jindal, M., Stancil, M., & Jones, S. J. (2020). Experiences of food insecurity and type 2 diabetes management in adults. *Journal of Hunger & Environmental Nutrition*, *0*(0), 1–17. https://doi.org/10.1080/19320248.2020.1826380

Mabli, J., & Ferrerosa, C. (2010). Supplemental nutrition assistance program caseload trends and changes in measures of unemployment, labor underutilization, and program policy from 2002 to 2008. *US Department of Agriculture. Princeton, NJ: Mathematica Policy Research Inc. March*. https://econpapers.repec.org/RePEc:mpr:mprres:320f4282aaf14c48a2455b0bfa447d53

March, R. J., Carpio, C. E., Boonsaeng, T., & Lyford, C. P. (2020). Do SNAP Recipients Get the Best Prices? *Journal of Agricultural and Applied Economics*, *52*(1), 135–159. https://doi.org/10.1017/aae.2019.37

McDonough, I. K., Roy, M., & Roychowdhury, P. (2020). Exploring the dynamics of racial food security gaps in the united states. *Review of Economics of the Household*, *18*(2), 387–412.

Mills, G. B., Vericker, T., Lippold, K., Wheaton, L., & Elkin, S. (2014). *Understanding the Rates, Causes, and Costs of Churning in the Supplemental Nutrition Assistance Program (SNAP) - Final Report* (tech. rep.). Prepared by Urban Institute for the US Departmentof Agriculture, Food and Nutrition Service. https://www.fns.usda.gov/snap/understanding-rates-causes-and-costs-churning-supplemental-nutrition-assistance-program-snap

Nord, M., Coleman-Jensen, A., & Gregory, C. A. (2014). Prevalence of US Food Insecurity Is Related to Changes in Unemployment, Inflation, and the Price of Food. https://poverty.ucdavis.edu/sites/main/files/file-attachments/usda%5C_food%5C_insecurity%5C_2014.pdf

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693. https://doi.org/10.2307/2525981

Ochsenfeld, F. (2017). The gender income gap and the role of family formation revisited. *Journal for Labour Market Research*, *50*(1), 131–141. https://doi.org/10.1007/s12651-017-0225-5

Oliveira, V., Prell, M., Tiehen, L., & Smallwood, D. (2018). *Design Issues in USDA's Supplemental Nutrition Assistance Program: Looking Ahead by Looking Back* (tech. rep. ERR-243). United States Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/publications/pub-details/?pubid=86923

Pearl, J. (1995). Causal diagrams for empirical research. *Biometrika*, *82*(4), 669–688.

Pearl, J. (2009). *Causality* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511803161

Ratcliffe, C., McKernan, S.-M., & Finegold, K. (2008). Effects of food stamp and tanf policies on food stamp receipt. *Social Service Review*, *82*(2), 291–334. https://doi.org/10.1086/589707

Ratcliffe, C., McKernan, S.-M., & Zhang, S. (2011). How much does the Supplemental Nutrition Assistance Program reduce food insecurity? *American journal of agricultural economics*, *93*(4), 1082–1098. https://doi.org/https://doi.org/10.1093/ajae/aar026

Rege, M., Telle, K., & Votruba, M. (2009). The Effect of Plant Downsizing on Disability Pension Utilization. *Journal of the European Economic Association*, *7*(4), 754–785. https://doi.org/10.1162/jeea.2009.7.4.754

Ribar, D. C., Edelhoch, M., & Liu, Q. (2008). Watching the clocks: The role of food stamp recertification and tanf time limits in caseload dynamics. *The Journal of Human Resources*, *43*(1), 208–239. http://www.jstor.org/stable/40057343

Ribar, D. C., Edelhoch, M., & Liu, Q. (2010). Food Stamp Participation among Adult-Only Households. *Southern Economic Journal*, *77*(2), 244–270. https://doi.org/https://doi.org/10.4284/sej.2010.77.2.244

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. *The Stata Journal*, *20*(1), 51–94. https://doi.org/10.1177/1536867X20909690

Schmidt, L., Shore-Sheppard, L., & Watson, T. (2016). The effect of safety-net programs on food insecurity. *Journal of Human Resources*, *51*(3), 589–614.

Schmieder, J., von Wachter, T., & Bender, S. (2018). *The costs of job displacement over the business cycle and its sources: evidence from Germany* (tech. rep.). Boston University: Mimeo. http://www.econ.ucla.edu/tvwachter/

Smith, J. P., & Welch, F. R. (1989). Black Economic Progress After Myrdal. *Journal of Economic Literature*, *27*(2), 519–564. http://www.jstor.org/stable/2726688

Smith, T. A., Valizadeh, P., Lin, B.-H., & Coats, E. (2019). What is driving increases in dietary quality in the United States? *Food Policy*, *86*, 101720. https://doi.org/10.1016/j.foodpol.2019.05.003

Stacy, B., Tienhen, L., & Marquardt, D. (2018). Using a policy index to capture trends and differences in state administration of usda's supplemental nutrition assistance program, err-244. https://www.ers.usda.gov/publications/pub-details/?pubid=87095

Sullivan, D., & von Wachter, T. (2009). Job Displacement and Mortality: An Analysis Using Administrative Data. *Quarterly Journal of Economics*, *124*(3), 1265–1306. https://doi.org/10.1162/qjec.2009.124.3.1265

Tanaka, V. T., Engelhard, G., & Rabbitt, M. P. (2020). Modeling Household Food Insecurity with a Polytomous Rasch Model. *Springer proceedings in mathematics & statistics* (pp. 319–331). Springer International Publishing. https://doi.org/10.1007/978-3-030-43469-4_24

Wilson, W. J. (2011). *When work disappears: The world of the new urban poor*. Vintage.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data, second edition*. MIT Press. https://books.google.com/books?id=hSs3AgAAQBAJ

Ziliak, J. P. (2015a). Why are so many americans on food stamps. *SNAP matters: How food stamps affect health and well-being*, 18–48.

Ziliak, J. P. (2015b). Why are so many americans on food stamps? the role of the economy, policy, and demographics. In J. Bartfeld, C. Gundersen, T. Smeeding, & J. P. Ziliak (Eds.), *Snap matters: How food stamps affect health and well-being* (pp. 18–48). Stanford University Press. http://www.sup.org/books/title/?id=24621

Ziliak, J. P. (2021). Food hardship during the covid-19 pandemic and great recession. *Applied Economic Perspectives and Policy*, *43*(1), 132–152.

Appendix A

A.1 SNAP Gap Detailed Table

Table A.1: [APPENDIX:] Detailed table Of SPE and APE of Black-White SNAP Gap

Sorted Partial Effects (SPE) SPE Percentile Index	Est	SE	90% PLB	90% PUB	90% ULB	90% UUB
0.02	0.003	0.000	0.003	0.004	0.003	0.004
0.03	0.004	0.000	0.003	0.005	0.003	0.005
0.04	0.004	0.001	0.003	0.005	0.003	0.005
0.05	0.005	0.001	0.004	0.006	0.004	0.006
0.06	0.005	0.001	0.004	0.006	0.004	0.006
0.07	0.006	0.001	0.005	0.007	0.005	0.007
0.08	0.006	0.001	0.005	0.007	0.005	0.007
0.09	0.007	0.001	0.005	0.008	0.005	0.008
0.1	0.007	0.001	0.006	0.008	0.006	0.008
0.11	0.007	0.001	0.006	0.009	0.006	0.009
0.12	0.008	0.001	0.006	0.009	0.006	0.009
0.13	0.008	0.001	0.007	0.010	0.007	0.010
0.14	0.009	0.001	0.007	0.010	0.007	0.010
0.15	0.009	0.001	0.007	0.011	0.007	0.011
0.16	0.009	0.001	0.008	0.011	0.008	0.011
0.17	0.010	0.001	0.008	0.012	0.008	0.012
0.18	0.010	0.001	0.008	0.012	0.008	0.012
0.19	0.011	0.001	0.009	0.013	0.009	0.013

0.2	0.011	0.001	0.009	0.013	0.009	0.013
0.21	0.012	0.001	0.010	0.014	0.010	0.014
0.22	0.012	0.001	0.010	0.014	0.010	0.014
0.23	0.013	0.001	0.010	0.015	0.010	0.015
0.24	0.013	0.001	0.011	0.015	0.011	0.016
0.25	0.014	0.001	0.011	0.016	0.011	0.016
0.26	0.014	0.002	0.012	0.017	0.012	0.017
0.27	0.015	0.002	0.012	0.017	0.012	0.017
0.28	0.015	0.002	0.013	0.018	0.012	0.018
0.29	0.016	0.002	0.013	0.019	0.013	0.019
0.3	0.016	0.002	0.013	0.019	0.013	0.019
0.31	0.017	0.002	0.014	0.020	0.014	0.020
0.32	0.017	0.002	0.014	0.020	0.014	0.020
0.33	0.018	0.002	0.015	0.021	0.015	0.021
0.34	0.018	0.002	0.015	0.022	0.015	0.022
0.35	0.019	0.002	0.016	0.022	0.015	0.022
0.36	0.020	0.002	0.016	0.023	0.016	0.023
0.37	0.020	0.002	0.017	0.024	0.017	0.024
0.38	0.021	0.002	0.017	0.024	0.017	0.025
0.39	0.021	0.002	0.018	0.025	0.017	0.025
0.4	0.022	0.002	0.018	0.026	0.018	0.026
0.41	0.023	0.002	0.019	0.027	0.019	0.027
0.42	0.023	0.002	0.019	0.027	0.019	0.028
0.43	0.024	0.003	0.020	0.028	0.020	0.028
0.44	0.025	0.003	0.020	0.029	0.020	0.029
0.45	0.025	0.003	0.021	0.030	0.021	0.030
0.46	0.026	0.003	0.022	0.030	0.021	0.031
0.47	0.027	0.003	0.022	0.031	0.022	0.032
0.48	0.027	0.003	0.023	0.032	0.023	0.032
0.49	0.028	0.003	0.023	0.033	0.023	0.033
0.5	0.029	0.003	0.024	0.034	0.024	0.034
0.51	0.030	0.003	0.025	0.035	0.024	0.035
0.52	0.030	0.003	0.025	0.036	0.025	0.036
0.53	0.031	0.003	0.026	0.036	0.026	0.037
0.54	0.032	0.003	0.027	0.037	0.026	0.038
0.55	0.033	0.003	0.027	0.038	0.027	0.038
0.56	0.033	0.003	0.028	0.039	0.027	0.039
0.57	0.034	0.004	0.028	0.040	0.028	0.040
0.58	0.035	0.004	0.029	0.041	0.029	0.041

0.59	0.036	0.004	0.030	0.042	0.030	0.042
0.6	0.037	0.004	0.031	0.043	0.030	0.043
0.61	0.037	0.004	0.031	0.044	0.031	0.044
0.62	0.038	0.004	0.032	0.045	0.032	0.045
0.63	0.039	0.004	0.033	0.046	0.032	0.046
0.64	0.040	0.004	0.033	0.047	0.033	0.047
0.65	0.041	0.004	0.034	0.048	0.034	0.048
0.66	0.042	0.004	0.035	0.049	0.035	0.049
0.67	0.043	0.004	0.036	0.050	0.035	0.050
0.68	0.043	0.004	0.036	0.051	0.036	0.051
0.69	0.044	0.004	0.037	0.052	0.037	0.052
0.7	0.045	0.005	0.038	0.053	0.037	0.053
0.71	0.046	0.005	0.038	0.054	0.038	0.054
0.72	0.047	0.005	0.039	0.055	0.039	0.055
0.73	0.048	0.005	0.040	0.056	0.040	0.056
0.74	0.049	0.005	0.040	0.057	0.040	0.057
0.75	0.049	0.005	0.041	0.057	0.041	0.058
0.76	0.050	0.005	0.042	0.058	0.041	0.059
0.77	0.051	0.005	0.042	0.059	0.042	0.060
0.78	0.052	0.005	0.043	0.060	0.043	0.060
0.79	0.052	0.005	0.044	0.061	0.043	0.061
0.8	0.053	0.005	0.044	0.062	0.044	0.062
0.81	0.054	0.005	0.045	0.062	0.044	0.063
0.82	0.054	0.005	0.045	0.063	0.045	0.064
0.83	0.055	0.005	0.046	0.064	0.045	0.064
0.84	0.055	0.006	0.046	0.065	0.046	0.065
0.85	0.056	0.006	0.047	0.065	0.046	0.066
0.86	0.057	0.006	0.047	0.066	0.047	0.066
0.87	0.057	0.006	0.048	0.066	0.047	0.067
0.88	0.058	0.006	0.048	0.067	0.048	0.067
0.89	0.058	0.006	0.049	0.067	0.048	0.068
0.9	0.058	0.006	0.049	0.068	0.048	0.068
0.91	0.059	0.006	0.049	0.068	0.049	0.069
0.92	0.059	0.006	0.050	0.069	0.049	0.069
0.93	0.059	0.006	0.050	0.069	0.049	0.069
0.94	0.060	0.006	0.050	0.069	0.049	0.070
0.95	0.060	0.006	0.050	0.070	0.050	0.070
0.96	0.060	0.006	0.050	0.070	0.050	0.070
0.97	0.060	0.006	0.050	0.070	0.050	0.070

0.98	0.060	0.006	0.051	0.070	0.050	0.071

Average Partial Effects				
	Est	SE	90% LB	90% UB
APE	0.030	0.003	0.025	0.035