THE DIGITAL DIVIDE AND E-GOVERNMENT: HOW INTERNET ACCESS AND ONLINE APPLICATIONS IMPACT ENROLLMENT IN THE SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM

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By

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ABSTRACT

The past two decades have seen an explosive rise in access to high-speed internet. At the same time, local, state, and national governments have greatly expanded the range of services available through the internet, including the use of online applications for assistance programs. Through econometric analysis of county-level data from the FCC, USDA, and other sources, I measure how internet access and the use of online applications impact enrollment in the Supplemental Nutrition Assistance Program (SNAP). My findings suggest that increased access to the internet leads to decreased enrollment in SNAP, even after controlling for fixed effects and confounding variables like unemployment rates and average income – potential evidence of a general quality of life improvement that arises through bridging the Digital Divide. Additionally, my analysis finds that introducing online applications had no measurable effect on SNAP enrollment in areas with high internet access – however, in counties with low internet connectivity, access to online applications was associated with a more than 10% decline in total SNAP enrollment. This likely arises from states diverting resources away from call centers and physical casework offices when rolling out online applications – leaving those without internet access behind. Overall, my results suggest that states which implement online applications should continue to support non-digital SNAP administrative work. Additionally, bridging the Digital Divide must remain an important focus for federal and state governments as more and more aspects of daily life move onto the internet.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

I. INTRODUCTION

In recent years, the United States and other countries throughout the world have greatly expanded the range of government services available through the internet. These services, commonly referred to as "e-government" resources, range from online applications for federal social services to electronic payments for local parking tickets. While a wide body of research has focused on the impact of offering e-government services on participation rates for various programs, little consideration has been made into whether the individuals who might benefit from these e-government resources have the internet access required to take advantage of them. In this thesis, I measure the impact of access to high speed internet on participation levels in the Supplemental Nutrition Assistance Program (SNAP). I also determine how that relationship varies based on whether the given county has access to online applications for SNAP. Further, I measure the effect of offering online applications on SNAP enrollment, as well as how that varies based on a county's internet access.

I measure this using a fixed effects regression that includes an interaction term between internet access and dummy variables representing the ability to apply online. The analysis will utilize annual county-level data obtained from the FCC's Form 477 dataset, the USDA's Bi-Annual County Level Participation and Issuance Data, and a variety of other sources.

I hypothesize that increased access to the internet will have a positive effect on per capita SNAP enrollment. This effect derives from the fact that improved internet connectivity allows communities and households to better access and understand the eligibility requirements and application process to obtain SNAP benefits – resulting in an increase in the SNAP take-up rate, or the rate of SNAP participation among those whom are already eligible. Additionally, many states offer e-government services like online applications for SNAP that can only be taken advantage of through the internet. That is why the relationship between internet access and SNAP enrollment will likely be the strongest in states that offer a wide range of e-government resources for the program. The relationship will likely be weaker in states without these resources; however, since every state provides at least some level of information on its SNAP program online, I still expect this relationship to have a positive correlation.

In 2009, 22 states offered online applications for their SNAP programs. By 2018, 46 states allowed online applications, with every state at least providing some information on eligibility or the application process through the internet. While the rollout of e-government resources in programs like SNAP has expanded greatly in recent decades, limited internet access in many areas across the country could be directly limiting the reach of these resources. By understanding the relationship between internet access, online applications, and participation in government programs, policymakers are better prepared to improve the reach and success of SNAP and other federal services. Failing to properly account for this relationship will directly hinder the efficacy of these important programs, preventing these services from reaching those in need and worsening the inequities of the Digital Divide.

The paper proceeds as follows. In the next section, I discuss the relevant background and previous academic work related to enrollment in SNAP, the use of online applications, and expansion of internet connectivity. Section III discusses the theoretical framework for my analysis, built off previous literature and my hypothesis on the impact of internet access and online government services on enrollment. Section IV contains my data and descriptive statistics. Using these data and the theoretical model, Section V discusses the empirical model I will use to assess my hypothesis. Section VI covers the results and analysis of my findings, while Section

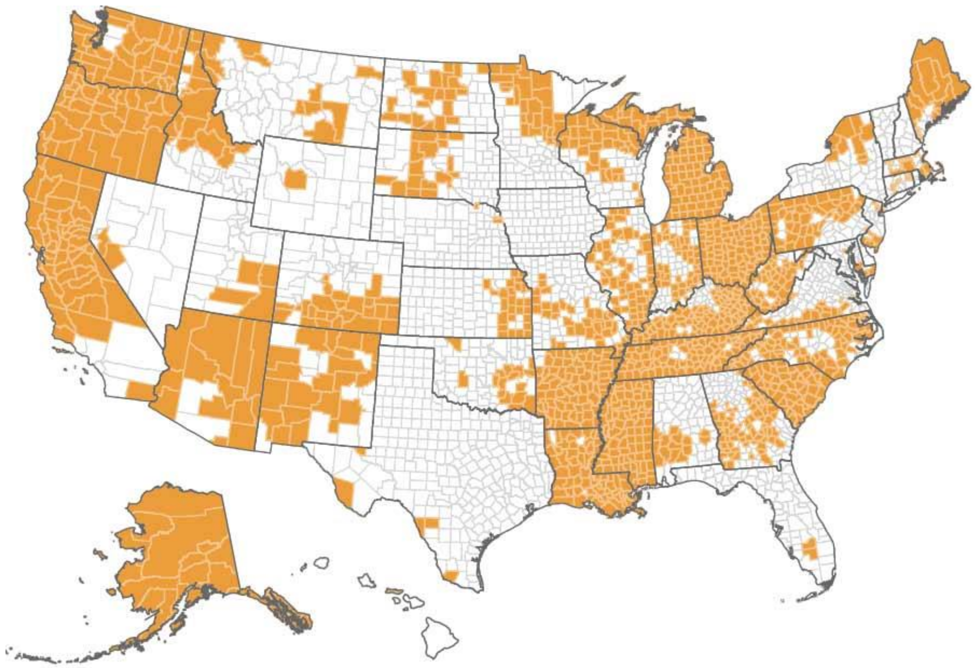
VII discusses the potential limitations of these results. Finally, Section VIII contains my conclusion, policy implications, and recommendations for future action on this issue.

II. BACKGROUND AND LITERATURE REVIEW

A. THE SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM

Administered by the U.S. Department of Agriculture's Food and Nutrition Service, the Supplemental Nutrition Assistance Program (SNAP) provides monthly food-purchasing assistance for roughly 40 million low- and no-income Americans. Eligibility for the program is determined by a variety of factors, including income, employment, age, disability status, and number of dependents. Generally speaking, individuals must have a gross monthly income below 130 percent of the federal poverty level and a net monthly income, after subtracting all acceptable deductions, below 100 percent of the federal poverty level.

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 also established two sets of work requirements under SNAP. Those between the ages of 16 and 59 must generally either be looking for work, not voluntarily quitting a job or reducing hours if already working, or otherwise be participating in state employment and training programs. Additionally, Able-Bodied Adults Without Dependents (ABAWDs) are required to work or participate in a work program for at least 20 hours a week to qualify for SNAP for longer than 3 months every 3 years. States can receive federal waivers exempting them from the work requirement for ABAWDs during periods of high unemployment, which can be used to assist the state as a whole or counties that are especially in need. While these waivers do not exempt ABAWDs from the general work requirement, they do help ensure those in need maintain food security during economic downturns. Figure 1 below shows the counties that received waivers from the ABAWD work requirement in 2008.



Source: CBPP Analysis of State Waivers

Figure 1: Areas Covered by SNAP's ABAWD Employment Requirement Waivers, 2008

Applicants are required to participate in an interview and provide documentation of residency, income and expenses. Those who receive benefits are then required to recertify every 6 to 24 months depending on their state. Those with no income receive the highest possible benefit level under SNAP, which varies based on size of the household but is consistent nationally except for Alaska and Hawaii. SNAP benefits generally decrease by $0.30 for every $1 of added income – the idea being that individuals are expected to contribute roughly 30 percent of their income towards food.

Since eligibility and benefits levels are directly tied to income and employment status, SNAP acts effectively as an automatic fiscal stabilizer – meaning that "as the economy and market incomes fall during recessions, participation in SNAP 'automatically' rises to smooth consumption … and as market incomes rise during economic expansions, participation falls," (Ziliak, 2013). Thus, a significant share of the changes in total SNAP issuance can be explained by macroeconomic changes.

For instance, Wallace and Blank (1999) studied the impact of the 1996 federal welfare reform on caseload levels for a variety of welfare programs. Changes made at this time to the then-called food stamp program included denying eligibility to most legal immigrants, the introduction of stricter work requirement for ABAWDs, and the mandated adoption of the debit card system known as Electronic Benefit Transfer (EBT) in states by 2002.[1] This reform was followed by a steep decline in the number of individuals enrolled in food stamps. Using state-level panel data, Wallace and Blank found that roughly 44 percent of this decline was due to the strengthening economy of the mid- to late-1990s, while only 6 percent was due to welfare reform (Wallace & Blank, 1999). They also estimated that a one-point decline in the unemployment rate produces a roughly 4 percent decline in food stamp caseload.

Similarly, Ziliak, Gunderson, and Figlio (2003) estimated that "one-percentage-point increase leads to about a 2.4 percent increase in food stamp caseloads after one year, a 3.7 percent increase after two years, and a 4.0 percent increase after three years." They also predicted that "a recession may trigger sizable increases in food stamp caseloads upward of at least 15 percent after two years," (Ziliak, Gunderson, and Figlio, 2003). And while macroeconomic factors had a significant effect on caseload, they found that welfare reform had a negligible effect on total caseload.

Other literature has found a more significant impact of various state and federal policies on SNAP caseload and spending. Using family-level data on SNAP participation, Ganong and

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[1] The Food Stamp Program was renamed to the Supplemental Nutrition Assistance Program by the 2008 Farm Bill. This legislation also replaced all references to "stamps" or "coupons" in federal law with "card" or "EBT" (Food, Conservation, and Energy Act of 2008).

Liebman (2013) found that between 71 percent and 98 percent of the increase in SNAP enrollment between 2007 and 2011 can be explained by the changes in duration of unemployment during the Great Recession. However, they also found statistically significant relationships between changes in government policy and SNAP participation. Specifically, they measured the impact of the adoption of Broad-Based Categorical Eligibility and temporary waivers for the work requirements for ABAWDs.

While the federal government sets certain requirements and restrictions in the administration of SNAP, significant flexibility is given to the individual states in adapting the program to “better target benefits to those most in need, streamline program administration and field operations, and coordinate SNAP activities with those of other programs” in the state (USDA-FNS, 2018). Broad-Based Categorical Eligibility (BBCE), first introduced in 2001, allows states to relax certain eligibility tests related to income and assets. States can also receive a waiver from the federal government to temporarily relax the employment requirement for Able-Bodied Adults Without Dependents to qualify during times of economic hardship. Ganong and Liebman found that between 2007 and 2011, states’ adoption of BBCE accounted for 8 percent of the increase in SNAP enrollment, while expanded eligibility for ABAWDs explained 10 percent of the increased enrollment (Ganong & Liebman, 2013). Klerman and Danielson (2011) also found that adoption of BBCE positively impacts SNAP caseload, with enrollment increasing by roughly 6.3 percent as a result of BBCE adoption. And while caseload grew “as states lengthened certification periods over the 2000s”, there was little to no increase as they introduced simplified reporting requirements (Klerman & Danielson, 2011). Other policy changes, for instance excluding vehicles from the asset test for eligibility, had no measurable effect on SNAP participation.

These results differ from Schwabish (2012), who used state-level data and found that those with simplified reporting had "per capita participation that is about 4 percent higher than in states without simplified reporting". This analysis also found a much smaller relationship between the unemployment rate and per capita SNAP participation than previous literature, with the unemployment rate only having a 5.5 percent impact on per capita participation when using a two-year lag (Schwabish, 2012).

Other research sought to identify the impact of state outreach in administering SNAP programs. For instance, Dickert-Conlin et al (2012) found that the presence of radio advertisement for a state's SNAP program is associated with a two to three percent increase in SNAP caseload. However, there was no measured relationship between advertisements and the number of newly approved applications (Dickert-Conlin et al, 2012). This suggests that the advertisements had a stronger impact on those already receiving benefits – for instance, by reminding them to recertify – than it did on eligible individuals who were not already receiving benefits. Mabli (2015) analyzed direct outreach programs, finding that when state agencies provide SNAP applications to those utilizing emergency food pantries "and submit their applications to SNAP administrative offices, the probability of household participation in SNAP increases 5–6 percentage points," (Mabli, 2015). This analysis also found statistically significant positive relationships between SNAP participation levels and a state using telephone interviews in lieu of face-to-face interviews.

B. ONLINE APPLICATIONS AND SNAP

The state policy option of greatest interest for this analysis is the ability to apply for SNAP benefits online. Between 2000 and 2018, the number of states offering online applications for SNAP increased from 0 to 46; unsurprisingly, the effectiveness of these programs has been subject to a great deal of scrutiny in academic and government research. Schwabish (2012) utilized a phase-in model with state-level data to find that the implementation of online applications "served to increase state participation in SNAP by nearly 5 percent over the course of a six-year period," (Schwabish, 2012). Using household level data, Mabli similarly found that the SNAP participation rate is "7.6 percentage points higher when households could submit the application online in all parts of the state (relative to not offering online applications)," (Mabli, 2015). However, other studies that included the presence of online applications in their analyses did not find a statistically significant relationship between a state offering online applications and SNAP enrollment (Ziliak, 2013) (Ganong & Liebman, 2013).

Some research suggests that the introduction of online applications may actually have a negative relationship with SNAP enrollment. Heflin et al (2013) conducted in-depth interviews with 26 individuals who applied for SNAP in Florida in January and February 2009. Of the 26 individuals interviewed, 15 "expressed a distinct preference for the traditional service delivery model" over the new online application system (Heflin et al, 2013). Those who experienced difficulties with the online system were more likely to be non-native English speakers. Additionally, Heflin found that modernization in Florida was "accompanied by a 43 percent reduction in staff and 33 percent reduction in state offices", meaning that the adoption of e-government systems with SNAP may have had an indirect negative effect on enrollment in the program due to the cuts in support staff accompanied it. However, they also note that most states "report no reductions in administrative costs from modernization," so this may not have an impact outside of Florida (Heflin et al, 2013).

Other literature has found a negative relationship between online applications and enrollment in government programs outside of Supplemental Nutrition Assistance. In an analysis of Wisconsin's ACCESS Internet portal for Medicaid and CHIP enrollment, Leininger et al (2011) found that those who submitted their applications online had the lowest probability of being approved for coverage compared to other methods. 69 percent of online applicants were approved, compared with 87 percent of those who applied over the phone, 83 percent who walked in, and 77 percent of mail-in applicants (Leininger, 2011). The authors posit that this difference is likely to do with document verification. Specifically, the online application requires manual transfer of paper documents that can only be verified to be correct once a caseworker has started processing the online application – resulting in a "significant departure from the ease and convenience of applying online," (Leininger, 2011).

C. E-Government and the Digital Divide

This push for expanded online services has occurred throughout every level of government, as end-user interfaces, communication technology, and automatic processes are poised to "increase effectiveness, efficiency, service quality, and transformation," (Macy, 2014). In addition to benefits to bureaucratic efficiency, the adoption of e-government services provides unique opportunities to improve transparency and trust in government. For instance, Myeong et al (2014) developed an index of e-government initiatives in South Korea and found that higher quality of e-government services offered correlates with higher trust in government. This ideal is also seen in the United States, as President Obama's Open Government Initiative sought to improve transparency through publicized data on spending, legislation, and internal government operations.

The integration of e-government resources in the U.S. has expanded rapidly since the start of the 21st century. West (2007) conducted a study of state e-government offerings, finding that in 2000 "only two percent of government sites offered three or more services online." By 2007, that figure was 58 percent (West, 2007). However, access to these resources is not distributed equally.

The term "Digital Divide" was first coined simply to indicate whether a person had access to a computer or the internet. In academics, the term is commonly used to compare two nations, i.e. developed countries with steady access to digital services versus developing without. However, it has also been used to describe the discrepancies in connectivity between individuals and communities within the United States – both physical access and the skills and knowledge required to properly utilize them. These discrepancies vary based on geography, age, income, race, disability status, and language.

Before discussing physical internet access, it is worth mentioning that many individuals either choose to not utilize the internet or lack the ability and knowledge necessary to do so. This non-physical divide especially impacts the elderly and those with disabilities. In 2007, less than half of state government websites complied with the World Wide Web Consortium (W3C) standards for disability access – meaning that even those with physical internet access might not be able to fully take advantage of state e-government services (Yun, 2010). Age is an even more significant factor, as "48 percent of non-users of the Internet are age 65 and older," (Macy, 2014).

In 2013, 85 percent of households nationwide had some level of physical internet connection; however, this number was 64 percent for black Americans and 63 percent for Hispanic Americans (Macy, 2014). According to the Pew Research Center's Internet and

American Life Project, only 62 percent of those in rural areas had access to broadband in 2013 (Rainie, 2013). Additionally, individuals with disabilities are 27 percent less likely to have physical internet access than other adults (Rainie, 2013).

The consequences of poor physical internet access have been well studied. Communities with reliable physical internet access tend to have higher educational attainment, better health outcomes, and improved business and job growth than communities with sub-standard access (Hupka, 2014) (OECD, 2016). While this may be an indication of the impact of internet access, it is also possible that there is reverse causation at play – wherein, for instance, those with low levels of education are simply more likely to live in areas with poor internet connectivity.

Physical internet access has also been shown to be positively correlated with use of e-government services in the United States (Belanger & Carter, 2006). Other literature has found similar relationships in India, Australia, South Africa, the United Kingdom, and Jordan (Kumar et al, 2018) (Dugdale et al, 2005) (Mutula & Mostert, 2010) (Carter & Weerakkody, 2008) (Abu-Shanab & Khasawneh, 2014). This should not be surprising, since the use of internet on a computer is still often necessary to fully access e-government resources. Other methods of internet access like smartphones are often incapable of navigating "electronic forms that may be difficult to read on small screens and aren't necessarily built for mobile technology as of yet, not to mention all the other activities that patrons need to do electronically, such as fill out job applications," (Macy, 2014).

D. Original Contribution to Existing Literature

Existing literature primarily focuses either on the impact of online applications on SNAP participation or the impact of internet access on the usage of e-government services – for instance, online applications. My thesis adds to this work by directly connecting physical internet access and online applications to participation in the Supplemental Nutrition Assistance Program. This combination will shed new light on the true impact of offering online applications while providing policymakers with a better understanding of the consequences of the Digital Divide.

III. THEORETICAL FRAMEWORK

Using the existing literature and my hypothesis on the relationship between internet access and online applications on enrollment in SNAP, I constructed the following simple theoretical model:

$$SNAP = f\,(IA, I, P, M, D, \varepsilon) \qquad (1)$$

SNAP denotes the total number of individuals enrolled in SNAP in a given county and year. IA denotes a county's access to fixed internet connections, while I is an interaction term measuring the impact of internet access in states that offer online applications. P encompasses the policy choices made by states in administering SNAP, for instance the use of online applications, BBCE, simplified reporting, and call centers. M indicates macroeconomic factors, for instance unemployment, poverty levels, and income. County demographic characteristics are denoted by D, which include factors such as total population, education, and the percent of individuals that are elderly, white, and Hispanic. The character "ε" indicates the error arising from an observational empirical study such as this.

This model presents a framework to understand the major factors that impact enrollment in SNAP. As previously discussed, since eligibility in SNAP is based largely on income and employment status, macroeconomic factors likely have the largest impact on per capita SNAP enrollment – potentially explaining as much as 98 percent of its variation (Ganong & Liebman, 2013). While total population will obviously have a significant relationship in the total number of individuals in a county enrolled in SNAP, previous literature has also focused on the significance of demographic characteristics like education and race as they relate to participation in SNAP. Most importantly, the model presents a framework of the relationship of interest for this study – namely between internet access, online applications, and enrollment.

My hypothesis is that increased access to the internet will have a positive effect on SNAP enrollment, and this relationship will be larger in states that offer online applications. Even when individuals cannot apply for benefits online, improved access to the internet allows individuals to more easily research SNAP eligibility and application requirements while taking advantage of other federal and nongovernmental online services designed to assist those on government support. This will lead to a slightly positive relationship between physical internet access and SNAP enrollment in counties whose states do not offer online applications. In those that do, the interaction term shows the difference in the impact of internet access on SNAP enrollment – a stronger relationship specifically arising from the direct ability to use the internet to apply for benefits.

IV. DATA AND DESCRIPTIVE STATISTICS

In order to empirically test this theoretical model, I collected panel data at the county level, recorded annually. Data come from a variety of U.S. government sources, most notably the USDA and FCC. The dependent variable for this analysis – the number of persons receiving SNAP benefits (*SNAPpersons*)– is a continuous variable pulled from the USDA Food and Nutrition Service's Bi-Annual (January and July) State Project Area/County Level Participation and Issuance Data. This source provides county-level data reported by states to the USDA twice annually between Fiscal Year 1989 and 2019 – for the purposes of this analysis, I use July levels. Using county-level data on SNAP enrollment ranging over multiple decades allows me to use a far more granular analysis than most previous literature focusing on the implementation of online applications.

Because states have a great deal of authority in the implementation of SNAP, there are some significant discrepancies in data recording and availability between certain states that must be addressed. Firstly, 16 states do not report SNAP data at the county level – meaning that I cannot include these states in any regression utilizing county-level data.[2] Additionally, certain states like Wisconsin report SNAP allocation to Native American tribes separately from allocation to counties. Since data are not available at a more granular level, I removed any tribes that reside in multiple counties from the analysis, as well as the counties in which they reside. I will discuss the potential impact of these limitations on the exogeneity of the analysis in a later section. Finally, some states divide certain high-population counties – for instance Cook County, Illinois – into multiple project areas for administrative and reporting purposes. I combined these

[2] These states are Alaska, Connecticut, Idaho, Maine, Massachusetts, Missouri, Montana, Nebraska, New Hampshire, New York, Oregon, Rhode Island, Utah, Vermont, West Virginia, and Wyoming.

project areas into full counties, and thus can include them in the analysis. Given these data restrictions, I can use roughly 2,400 county and county-equivalents from 34 states and D.C. between 2008 and 2016 for this analysis. The highest measured annual SNAP enrollment was in Los Angeles County, California, in 2014, with 1,178,346 out of its population of 10,048,408 enrolled in the program. Multiple counties had no SNAP enrollees in at least one year, including King County, Texas, in 2008 – not overly surprising given the county's total population of 272 that year.

The two primary independent variables of interest are internet access (*internetaccess*) and the ability to apply for SNAP benefits online (*onlineapp*). Data on internet access come from the FCC's Form 477 County Data on Internet Access Services. Every broadband provider is required to file data with the FCC each June and December on locations where they offer internet services at speeds above 200 kilobits per second (kbps) in at least one direction; 200 kbps was the FCC-defined minimum speed for broadband between 1996 and 2010. The Form 477 County Data provides this information at the county level between 2008 and 2016. They measure the percentage of households in a given county and year (using June levels) with access to fixed internet of speeds at least 200 kbps in one direction on a scale of 1 and 5. Each ordinal level corresponds to 20 percentage points, so 1 indicates that between 0 and 20 percent of households in a given county and year have access to fixed broadband, 2 indicates between 20 percent and 40 percent of households have access, and so forth.

I used these data to create the instrument variable *internetaccess*, which records a 1 if between 40% and 100% of households in a given county and year have access to highspeed internet, and a 0 if between 0% and 40% have access. I chose this specific cutoff point so that my analysis can more fully focus on the effects of *low* internet access, instead of the difference between middling and high access. This uneven division unsurprisingly results in many more observations with *internetaccess* = 1 than *internetaccess* = 0, especially later in the range of dates included. However, the large number of total observations should prevent any quirks in the analysis that may arise from this cutoff point. The figure below shows the growth of internet connectivity between 2008 and 2016:

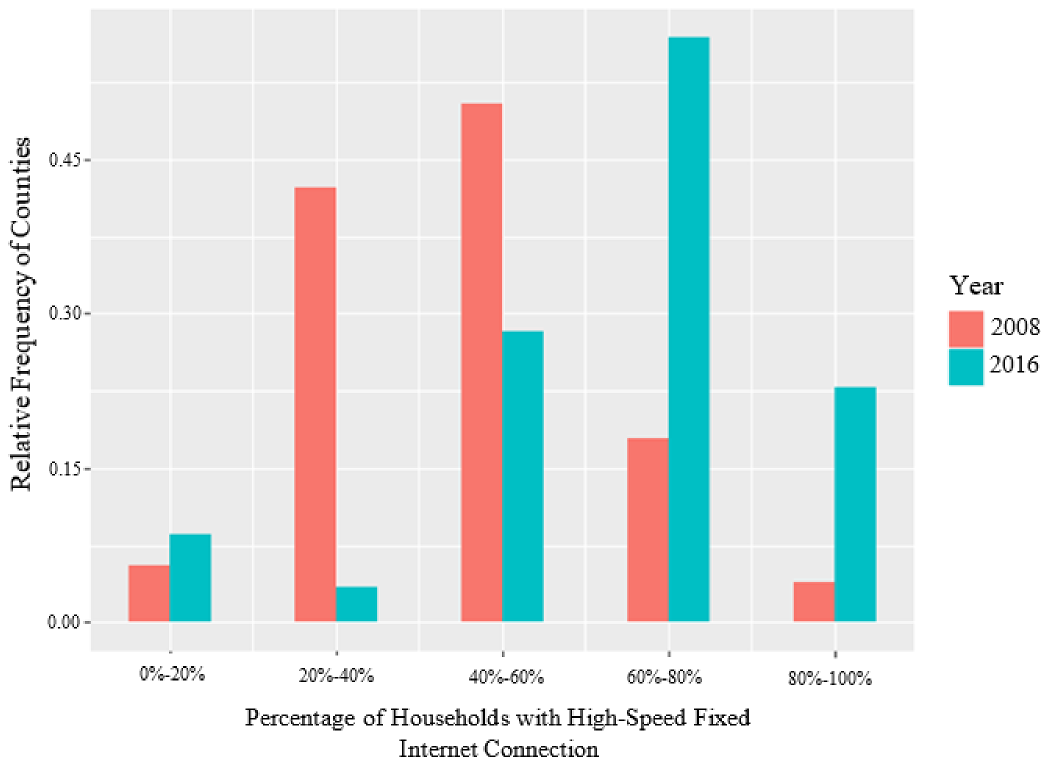

Figure 2: Growth of Fixed Internet Access, 2008 to 2016

Data on the ability to apply for SNAP benefits online were taken from the USDA Economic Research Service's SNAP Policy Database. As previously stated, each individual state has a significant degree of autonomy when it comes to the administration of SNAP. The SNAP Policy Database records the differences in state policy choices for all 50 states and the District of Columbia each month between 1996 and December 2016. The variable for online applications, *onlineapp*, is a dummy variable that records a 0 for states that do not offer online applications in a given year, and a 1 for those that offer online applications statewide. States which offer online applications in only select parts of the state were recorded as a 2. I used July levels for this analysis.

In addition to online applications, the SNAP Policy Database provided data for multiple additional variables. Eight of these variables are simple binaries, wherein 1 indicates a state offers this policy or service, and 0 indicates the state does not. These include whether or not a state uses Broad-Based Categorical Eligibility in determining applicant eligibility (*bbce*), operates call centers (*call*), utilizes the USDA simplified reporting option (*reportsimple*), offers transitional SNAP benefits to families leaving the TANF program (*transben*), and excludes vehicles in the SNAP asset test (*vehicleexemption*). The amount of outreach spending in a given state (*outreach*) is recorded as a continuous variable in thousands of dollars. While the binary state options variables use July levels, *outreach* is recorded as the sum of all 12 months in each given year in thousands of dollars. Since these variables indicate state policy decisions, they have the same value for each county in a given state in a given year. In addition to the policies collected through the SNAP Policy Database, I collected data on whether a given county in a given year was waived from the work requirements for ABAWDs from the Center on Budget and Policy Priorities (CBPP). This information was used to code the variable *abawdwaived*, which is equal to 1 in counties with such a waiver in a given year and 0 in counties that without.

Finally, my analysis accounts for various economic and demographic control variables. I took the unemployment rate (*unemployment*) from the USDA Economic Research Service and recorded it as a continuous variable. I also took poverty rates (*povpct*) from the U.S. Census's Small Area Income and Poverty Estimates (SAIPE) Program. This variable utilizes the U.S. Census definition of family poverty and is recorded as a continuous variable indicating the percentage of a county's population that is in a family in poverty[3]. Median annual income (*income*) is a continuous variable that I took from the Bureau of Labor Statistics. I used data from the Centers for Disease Control and Prevention Bridged-Race Population Estimates to construct variables representing total population (*population*), percent of the population over 65 (*pctelderly*), percent of the population that is white (*pctwhite*), percent of the population that is male (*pctmale*) and percent of the population that is Hispanic (*pcthispanic*), all recorded as continuous variables. Lastly, I compiled data from the Census Bureau's American Community Survey (ACS) to compile two continuous variables measuring education attainment – *hsplus*, showing the percentage of the county's population with at least a high school degree, and *collegeplus*, measuring the percentage with at least a college degree. Unfortunately, because the ACS only measures nationwide county-level data in five-year estimates, each county has one value for the years 2008-2012 and another between 2013 and 2016. Additionally, there are clear collinearity issues in this choice of variables that will affect the interpretation of my results – I discuss the consequences of these limitations later in this paper. A table of the summary statistics for these variables can be seen on the following page.

[3] The Census poverty threshold varies by year, number of children, and size of family unit. For instance, a family with two parents and two children in 2018 would have to have an annual household income below $25,465 to fall under the threshold.

Table 1: Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Min	Max
SNAPpersons	26,806	14,139.68	49,767.27	0	1,178,346
internetaccess	31,423	0.8476	0.3594	0	1
onlineapp	24,564	0.706	0.4556	0	1
abawdwaived	31,462	0.6883	0.4632	0	1
bbce	25,752	0.6528	0.4761	0	1
callcenters	19,844	0.5499	0.4975	0	1
outreach	25,752	1,239.98	2,287.82	0	22,575.14
reportsimple	25,752	0.9764	0.1518	0	1
transben	25,752	0.3618	0.4805	0	1
vehicleexemption	22,894	0.7661	0.4233	0	1
population	33,694	100,793.70	323,642.40	61	10,120,540
pctelderly	33,694	17.1243	4.5017	3.1893	57.5783
pctwhite	33,694	86.2767	16.2885	9.0221	100
pctmale	33,694	50.0376	2.2588	42.8115	73.4391
pcthispanic	33,694	8.9921	13.5572	0	96.3596
income	31,399	36,298.99	8,612.18	0	126,707
povpct	31,397	16.4323	6.4255	2.9	62
unemployment	33,701	6.7816	3.0156	1.1	28.9
hsplus	31,400	85.1667	6.8406	41.3	98.9
collegeplus	31,400	20.34962	9.0686	3.7	78.1

V. EMPIRICAL MODEL SPECIFICATION

Using these data and the variables I have described, I will empirically test the theoretical model (1) using the empirical framework I describe in this section. It is first necessary to address variables that are heavily skewed in their distribution. This can be seen clearly in Table 2 with variables that have standard deviations larger than their average value – namely *SNAPpersons*, *outreach*, and *population*. While not as drastic as those examples, *income* is also positively skewed. Thus, it is necessary to logarithmically transform these variables before I can use them for any substantive quantitative analysis. As an example, the distribution of *SNAPpersons* before and after being logarithmically transformed is shown below:

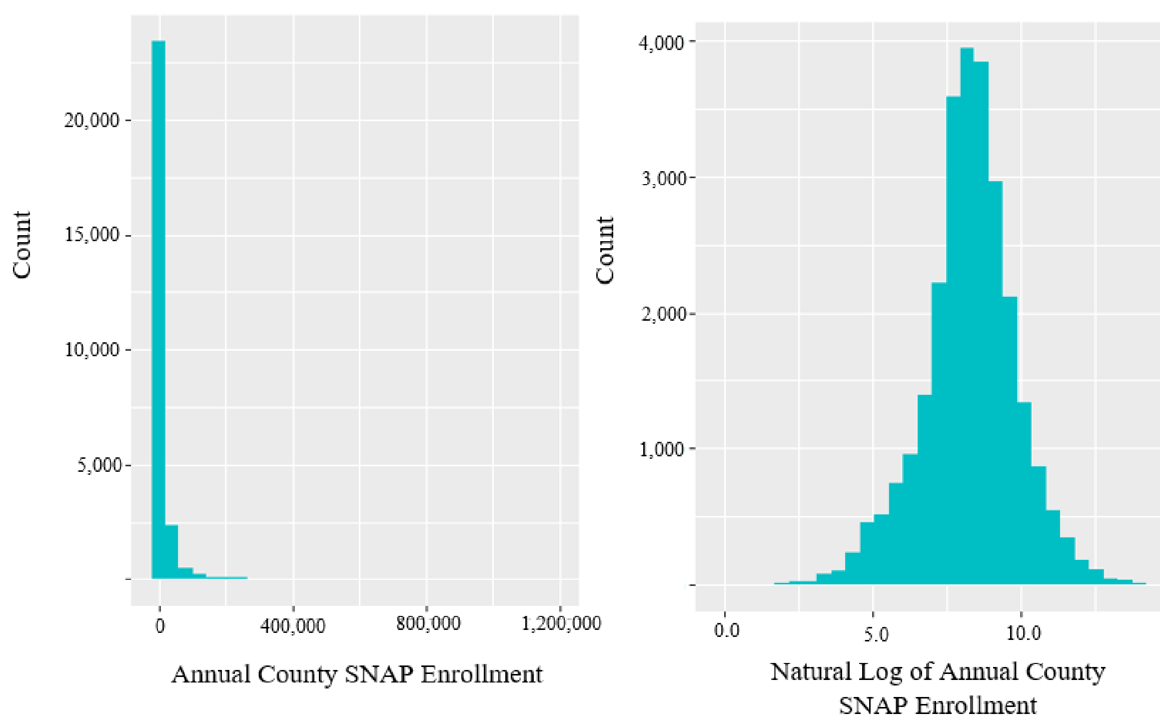

Figure 3: Distribution of Annual County SNAP Enrollment, Before and After Logarithmic Transformation

With each variable now in their proper functional form, I construct four empirical models to test my hypothesis. First, the econometric equation below is a simple multivariate regression incorporating each of aforementioned independent variables to predict the level of enrollment in SNAP:

$$\ln(\textit{snappersons})_t = \beta_0 + \beta_1 \textit{internetaccess}_t + \beta_2\, \textit{onlineapp}_t + \beta_3\, \textit{abawdwaived}_t + \beta_4\, \textit{bbce}_t + \beta_5\, \textit{callcenters}_t + \beta_6 \ln(\textit{outreach})_t + \beta_7\, \textit{reportsimple}_t + \beta_8\, \textit{transben}_t + \beta_9\, \textit{vehicleexempt}_t + \beta_{10} \ln(\textit{population})_t + \beta_{11}\, \textit{pctelderly}_t + \beta_{12}\, \textit{pctwhite}_t + \beta_{13}\, \textit{pctmale}_t + \beta_{14}\, \textit{pcthispanic}_t + \beta_{15}\, \textit{hsplus}_t + \beta_{16}\, \textit{collegeplus}_t + \beta_{17}\, \textit{unemployment}_t + \beta_{18}\, \textit{income}_t + \beta_{19}\, \textit{povpct}_t + \varepsilon_t + \delta_t \quad (2)$$

Where ε_t indicates the error term and δ_t represents the total of the time-variant effects, accounted for by controlling for each year. This term can be written out as follows:

$$\delta_t = \delta_0 + \delta_1\, \textit{YR2008} + \delta_2\, \textit{YR2009} + \delta_3\, \textit{YR2010} + \delta_4\, \textit{YR2011} + \delta_5\, \textit{YR2012} + \delta_6\, \textit{YR2013} + \delta_7\, \textit{YR2014} + \delta_8\, \textit{YR2015} + \delta_9\, \textit{YR2016} \quad (3)$$

The coefficient β_1 on the variable *internetaccess* allows me to find the estimated percent difference in SNAP enrollment in counties with medium and high internet access vs those with low internet access in a given year. Since the dependent variable has been logarithmically transformed, interpreting the coefficients on variables that have not also been transformed requires the use of the following equation:

$$\%\Delta\, \textit{SNAPpersons} = 100 * (e^{\beta x} - 1) \quad (4)$$

Given my hypothesis and explanation under the theoretical model, I expect β_1 in equation (2) to be positive. β_2 indicates the estimated relationship between offering online applications and SNAP enrollment. I expect this to be positive as well, as access to online applications will make it easier for many to take advantage of the government service – increasing the take-up rate and subsequently the total enrollee population.

The variables with coefficients β_3 through β_9 account for policy choices in administering SNAP, outside of offering online applications – for instance, receiving a waiver from the work requirements for ABAWDs, utilizing BBCE, and providing transition benefits for TANF recipients. Demographic characteristics of population, education, age, race, gender, and ethnicity are accounted for in the variables with coefficients β_{10} through β_{16}. Finally, the variables with coefficients β_{17} through β_{19} take into consideration time-varying macroeconomic factors – namely poverty, unemployment, and income.

While this model incorporates the multiple control variables I have outlined, it does not include an interaction term between *internetaccess* and *onlineapp*. Including this term allows me to measure the difference in the relationship between SNAP enrollment and internet access in areas with online applications vs areas without. It also measures the difference in the relationship between SNAP enrollment and online applications in areas with low internet access vs areas with high access. To accomplish this, I add the interaction term *internetaccess*onlineapp* to the previous model:

$$\begin{aligned}
&\ln(snappersons)_t = \beta_0 + \beta_1 internetaccess_t + \beta_2\, onlineapp_t + \\
&\beta_3\, internetaccess_t * onlineapp_t + \beta_4\, abawdwaived_t + \beta_5\, bbce_t + \beta_6\, callcenters_t + \\
&\beta_7 \ln(outreach)_t + \beta_8\, reportsimple_t + \beta_9\, transben_t + \beta_{10}\, vehicleexempt_t + \\
&\beta_{11} \ln(population)_t + \beta_{12}\, pctelderly_t + \beta_{13}\, pctwhite_t + \beta_{14}\, pctmale_t + \beta_{15}\, pcthispanic_t + \\
&\beta_{16}\, hsplus_t + \beta_{17}\, collegeplus_t + \beta_{18}\, unemployment_t + \beta_{19}\, income_t + \beta_{20}\, povpct_t + \\
&\delta_t + \varepsilon \qquad (5)
\end{aligned}$$

The interpretation for each variable's coefficient remains the same as they were for equation (2), except for the coefficients on *internetaccess* and *onlineapp*. The coefficient β_1 on the variable *internetaccess* now allows me to find the estimated relationship between SNAP enrollment and internet access, but only in areas that do not have access to online applications. I expect β_1 to be positive but closer to 0 than it was in the previous model, since without online applications, the benefits of improved internet access are more limited. However, I still expect it to be slightly positive due to the improved ability to discover eligibility requirements and application procedures thanks to greater internet access. The coefficient β_2 in the model now measures the relationship between offering online applications and SNAP enrollment, but only in areas with low internet access. I expect this relationship to again be slightly positive but near 0, since counties with the lowest levels of internet access are also the least able to take advantage of online applications for SNAP.

β_3, the coefficient on the interaction term between internet access and online applications, indicates the difference in the relationship between SNAP enrollment and high internet access in states that offer online applications versus those in states that do not. The interaction can also be interpreted as measuring the difference in the relationship between SNAP enrollment and offering online applications in areas with low internet access vs areas with medium to high access. According to my hypothesis, I expect this coefficient to be positive. This would indicate that increased internet access is associated with a greater increase in SNAP enrollment in areas with online applications than areas without. It would also indicate that offering online applications is associated with a greater increase in SNAP enrollment in areas with high levels of internet access than areas with low levels.

My use of panel data also allows me to utilize fixed effects regressions. My final regression models, based on the models outlined by equations (2) and (5), hold constant all time-invariant individual effects that could potentially be biasing the results of the regression. The equation below builds on (2), with no interaction term between internet access and online applications:

$$\ln(\textit{snappersons})_{it} = \beta_0 + \beta_1 \textit{internetaccess}_{it} + \beta_2\, \textit{onlineapp}_{it} + \beta_3\, \textit{abawdwaived}_{it} + \beta_4\, \textit{bbce}_{it} + \beta_5\, \textit{callcenters}_{it} + \beta_6 \ln(\textit{outreach})_{it} + \beta_7\, \textit{reportsimple}_{it} + \beta_8\, \textit{transben}_{it} +$$

$$\beta_9\ vehicleexempt_{it} + \beta_{10} \ln(population)_{it} + + \beta_{11}\ pctelderly_{it} + \beta_{12}\ pctwhite_{it} + \beta_{13}\ pctmale_{it} + \beta_{14}\ pcthispanic_{it} + \beta_{15}\ income_{it} + \beta_{16}\ povpct_{it} + \beta_{17}\ unemployment_{it} + \beta_{18}\ hsplus_{it} + \beta_{19}\ collegeplus_{it} + \alpha_i + \delta_t + \varepsilon \qquad (6)$$

In this case, α_i represents individual effects that are fixed over time, which can be written out as:

$$\alpha_i = \alpha_0 + \alpha_1\ County1 + \alpha_2\ County2 + \ldots + \alpha_N\ CountyN \qquad (7)$$

Where i= 0, 1, … N indicates the number of counties included in the regression for a given year – roughly equal to 2,400, with some variance by year.

Interpreting the coefficients in equation (6) is similar to as it was for equation (2) – except now they are measuring the *change* in SNAP enrollment in a given county and year, not its absolute level. The final econometric model – a fixed effects regression with an interaction term between *internetaccess* and *onlineapp* – can be seen below:

$$\ln(snappersons)_{it} = \beta_0 + \beta_1 internetaccess_{it} + \beta_2\ onlineapp_{it} + \beta_3\ internetaccess_{it}{*}onlineapp_{it} + \beta_4\ abawdwaived_{it} + \beta_5\ bbce_{it} + \beta_6\ callcenters_{it} + \beta_7 \ln(outreach)_{it} + \beta_8\ reportsimple_{it} + \beta_9\ transben_{it} + \beta_{10}\ vehicleexempt_{it} + \beta_{11} \ln(population)_{it} + + \beta_{12}\ pctelderly_{it} + \beta_{13}\ pctwhite_{it} + \beta_{14}\ pctmale_{it} + \beta_{15}\ pcthispanic_{it} + \beta_{16}\ income_{it} + \beta_{17}\ povpct_{it} + \beta_{18}\ unemployment_{it} + \beta_{19}\ hsplus_{it} + \beta_{20}\ collegeplus_{it} + \alpha_i + \delta_t + \varepsilon \qquad (8)$$

Again, coefficient interpretation is similar to equation (5), but now measuring the change in SNAP enrollment and not absolute levels. This will be the primary model of interest for my analysis. The use of a fixed effects regression allows it to automatically account for every aspect of a county that does not vary over time, while the interaction term allows it to fully measure the relationship between internet access, online applications, and SNAP enrollment.

VI. FINDINGS AND ANALYSIS

As described in Section V, I tested four statistical models to measure the relationship between internet access, online applications, and SNAP enrollment. First, I tested a simple multivariate regression without fixed effects and without an interaction term between *internetaccess* and *onlineapp* (Model 1). Next, I ran a simple multivariate regression with no fixed effects but including an interaction term between the variables of interest (Model 2). Third, I tested a fixed effects model with no interaction term (Model 3). Finally, I estimated the primary model of interest: a fixed effects regression that includes an interaction term between internet access and the availability of online applications (Model 4). Table 2 below shows the results of these regressions:

Table 2: Regression Results

`	Dependent Variable: Natural Log of SNAP Enrollment			
	Model 1 (No Fixed Effects, No Interaction)	**Model 2** (No Fixed Effects, Interaction)	**Model 3** (Fixed Effects, No Interaction)	**Model 4** (Fixed Effects and Interaction)
internetaccess	-0.029*** (-3.10)	-0.042** (-2.52)	-0.041*** (-4.72)	-0.095*** (-5.42)
onlineapp	-0.013 (-1.39)	-0.026 (-1.44)	-0.051** (-2.29)	-0.107*** (-4.06)
internetaccess * onlineapp		0.017 (0.91)		0.072*** (3.77)
abawdwaived	0.051*** (5.72)	0.051*** (5.70)	0.063** (2.30)	0.065** (2.44)
bbce	-0.020*** (-2.80)	-0.020*** (-2.73)	0.046 (1.55)	0.051* (1.79)
callcenters	0.093*** (10.47)	0.093*** (10.48)	0.063 (1.67)	0.064* (1.72)
ln(outreach)	-0.010*** (-4.88)	-0.010*** (-4.87)	0.00007 (0.01)	0.0014 (0.25)
reportsimple	0.188*** (5.18)	0.187*** (5.14)	0.124*** (5.15)	0.126*** (5.41)
transben	0.074*** (9.07)	0.074*** (9.03)	0.139*** (3.66)	0.137*** (3.65)
vehicleexemption	-0.020*** (-3.27)	-0.020*** (-3.27)	0.068** (2.33)	0.064** (2.27)
ln(population)	1.096*** (299.56)	1.096*** (299.41)	0.243 (0.91)	0.198 (0.75)
pctelderly	-0.0007 (-0.89)	-0.0007 (-0.90)	0.011 (1.22)	0.011 (1.19)
pctwhite	-0.0008*** (-3.21)	-0.0008*** (-3.19)	-0.023*** (-3.04)	-0.022*** (-1.77)
pctmale	-0.050*** (-38.09)	-0.050*** (-38.15)	-0.023* (-1.85)	-0.022* (-1.77)
pcthispanic	0.0005* (1.75)	0.0005* (1.71)	0.011 (0.67)	0.010 (0.65)
ln(income)	-0.028 (-1.31)	-0.028 (-1.31)	-0.296*** (-3.54)	-0.296*** (-3.48)
povpct	0.047*** (49.32)	0.047*** (49.29)	0.008*** (3.74)	0.008*** (3.81)
unemployment	0.024*** (12.27)	0.024*** (12.32)	0.003 (0.77)	0.004 (0.99)
highschoolgrad	0.0004 (0.41)	0.0004 (0.39)	-0.003* (-2.03)	-0.003* (-1.89)
collegegradplus	-0.022*** (-33.79)	-0.022*** (-33.83)	0.009** (3.43)	0.009*** (3.41)
Intercept	-0.012*** (-4.65)	-0.012*** (-4.59)	0.011*** (5.03)	0.011*** (5.13)
Number of Observations	11,627	11,627	11,627	11,627
F-Statistic	11959.23***	11514.04***		
Adjusted R-Squared	0.963	0.963	0.600	0.545

* Significant at the 90% level of confidence; ** 95% level of confidence; *** 99% level of confidence.
Coefficients on variables for each year not included.

It is first worth noting the overall similarities in the coefficients on the variables of interest between the models that do not include fixed effects (Models 1 & 2) and those that do (Models 3 & 4). In all four, both higher internet access and access to online applications correspond with lower SNAP enrollment. However, as I will discuss, the coefficients' level and statistical significance differ between the models.

The results from Model 2 indicate that higher access to fixed internet connections in states without online applications is associated with roughly 4.11% lower SNAP enrollment than in low-internet counties without online applications, holding constant the other control variables. This relationship is statistically significant at the 95% level. The coefficient on *onlineapp* indicates that SNAP enrollment is roughly 2.57% lower in low-internet counties with online applications than in low-internet counties without online applications. However, this relationship is not statistically significant. Additionally, Model 2 indicates that the interaction term between *internetaccess* and *onlineapp* may not be necessary, as the coefficient is not statistically significant either.

The most likely reason for the discrepancy between the regressions without fixed effects (Models 1 & 2) and the regressions with (Models 3 & 4) is the existence of certain omitted variables that correlate with both internet access/access to online applications and per capita SNAP enrollment, but that are roughly fixed over time in each county. The omission of these variables causes the regression to be biased – affecting the values and statistical significance of the coefficients on the variables included in the regression. However, since these variables are fixed over time, they are controlled for in the fixed effects regressions (Models 3 & 4). Because of this likely issue of omitted variable bias in the non-fixed effects regressions, the results of

Models 1 & 2 should be mostly ignored, except as a point of comparison for the more robust regressions.

Turning to the results of Model 3 & 4, we can see that the inclusion of the interaction term between internet access and online applications is necessary to fully understand their relationships with per capita SNAP enrollment. The coefficient on the interaction term *internetaccess*onlineapp* is statistically significant – meaning that the relationship between internet access and per capita SNAP enrollment differs in states that offer online applications vs those that do not. Similarly, the relationship between offering online applications and per capita SNAP enrollment differs in counties with low internet access vs those with high internet access. Because of this, I use the results of Model 4 – the regression including fixed effects and the interaction term – to draw my conclusions.

A. Internet Access and SNAP Enrollment

In Model 4, the coefficients on *internetaccess*, *onlineapp*, and their interaction term are all statistically significant at the 99% confidence level. Specifically, the model indicates that in areas without online applications, having high internet access is associated with an approximately 9.06% lower SNAP enrollment than having low internet access. In areas *with* online applications, having high internet access is associated with an expected SNAP enrollment that is approximately 2.31% lower. The visualization below shows the difference in the marginal effects of having high internet connectivity on SNAP enrollment in areas without online SNAP applications vs those with online applications:

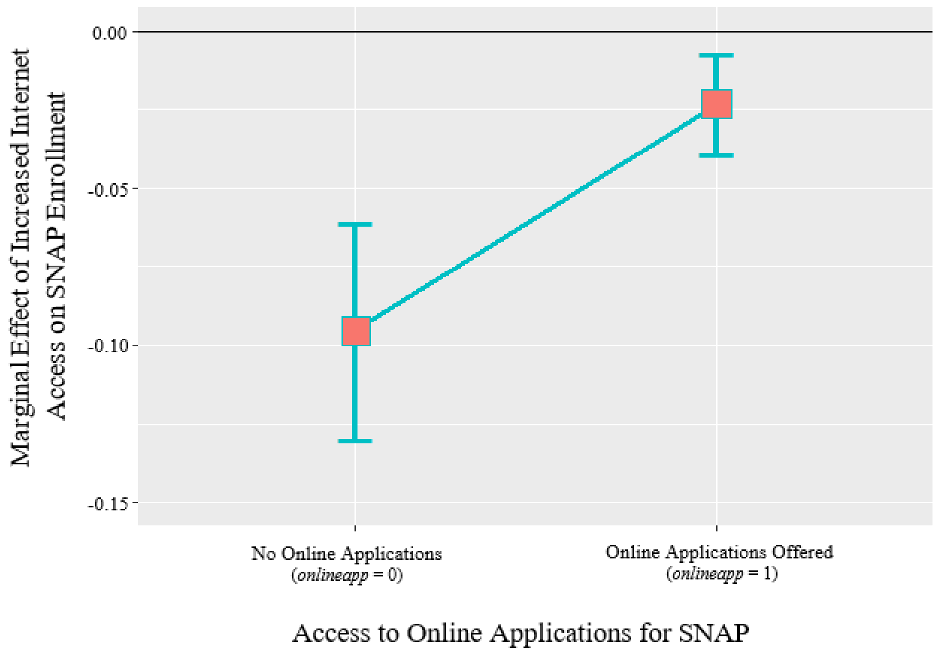

Figure 4: Average Marginal Effect of Greater Internet Access, Online Applications vs No Online Applications, with 95% Confidence Intervals

On the left are areas without online applications, while the right are areas with online applications. The bars for each point show the 95% confidence range.

A negative measured relationship between increased internet access and SNAP enrollment (other variables held constant) is unexpected. My hypothesis was that increased internet access would lead to increased SNAP enrollment, and that this would be higher in areas with access to online applications. Internet connectivity allows communities and households to better access and understand the eligibility requirements and application process to obtain SNAP benefits, while online applications allow individuals to directly use internet connectivity to enroll. The expected relationship between internet access and SNAP enrollment would then be positive after controlling for all other relevant factors like education, wages, and unemployment.

It is likely that this unexpected negative relationship is due to omitted variable bias. Even with the use of a fixed effects regressions and including multiple control variables in the regression, there are likely some other factors that are related to both internet access and SNAP enrollment the exclusion of which is biasing the results of the regression. For instance, high internet access could make it easier for individuals in need to access private charities like food banks, making it less likely that they would bother going through the necessary hurdles to enroll in SNAP. Excluding this factor and others like it could then downwardly biases the model and create the negative relationship measured in the models.

B. ONLINE APPLICATIONS AND SNAP ENROLLMENT

The coefficient of -0.107 on *onlineapp* in Model 4 indicates that the availability of online applications is associated with a roughly 10.11% decrease in SNAP enrollment in counties with low internet access. Additionally, there is no statistically significant relationship with between online applications and SNAP enrollment in areas with high internet access. This is once again visualized below:

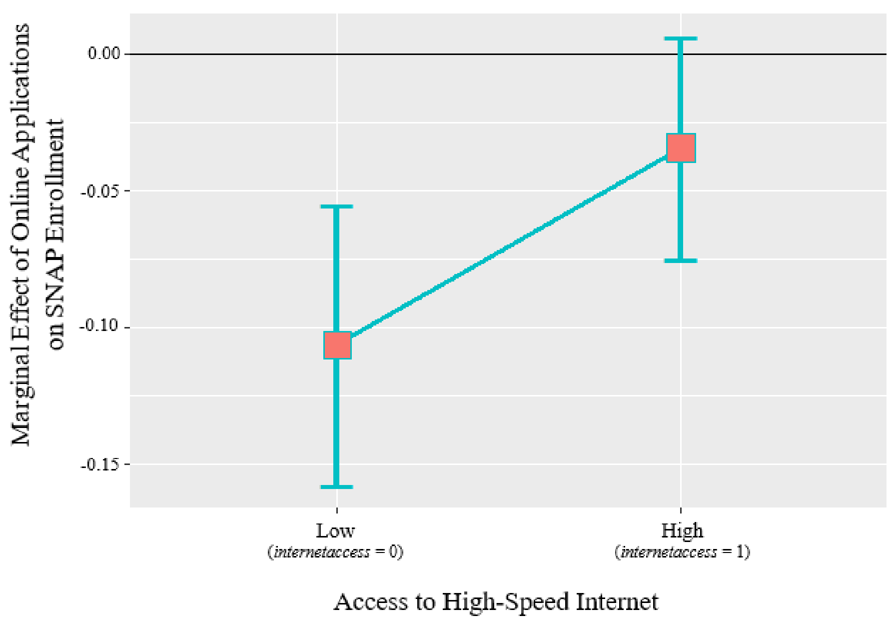

Figure 5: Average Marginal Effect of Online Applications, Low vs High Internet Access, with 95% Confidence Intervals

This negative relationship between online applications and SNAP enrollment is also unexpected. My hypothesis was that counties with access to online applications would have higher SNAP enrollment, holding other variables constant, since offering more ways to enroll for the program would ostensibly correspond with more enrollment. The results of Model 4 show that this is not the case. However, there is a logical explanation backed by previous literature that can account for this phenomenon.

While some past research has found a positive relationship between online applications and SNAP enrollment – for instance Schwabish (2012) and Mabli (2015) – others found no measurable relationship at all (Ziliak, 2013) (Ganong & Liebman, 2013). Some even suggested that the introduction of online applications results in decreased SNAP enrollment, as is found in my results (Heflin et al, 2013) (Leininger, 2011).

When a state introduces online application systems, they must either increase funding to fully implement the e-government program, or reallocate civil servants otherwise handling physical casework or aiding in other capacities – for instance staffing call centers. As Heflin et al (2013) found, some states like Florida will introduce online applications specifically as a cost saving measure, “allowing” them to cut staff in these other arenas while relying on the automatic processes afforded by e-government programs. While e-government initiatives do generally present a promising opportunity for governments to promote efficiency, it is worth remembering that not everyone can equally access and utilize e-government programs like online applications. Geography, age, native language, and disability status can all significantly affect one’s ability to use the internet fully (Yun, 2010). Other factors like difficulties providing and verifying documentation can also lead to poor outcomes, even among those who might otherwise be able to access online applications.

My results suggest that this line of reasoning is supported in the data. As seen in Model 3, counties with access to online applications have on average 4.97% lower SNAP enrollment than areas without access to online applications, holding the other variables constant. When you take into consideration that county's access to the internet, the consequences of the Digital Divide become clear. Offering online applications has no measurable effect on SNAP enrollment in counties with higher internet access. But in those with lower internet connectivity – in the counties that are less able to take advantage of e-government and rely more intensely on call centers and physical caseworkers – offering online applications reduces SNAP enrollment by more than 10%.

C. Other State Policies, Demographics, and Economic Factors

The findings from Model 4 also show statistically significant relationships between certain state policies and SNAP enrollment. Counties with active waivers from the federal work requirements for Able-Bodied Adults Without Dependents have 6.74% higher SNAP enrollment than counties without such waivers, while counties in states which exempt vehicles from the asset test for SNAP eligibility have 6.64% more SNAP enrollees than those that do not, holding other variables constant. Both relationships are statistically significant at the 95% confidence level. The strongest changes to SNAP enrollment due to state policies are simplified reporting (*reportsimple*) and transitional benefits for those leaving TANF (*transben*). These factors are associated with a 13.41% and 14.64% increase in total SNAP enrollment respectively, holding constant the other variables, and are statistically significant at the 99% confidence level. Finally, using Broad-Based Categorical Eligibility is associated with 5.26% more SNAP enrollees, while operating call centers corresponds to a 6.57% increase, other variables held constant; both relationships are statistically significant at the 90% confidence level. The only state policy choice included in the regression that did not have a measurable relationship with SNAP enrollment was state spending on outreach.

In addition to these state policies, certain demographic characteristics had statistically significant relationships with SNAP enrollment in Model 4. Specifically, the coefficient on *pctmale* indicates that a 1-percentage-point increase in the portion of the population that is male is associated with a 2.17% decrease in the number of SNAP enrollees (statistically significant at the 90% confidence level), while the coefficient on *pctwhite* shows that a 1-percentage-point increase in the portion of the population that is white is associated with a 2.15% decrease in SNAP enrollment (statistically significant at the 99% confidence level), controlling for the other variables.

The model also indicates that educational attainment has a measurable relationship with SNAP enrollment. A 1-point increase in the percentage of the population that has at least a high school degree is associated with 0.28% decrease in the number of enrollees (statistically significant at the 90% confidence level), while a 1-point increase in the percentage of the population with at least a college degree is associated with a 0.91% increase in SNAP enrollment.[4] A 1% increase in a county's median income is associated with a 0.30% decrease in SNAP enrollment, while a 1-point increase in a county's poverty percentage is associated with a 0.81% increase in SNAP enrollment, holding constant the other variables in the regression.

[4] With many of these variables – especially related to educational attainment, income, and poverty percentage – the reported relationships should not be taken at face value, as many of these variables have extremely high collinearity and interdependency. For instance, the percent of the population with more than a high school degree inherently includes the percent of the population with at least a college degree. Similarly, family income is one of the components used by the Census Bureau to generate their data on poverty percentage. This collinearity is acceptable for my purposes since these variables are solely being used to account for potential omitted variable bias, and their reported relationships are not being used for any policy recommendations.

VII. Limitations and Sensitivity Testing

As with any quantitative analysis, certain factors likely limit the internal and external validity of my results. First, the data that I used for my analysis are not perfect, and their construction and accuracy are worth discussing here. These issues generally arise from my use of annual county-level observations. Most sources of data, such as the U.S. Census, either do not offer data on most variables at the county level, or only provide county-level data in three- or five-year estimates. Those that do offer data at this level often advise against their use in certain instances – I followed their guidance fully when constructing and testing my dataset. For example, the CDC recommends against using its Bridged-Race Population Estimates at the single-year-of-age level, wherein one would measure the total number of people in a county that are age 8, age 9, age 10, and so forth, each year. My analysis does not use this very granular age estimate, instead only using their estimate of the population size over 65.

Even when following proper data usage guidelines to the best of my ability, it is possible there are still some underlying data inaccuracies that I am not aware of. As an example, the Center on Budget and Policy Priorities' data on recipients of ABAWD waivers were essentially constructed in a black box, so the accuracy of this information is reliant on the dependability of their research. That being said, the CBPP disclosed some of their methodology, for instance explaining their procedures for cases where counties received a waiver for only part of the year. After reviewing their technical notes and comparing that with other potential sources of these data, I decided that this information was reliable enough for my purposes.

Additionally, these potential limitations only apply to variables used to control for potential Omitted Variable Bias, and their measured relationships with SNAP enrollment are not part of my central results or policy implications. While data provided by the USDA on SNAP enrollment and the FCC on internet access may not be perfect, they are trustworthy enough for my use. As always, more accurate and granular data would improve future research.

The internal validity of my study may also be harmed due to Omitted Variable Bias. I accounted for this as well as was possible through the use of a fixed effects regression that included likely confounding time-varying factors like income, poverty, unemployment, and education. However, as I explained in Section VI, the negative relationship measured between internet access and SNAP enrollment is most likely explained by the existence of other variables whose omission is biasing the results. Future research would benefit from more complete data to directly measure variables I could not, such as total SNAP eligibility, take-up rates, average unemployment duration, use of private food charities, and other potentially relevant factors.

Additionally, the internal validity of my study may be damaged by misspecification of the econometric model. I took several steps to mitigate this issue, for instance by logarithmically transforming certain variables that are heavily skewed. I also conducted limited subsample testing by evaluating the regression with additional interaction terms that are theoretically likely to be significant – for instance, online applications and the percent of the population that is elderly. None of these varieties produced interaction terms with statistically significant coefficients, implying that there is no difference in the measured relationship between the subgroups. I also ran a model specification link test for Model 2, the non-fixed effects regression with an interaction term between *internetaccess* and *onlineapp*, since these tests cannot be conducted on fixed effects regressions. The link test demonstrated model misspecification at the 99% confidence level, implying that further transformation of the independent variables would improve the validity of the results.

There are also factors that may limit the external validity of my analysis, making it potentially erroneous to apply the results of my study beyond the scope of the observations included in it. The most obvious threat to external validity is the limited availability of data on SNAP enrollment in certain states. As discussed in Section IV, 16 different states do not record SNAP enrollment data at the county level whatsoever. If there is some factor that makes a state less likely to report county SNAP data, then the observations included may not be a random sample, and the external validity is in question. One method to check for this issue is by calculating the difference in the average values of certain variables for observations which have SNAP data vs those that do not. If there is a significant difference between the two, it is possible that this sampling bias exists. The results of my simple difference of means t-test for eight different variables are shown below:

Table 3: Difference of Means T-Test for Select Variables, SNAP Data Reported vs No SNAP Data Reported

Variable	**Mean 1** (No SNAP Data)	**Mean 2** (SNAP Data Reported)	**Difference** (Mean 1 – Mean 2)	**S.E.** (of difference)
internetaccess	0.882	0.838	0.044***	0.005
transben	0.302	0.372	-0.07***	0.009
bbce	0.563	0.668	-0.105***	0.008
abawdwaived	0.701	0.685	0.0159**	0.006
income	36163.43	36337.91	-174.481	116.6207
pctwhite	92.137	84.733	7.404***	0.215
pctelderly	17.562	17.009	0.553***	0.060
cdplus	22.066	19.855	0.105***	0.008

* Significant at the 90% level of confidence; ** 95% level of confidence; *** 99% level of confidence
(H_0: Mean 1 = Mean 2)

This basic test indicates that counties which did not report SNAP data had higher average access to high-speed internet. They were also less likely to be in a state that offered Broad-Based Categorical Eligibility or transitional benefits for those on TANF, but were more likely to have a waiver from the work requirements for ABAWDs. The populations of these counties also tended to be more white, more elderly, and better educated. There is no statistically significant difference in average income for counties that had SNAP enrollment data versus those that do not.

However, it's important to note that this is a very basic test of external validity, and these differences do not necessarily mean that the relationships between the variables of interest and SNAP enrollment would be different from what my analysis found in these other areas. More research and improved data collection would be needed to have full understanding of the states not included in my analysis. Additionally, while multiple variables had statistically significant differences in means, the substantive difference should also be kept in mind. For instance, while areas without SNAP data had statistically higher average internet access, the difference is substantively relatively small. This can be seen in the figure below, using the full quintile data from the FCC:

Figure 6: Access to High Speed Internet, SNAP Enrollment Data Reported vs Not Reported

Compared with the severe difference in internet access between the years 2008 and 2016, this difference is much smaller. This is also mostly true with the policy choices I tested. Only the use of BBCE had an estimated difference in means greater than 10%; the other differences, while still statistically significant, were once again substantively small. This is shown below:

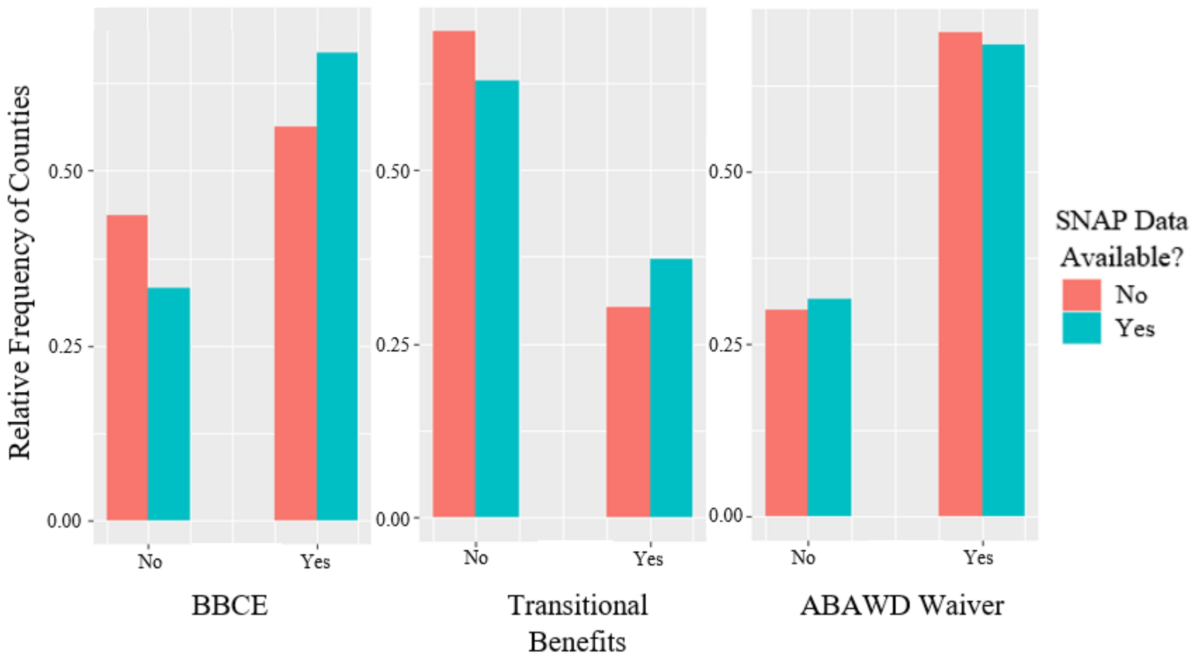

Figure 7: SNAP Policy Choices, SNAP Enrollment Data Reported vs Not Reported

As I have outlined in this section, there are serious factors that potentially limit the validity of my analysis. While I have done all that I can to address these limitations with the data available to me, the remaining issues of potential OVB, misspecification, and sampling bias should not be ignored when discussing my results. Future research should seek to improve on my work here through more accurate and granular data collection, the inclusion of other potentially relevant variables, and more robust econometric analysis.

VIII. Conclusion and Policy Implications

The purpose of this thesis was to analyze the relationship between internet access, online applications, and enrollment in the Supplemental Nutrition Assistance Program. Given the previous literature discussing the impact of the Digital Divide, I hypothesized that increased access to fixed internet connections would lead to increased enrollment in SNAP, holding constant other factors like unemployment, income, and education levels. This hypothesis was based on the assumption that improved internet connectivity would allow people to better access and understand the eligibility requirements and application processes to obtain SNAP benefits. I also predicted that the relationship between internet access and SNAP enrollment would be even higher in areas that have access to online applications for the program, since this form of e-government provides a direct route for obtaining SNAP benefits through the internet. I further hypothesized that offering online applications would lead to higher SNAP enrollment in areas with medium to high internet access – however, I predicted that online applications would have little to no affect on SNAP enrollment in areas with low internet connectivity.

The evidence suggests that increased access to the internet leads to decreased enrollment in SNAP, even after controlling for fixed effects and potentially confounding variables like unemployment, income, poverty rates, and other demographic factors. These results contradict my hypothesis. As I discussed previously, given the lack of support in existing literature for internet access itself causing this decline, the most likely explanation for this is the existence of an omitted variable that is biasing the results. Without any one obvious variable to account for this relationship, these results could be evidence of a more abstract "quality of life improvement" that arises through bridging the Digital Divide, which in turn makes individuals less reliant on SNAP. In other words, the decline in enrollment may not be a result of declining *access* to benefits for those who need them, but instead overall declining *need* of government support. While such an affect from improved internet access is supported in existing literature, further research should be done to identify any potential omitted variables that were excluded from my analysis.

While these specific results should be interpreted carefully, there are other substantive conclusions related to e-government and the Digital Divide that can be drawn from my analysis. First, my findings indicate that the relationship between internet access and SNAP enrollment is less negative in areas with access to online applications. This difference is consistent with my hypothesis that counties with high internet access and online applications will have higher SNAP enrollment than counties with high internet access and no online applications. This relationship implies that, while internet connectivity may on the whole reduce the need for government support, it also allows those in need to more easily access SNAP benefits through e-government programs like online applications. The increased SNAP take-up rate allowed by easy use of online applications helps offset some of the previously discussed decline in SNAP enrollment arising from improved internet access.

Perhaps most significantly, my analysis found that introducing online applications had no measurable effect on SNAP enrollment in areas with high internet access. However, in counties with low internet connectivity, access to online applications was associated with a more than 10% decline in total SNAP enrollment. These results, while not strictly aligned with my hypothesis, are consistent with existing literature. When states offer online applications, they often divert staff and resources away from call centers and physical casework centers (Heflin et al, 2013). Additionally, many can struggle to complete online applications due to age, disability, native language, or just the inherent difficulty involved in submitting forms online (Yun, 2010)

(Leininger et al, 2011). My analysis suggests that in areas with high internet access, these factors limit any potential growth in SNAP enrollment arising from individuals taking advantage of the new way to apply for benefits. However, areas with low internet access are fundamentally less able to utilize e-government services like online applications. That means they are left behind as states divert resources away from the call centers and casework offices they rely on. The SNAP take-up rate in these areas decline, and fewer Americans in need receive government support.

These findings imply that states which implement online applications must continue to support non-digital SNAP administrative work like operating call centers, offering in-person casework opportunities, and pursuing non-digital outreach in order to service those individuals lacking reliable internet connectivity. Without taking these steps, introducing online applications will overall harm those without access to the internet.

My findings also suggest that bridging the Digital Divide must remain an important focus for federal and state governments, and policymakers should further efforts to expand broadband infrastructure into currently under-connected areas. Federal broadband expansion programs – for instance through USDA Rural Development, the FCC, the Department of Housing and Urban Development, and the Department of Transportation – should continue to receive authorization and full appropriations from Congress, and greater effort should be made to leverage private sector investment to help in these endeavors. Improved internet connectivity will not just help make e-government services more effective, the evidence suggests it could also help improve the quality of life of thousands of Americans and reduce their need to apply for government welfare services in the first place.

One of the principal goals of implementing e-government programs is to improve the efficacy and efficiency of government services. While these are worthwhile goals, it is always important to remember that access to these resources is not equally distributed throughout our society. Without addressing the ongoing problem of the Digital Divide, we will leave hundreds of thousands of people in need behind as we transition to a more and more digitally-focused world.

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