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SNAP Efficacy and Food Access – A Nationwide Spatial Analysis

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SNAP Participation and Food Access – A Nationwide Spatial Analysis

Abstract

As the public expenditure for the Supplemental Nutrition Assistance Program (SNAP) - formerly the Food Stamp Program (FSP) - increases, improving the effectiveness of the policy becomes pivotal to limit further surges in public spending. Along with social stigma, transaction costs, associated in part to the accessibility and proximity to food outlets, are the main deterrent to program participation. This study presents an empirical assessment of the relationship between food access and FSP participation among eligible population. The analysis uses county-level data for the continental U.S., distinguished by different stores formats (grocery stores, convenience stores and a non-traditional, low-priced alternative, Wal-Mart Supercenters) accounting for the endogeneity of their location decision. To estimate the parameter of the model we use a relatively novel estimator: the spatial generalized two-stage least square (GS2SLS) estimator with heteroskedastic autoregressive disturbances of order (1, 1) or SARAR(1,1), developed by Kelejian and Prucha (2010). Empirical results show that, among eligible individuals, the presence of small convenience stores, large grocery stores, and Walmart supercenters entice participation in the food stamp program. In sum, increasing the number of stores for which commuting by car is not strictly necessary (convenience stores) or the proximity to stores with wider assortment of low-priced items may act as catalysts to ability to the policy ability to reach the underprivileged.

JEL codes: Q18, L81, C21

Keywords: Food Stamps, Food Access, Spatial modelling.

SNAP participation and Food Access – Evidence from the Northeast

1. Introduction

The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program (FSP) is the largest welfare program in the United States in both terms of number of recipients and expenditure: by December 2009 almost 39 million persons were using the program, for which over \$55.6 billion were spent in the same year (USDA, 2010). The scope of the program is ever growing: participation has increased by over 41 percent since the onset of the current recession in December 2007, and the latest proposed budget for SNAP is of \$72.5 billion (USDA, 2010). Figure 1 gives a representation of federal expenditures, number of participants, poverty rate and the share of population enrolled in the program over time. Clearly, the number of program participants varies along with poverty rates (and as Ziliak, Gunderson, and Figlio, (2003) have pointed out, unemployment rates), which follow countercyclical variations with the business cycles, and so does the percentage of the population benefiting from the program.

However, economic fluctuations are not the only factors impacting the performance of the FSP over time. Changes in policy affect heavily program participation: the gap between poverty rate and percentage of population participating in the program has widened in the late 1990's perhaps as consequence of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 which has changed the base of eligible individuals, barring new legal immigrants from federal funded assistant program for their first five years in the U.S. and placed a time limit on the length that eligible individuals can benefit from the policy (Ziliak, Gunderson, and Figlio; 2003). Late amendment to the policy revoked some of the restrictions to elderly and young legal immigrant, while changes that required the implementation of Electronic Benefit Transfer (EBT) mandatory by 2002 in all states facilitated redemption by reducing transaction costs.

In spite of the several changes that the program has gone through since the Food Stamps Act of 1964, the main goal of the policy - to help low-income individuals and families to buy the appropriate amount of food they need for good health - has remained the same. In order to achieve this goal, recipients must necessarily have access to food to satisfy their alimentary needs. The plethora of studies assessing the efficacy of the FSP has focused mostly on the endogenous determinants of household's decision of whether or not to join the program and to understand the outcomes to such decision. Existing research has addressed the impact of FSP on food expenditures (Wilde, Troy and Rogers; 2009), the recipients' quality of diet (Wilde, McNamara and Ranney; 1999), their level of food security (Gundersen and Oliveira, 2001; Jensen, 2002; Borjas, 2004; Wilde and Nord, 2005; Yen *et al.*, 2008), children's welfare (Joilliffe *et al.*; 2005) and obesity (Chen, Yen and Eastwood, 2005; Meyerhoffer and Plypchuck, 2008). Little research exists that focuses on understanding how the elements of the built environment (such as food access) may impact program participation. As food stores' availability is exogenous to low-income individuals (they have limited resources, and therefore limited mobility) the characteristics of the built environment surrounding them becomes a key factor for the success of the program.

As a first step to understand the interaction of food access and the outcome of the FSP/SNAP policy, one should determine whether or not eligible individuals' participation choice is impacted by food access. As one of the deterrents to program participation is the existence of transaction costs, which is in part function of the distance to food outlets (Moffit, 1983; Gundersen and Oliveira, 2001), one should investigate how the presence (and type) of food stores impacts such transaction costs. Reduced food access is a key determinants of the lack of availability of healthy foods for SNAP recipients (Kaiser, 2008), as there is a positive relationship between the quality of the food choices that FSP recipient households make and the access to food outlets (Rose and Richards, 2004). King *et al.* (2004) find also that low-income areas, where the number of SNAP recipients is larger, tend to have less food access,

characterized not only by fewer food stores but also by stores offering lower quality. Feather (2003) finds strong evidence of welfare gains from food stamps' recipients having access to larger selections of food products, which is equivalent to upgrading from small grocery stores of the type found in many low-income neighborhoods to larger food stores and supermarkets.

However, consumers' characteristics and market structure contribute to the determination of retailers' location and store format: empirical evidence shows that areas with a prevalence of less-privileged individuals are characterized by limited access to large (or "high quality") food stores (see for example Alwitt and Donley, 1997; Ball *et al.*, 2008; Cotterill and Franklin, 1995; Moore and Diez Roux, 2006; Morland *et al.*, 2002; Powell *et al.*, 2007; Zenk *et al.*, 2005). In fact food retailers position themselves *endogenously* into a low quality fringe of grocery stores serving consumers who do not (or simply cannot, due to income constraint) pay for quality, and a natural oligopoly of high quality supermarkets (Ellickson, 2006), offering higher prices and a higher level of services (Bonanno and Lopez, 2009). Some of the recent structural changes in the food retailing industry driven by the expansion of non-traditional food retailers (Martinez, 2007), led by Walmart's Supercenters format,¹ may be beneficial for low-income households for three reasons: 1) since Wal-Mart locates its stores preferentially in areas where competition is scant (Jia, 2008; Bonanno, 2010), its expansion could improve food access for low-income households; 2) the company has been found to increase consumers' surplus by offering lower prices and greater product variety (Hausman and Leibtag, 2007) providing relief to low-income individuals giving access to fresh produce at lower prices (Volpe and Lavoie 2008, Basker and Noel, 2009); and 3) the rate of conversion of Discount Stores into Supercenters (representing the main strategy

¹ The company has moved away from its Discount Stores format (carrying a limited number of food products, mostly shelf-stable) to the Supercenter format, which offers fresh produce, meat, bakery, deli and fresh seafood departments, becoming the larger food retailer in the U.S. (Food Marketing Institute, 2007). As of July 31 2008, Wal-Mart operated (in the U.S. alone) 2,572 Supercenters and 915 Discount Stores (Wal-Mart Stores Inc, 2008).

followed by the company to expand into food retailing) is positively related with higher percentages of population being food stamp recipients (Bonanno, 2010).

The thrust of this paper is to present an empirical assessment of the relationship between food access and FSP participation decision among the eligible population, using a panel data of county-level observations for all the continental United States, accounting for different stores formats (grocery stores and convenient stores, divided by establishment size, and a non-traditional, low-priced alternative, Wal-Mart Supercenters) and the endogeneity of food retailers' location decision.

Empirical results show that, among eligible individuals, the presence of small convenience stores, large grocery stores, and Walmart supercenters can act as catalysts of the participation in the food stamp program. The result point out that among stores that offer limited assortment and higher prices (convenience stores) location and accessibility plays an important role, as small stores are preferred to larger ones, perhaps associated with gas stations and being reachable by car. Furthermore increasing the proximity to large stores with wider assortment of low-priced items (in particular Walmart supercenters) may improve to ability to the policy ability to reach the underprivileged, as the benefits of enrolling the program could be larger.

2. The Model

The methodological underpinning of the model draws extensively from the existing literature explaining participation in the FSP. Eligible households decide whether or not to join the program if the (indirect) utility gained from program participation is larger than the utility from non-participating (see for example Moffitt, 1983; Fraker and Moffitt, 1988; Keane and Moffitt, 1998; Jensen, 2002; Ziliak, Gundersen and Figlio, 2003). One common key feature of these models is that the difference between the utility of participating and that of non-participating (or the disutility of program participation) is function of: 1) the negative

feelings that participants associate with other people disapproval and the aversion to receiving public assistance, or *stigma* (Moffitt, 1983); and 2) *transaction costs*, which are impacted by the distance to food outlets and time spent collecting and filing the paperwork necessary to enroll the program, or to recertify eligibility (Gundersen and Oliveira, 2001). One standard assumption of these models is that preferences are additively separable in the utility from consumption and participation disutility. This allows food access to enter linearly the FSP participation decision as it is hypothesized that food access will reduce the transaction cost component of the disutility in joining the program.

Following Moffitt's (1983) model, the utility that the maximization problem of household i located in area j leads to the following inequality, representing participation decision:

$$U_{ij}(Y_{ij} + B_j) - U_{ij}(Y_{ij}) > \phi_{ij} \quad (1)$$

where Y_{ij} is private income source, B_j is the level of benefit from the food stamps program and ϕ_{ij} is the "cost", or disutility of accessing food stamps. One can rewrite (1) as:

$$U_{ij}(Y_{ij} + B_j) - TC(S_j) - \xi_j > U_{ij}(Y_{ij}) \quad (1-a)$$

where the disutility term ϕ_{ij} can be decomposed in transaction costs $TC(S_j)$ and an unobservable component of social stigma ξ_j assumed to be distributed normally with mean 0. S_j are structural county-level characteristics and other variables related with the policy regimes which could impact transaction costs.

One can introduce consumers' heterogeneity in the model in the form of an idiosyncratic random term e_{ij} , assumed to be i.i.d extreme value.² Furthermore, one can assume that, besides household income Y_{ij} , the indirect utility that household i receives by

² This is a necessary assumption for the share functions to take the form as in equation (4). That said, preferences need not to be the same across consumers that live in the same county. One can specify a more complex form of consumer heterogeneity as in Berry (1994), for which individual-specific variables need to be used in the estimation of the model.

participating in the program (U_{ij}^P) and that of non-participating (U_{ij}^{NP}) are the same across eligible individuals in the same county:

$$U_{ij}^P = Y_{ij} + B_j - TC(S_j) + \xi_j + e_{ij} \quad (2-a)$$

$$U_{ij}^{NP} = Y_{ij} + e_{ij}. \quad (2-b)$$

Let the portion of utility common to all households in county j joining the program be $\delta_p = B_j - TC_j + \xi_j$ and let $\delta_{NP} = 0$ be the normalized utility of not joining the program. The utility to the net of private income is:

$$U_{ij}^P - Y_{ij} = B_j - TC(S_j) + \xi_j + e_{ij} = \delta_p + e_{ij} \quad (3-a)$$

$$U_{ij}^{NP} - Y_{ij} = \delta_{NP} + e_{ij} \quad (3-b)$$

Following Berry's (1994) discrete choice models of product differentiation one can define the following "share functions" which represent an expression of the (aggregate) likelihood for an eligible individual to either not participate (\widetilde{s}_{NP}) or to participate (\widetilde{s}_p) in the program.

$$\widetilde{s}_{NP} = \frac{\exp(\delta_{NP})}{\exp(\delta_{NP}) + \exp(\delta_p)}; \text{ and } \widetilde{s}_p = \frac{\exp(\delta_p)}{\exp(\delta_{NP}) + \exp(\delta_p)}; \quad (4)$$

which, under the assumption above gives

$$\ln(s_p) - \ln(s_{NP}) = B_j - TC(S_j) + \xi_j \quad (5)$$

Note that no functional form has been specified for B_j and $TC(S_j)$. For simplicity, the benefit function is assumed to be a linear function of local economic characteristics and other county-specific factors (L). Transaction costs can also be function of some of the same demographic characteristics, as well as ease to access food (or food access, FA), state-level specific differences ($State$) in policy adoption.³ The econometric model to be estimated is:

³ Several papers have investigated related issues; see for example, Borjas (2004) illustration of the different state-level food stamps offerings to non-eligible immigrant that followed the adoption of PROWRA.

$$\ln(s_p) - \ln(s_{NP}) = L_j\alpha + FA_j\beta + State_j\gamma + \xi_j \quad (6)$$

where α , β , and γ are vectors of parameters to be estimated. Note that since L_j and FA_j may affect both transaction costs and benefits⁴ there is no means to understand what the source of their actual impact on the LHS is (benefits, transaction costs or both). It follows that the coefficients in (6) are not directly related with the specification of the utility in (1) and therefore their magnitude is not directly interpretable. However, one can quantify the effect of food access (or the other variables in L) on the likelihood of joining the program, by calculating the following marginal effect:

$$\frac{\partial s_p}{\partial FA_j} = \beta s_p (1 - s_p).^5 \quad (7)$$

It should be mentioned that the model illustrated above relies on the assumption that the variables entering B , and TC are not correlated with the error term, which is the unobservable component of stigma. As Moffitts (1983) points out this is unlikely to hold for a series of different reasons. In the first place, stigma is likely to be impacted by households' characteristics. Secondly, unemployment (or labor participation) is likely to be correlated with income or other variables; other works have dealt with this issue by either estimating jointly FSP and labor force participation decisions (Hangstrom, 1996) or using instead an instrumental variable approach (Goetz, Rupasingha and Zimmerman, 2004). Third, the level of FSP benefits are determined by labor participation which is also correlated with demographics, and therefore with stigma (Borjas and Hilton, 1996; Borjas, 2002; Bollinger and Hagstrom, 2008). Fourth, some characteristics, such as age, education, labor market conditions have both an impact on income and therefore eligibility, which do not enter the

⁴ For example, as the presence of Walmart supercenters has been found to significantly lower food prices (Volpe and Lavoie 2008, Basker and Noel, 2009), it is conceivable to hypothesize that FSP participants patrons in these stores may be able to buy more food with the same amount of subsidy which may increase the benefit coming from joining the program.

⁵ Equation (7) comes directly from the expression of elasticity for the multinomial logit or:

$$\frac{\partial \ln(s_p)}{\partial \ln(FA_j)} = \frac{\partial s_p}{\partial FA_j} \frac{FA_j}{s_p} = FA_j \beta (1 - s_p).$$

model directly and could be embodied in the error term, causing further problems of endogeneity. For the purpose of this paper we are going to neglect these potential problems and focus on others which are directly related with the issue in analysis.

Food retailers' location and store format decisions are function of supply (competition, business-friendly environments, existence of infrastructures etc...) and demand factors (population characteristics, market growth potential etc...) the latter being likely to be correlated with the error terms of the food stamps participation equation. Following some of the previous literature on entry in the retailing industry (Cotterill and Haller, 1992; Jia, 2008; Bonanno, 2010) first-stage equations based upon reduced-form expected profit equation can be used to capture the entry decision of food retailers. This analysis will construct instruments for the number of food retailers in the market by isolating the supply-side determinants of firms' location decision. The details of the identification strategy are discussed below.

3. Data and identification strategy

The data used in the analysis are county-level annual observations encompassing all the continental United States, obtained from publicly available sources. Data on the number of food stamps recipients and poverty rates come from the Small Area Income and Poverty Estimates (SAIPE) of the U.S. Bureau of Census which will be used to obtain the log odds of program participation (*i.e.* the dependent variable in equation(6)). Since eligible population is not recorded, the participation share will be calculated by dividing the number of food stamps recipients by the number of people living below the poverty line augmented by a factor of 1.85.⁶ The SAIPE poverty and food stamps data is available from 1993 (1994 and 1996

⁶ One of the eligibility criteria is that household's income is not to exceed the 125% of the poverty line. From data of the U.S. Bureau of the Census, Current Population Survey, Annual Social and Economic Supplements, it emerges that the ratio of the population in poverty and that of the population being on 125% of the poverty line varies from 1.3 to 1.45 in the years

being not available), the last year available at the moment of the collection of the data being 2008. Cross sections for 1998 and 2006 will be used. The 1998 cross section contains 2932 observations while the 2006 cross section contains 2,827 observations. The latter cross section contains fewer observations because of incomplete demographic data on some counties in Georgia, Louisiana and Nevada.

The selection of the years 1998 and 2006 is dictated by both economic reasons and data availability. As discussed in the introduction section, the gap between poverty rate and the percentage of population recipient of food stamps had been widening in the period 1994-2000 and shrinking in the subsequent period. These changes are related to changes in both economic conditions nationwide and with the adoption of different federal policies; accounting for both these effect, it could help identifying the impact of food access on participation. However, instead of using a pre-PRWORA year, we use 1998 merely because that is the first year for which the Census switched from the old SIC (Standard Industrial Classification) classification system to the NAICS (North American Industrial Classification System, NAICS). Using years previous to 1998 may create problems as of the consistency of the aggregates used. 2006 is chosen as the second period of analysis simply because that is the last year for which Walmart Supercenters' location data is available.

Data on traditional food retailers' and convenience stores' location is obtained from the County Business Pattern of the U.S. Census Bureau. The number of traditional food retailers is that of the NAICS 445110 (grocery stores) industry, while the number of convenience stores' establishments is obtained summing establishments belonging to the NAICS 445120 (Convenience Food Stores) and NAICS 447110 (Gasoline Stations with Convenience Stores) industries. The County Business Pattern database contains information on the number of establishments, number of employees, annual payroll by industry. Number

included in the sample. However, in order to avoid the risk of the recipient population exceeding the eligible one, a factor of 1.85 will be used, as 185% is the criterion used by the Current Population Survey for household to be self-identified as low-income.

of establishments by class of employment size is used to create three categories of stores which will capture differences in stores offerings in terms of prices and assortments: Small (1 to 4 employees); medium (5 to 49 employees), and large (more than 50 employees). Two establishment-size categories are used instead for convenience stores: small (1 to 4 employees) and others (more than 4 employees). Data on Wal-Mart stores' location, opening date and store types is obtained from T.J. Holmes' database (Holmes, 2008) publicly available for academic use on his website (<http://www.econ.umn.edu/~holmes>) which includes also information on store formats, opening dates, and date of store conversions. The data is aggregated to obtain county-level observations as in Bonanno (2010).

The instrumented number of grocery stores establishments and convenience stores (see more detailed below regarding the identification assumptions used) is then divided by county-level population obtained from the Population Estimates Program (PEP) of the U.S. Bureau of Census, to obtain values of store density, while the number of Wal-Mart supercenters is instead divided by hundreds of thousands of people.

Population characteristics are used in the analysis to control for average levels of heterogeneity across counties. The control variables used are percentage of population being female, Hispanic, Black, those in the age groups of 0 to 14 years old and over 65, all obtained from the PEP. Unemployment rate and wages for low-skill individuals are used to control for the economic characteristics of the counties. Unemployment rate data come from the Local Area Unemployment Statistics Database of the United States Bureau of Labor Statistics. We calculated a proxy for low-skill wages by dividing annual payroll by the number of employees aggregated across three sectors characterized by a low-wage-low-skill jobs, such as grocery stores, convenience stores and gas-cum-convenience stores.

An indicator variable to capture between the differences of metro and non-metro counties is also used, to capture differences among different types of counties, from the

ERS/USDA Rural-Urban Continuum Code.⁷ To account for unobservables and for the state-level differences in implementation of the FSP policy, state-level fixed effects are also used.

As discussed in the previous section, food stores' location is endogenous. An instrumental variable procedure is used to correct for such source of bias in the estimated parameters. The identifying assumption is that, accounting for the supply-side drivers of food retailers' location decision, such as tax climate and the presence of infrastructures one will be able to isolate such exogenous component in these variables that are not correlated with the error terms in equation 6. Tax climate is measured by the Corporate Income Tax rates of the U.S. Census Bureau's Tax Foundation. Minimum corporate tax rates are used for convenience stores and for small grocery stores, while the maximum rates are used for medium and large grocery stores and Walmart supercenters. Infrastructures are measured by the state-level number of miles of federal highways in the year 1950 per square-mile of land obtained from the Highway Statistics of the U.S. Department of Transportation, Federal Highway Administration, and combined with the U.S. Census Bureau Gazetteer of Counties measure of squared miles of land in each state. A county-level measure of land availability is obtained dividing square miles of land being a natural park by total land in a county. Total population is also used to account for difference in market size, under the assumption that the likelihood of participation in the FSP is uncorrelated with market size.

Additional instruments are used to account for the location of Wal-Mart Supercenters location endogeneity, exploiting the Hub-and-spoke location strategy of the company (Walton and Huey, 1992) by interacting the distance from Benton County, AK (where Wal-Mart headquarters is located) with state-level indicators. This approach is similar to that used by Neumark, Zhang and Ciccarella (2008), to instrument the number of the company's store

⁷ The ERS/USDA Rural-Urban Continuum Codes is a nine-part codification that distinguishes metropolitan counties by the population of their metro area, and nonmetropolitan counties by degree of urbanization and adjacency to metro areas. The counties indicated as metro in this analysis are those identified as metropolitan by the Rural-Urban Continuum code (codes 1, 2 and 3), while those identified as non-metro are the remaining ones (codes 4 to 9).

openings over time, and resembles also that used by Courthemance and Carden (2010). The same supply-side variables described above are also used. Furthermore, as Wal-Mart selects preferentially rural areas population density and the metro/non-metro indicator discussed above are used as additional instruments. A recap of the variables used in the estimation is presented in Table 1, while Table 2 reports sample statistics for the two cross-sections.

4. Estimation

The model described in section 2 assumes that economic agents (both local food stamp agencies and eligible households) and economic conditions are isolated from one another. However, the assumption of spatial independence across counties is unlikely to hold in the context of county-level nationwide analysis (see Goetz *et al.* (2004) for an application of the spatial econometric techniques to an analysis of food stamps participation that uses county-level data). More favorable economic conditions in neighboring counties may have a spillover effect on the efficacy of the policy; similarly, spatial competition is an extremely important factor for food retailers' location (Cotterill and Haller, 1992) and some chains (for example Wal-Mart) locate their stores in geographic clusters. Furthermore, some of the unobservables such as local policies, or programs to facilitate the efficacy of food stamps policy, may attract (or discourage) low income individuals to locate in a given area, which may impact mobility (or spillovers) across areas. It follows that both a spatial lag and a spatial autocorrelation term could be, at least in principle, included in the model.⁸

Consider the following representation of the food stamps' participation rate equation (equation 6) which allows for both spatial lags in the dependent variable and spatial correlation of the disturbances:

⁸ A Wald test can be used to establish whether the SARAR (1,1) structure fits appropriately the data. Goetz, Rupasingha and Zimmerman (2004) who uses a similar approach to determine the changes in food stamps participation across U.S. counties, found that a SAR (1) model could fit the data better than a SARAR (1,1).

$$Y = \lambda \mathbf{W}Y + \mathbf{X}\beta + \rho \mathbf{M}u + \varepsilon, \quad (8)$$

where \mathbf{W} and \mathbf{M} are $n \times n$ matrixes of spatial weights whose diagonal elements are 0s, Y represents the log-odds of participating in the program (or the LHS of equation 6) and the matrix $\mathbf{X} = [L, FA, State]$. The parameter λ captures the magnitude of the spillover effect that economic conditions and food access in neighboring areas can have on food stamp redemption rate, and ρ represents the level of correlation among disturbances in neighboring counties. Consistently with the nomenclature used by Anselin (1988) the model in (8) is defined as a linear spatial autoregressive model with autoregressive disturbance of order (1,1) or SARAR(1,1).

The elements of the vector of innovations ε are assumed to be i.i.d. from a mean zero distribution with non-constant variance (i.e. they are heteroskedastic). Formally, let the distribution of the j -th element of ε , (ε_j) be characterized as follows: $E[\varepsilon_j] = 0$;

$E[\varepsilon_j \varepsilon_j] = \sigma_j^2$; and $E[\varepsilon_j \varepsilon_{-j}] = 0$. The heteroskedasticity of the elements of ε is the result of the notion that, when cross-sectional spatial units that differ in size and/or in other characteristics (such as population or population density) are used, innovations of the disturbances are very likely to be heteroskedastic (Kelejian and Prucha, 2007; 2010). In the presence of heteroskedastic disturbances, the classical Maximum Likelihood estimators discussed in Anselin (1988) can perform poorly, leading to a higher chance of incurring into Type-1 errors (Arraiz *et al.* 2010).

To circumvent these issues, we adopt the spatial generalized two-stage least square estimator (GS2SLS) proposed by Kelejian and Prucha (2010) which allows for heteroskedastic disturbances of unknown form in autoregressive linear models of order (1,1) or SARAR(1,1). This estimator is based on - and expands upon - other moment estimators proposed by the same authors in previous work, where the disturbances are homoskedastic (Kelejian and Prucha, 1998; 1999) and heteroskedastic (Kelejian and Prucha, 2007). This

family of moment estimators relies on the assumption that the explanatory variables \mathbf{X} are exogenous (Kelejian and Prucha, 1998; 1999; 2007 and 2010; Arraiz, 2010) and that one can use \mathbf{X} and its spatial lags to define a set of moment conditions. The rationale of this approach comes from the fact that equation (1) can be rewritten as

$$Y = (\mathbf{I} - \lambda \mathbf{W})^{-1} [\mathbf{X}\beta + u], \quad (9)$$

where $u = (\mathbf{I} - \rho \mathbf{M})^{-1} \varepsilon$. Under the assumption of disturbances being i.i.d. mean zero, being the roots of \mathbf{W} and \mathbf{M} less than 1 in absolute value, one has: $E(Y) = [\mathbf{I} + \lambda \mathbf{W} + \lambda^2 \mathbf{W}^2 + \dots] \mathbf{X}\beta$. The matrix of instruments can therefore contain all the linearly independent columns of $\mathbf{H} = (\mathbf{X}, \mathbf{W}\mathbf{X}, \dots, \mathbf{W}^q \mathbf{X}, \mathbf{M}\mathbf{X}, \mathbf{M}\mathbf{W}\mathbf{X}, \dots, \mathbf{M}\mathbf{W}^q \mathbf{X})$, where $q \leq 2$. In this application the two weighting matrixes are assumed to be the same ($\mathbf{W}=\mathbf{M}$) and q is assumed to be 2, so that the matrix of instruments is $\mathbf{H} = (\mathbf{X}, \mathbf{W}\mathbf{X}, \mathbf{W}^2 \mathbf{X})$.⁹ The reader should keep in mind that, in this application, since the food access is endogenous, the instrumented values obtained as described in the previous section are used in place of the actual ones.

As described in Arraiz *et al.* (2010), the SARAR (1, 1) GS2SLS estimator uses a two-stage procedure to recover all the parameters of the model.¹⁰ In the first stage one recovers a first estimate of the autoregressive parameter ρ using a procedure similar to a three-step procedure described in Kelejian and Prucha (2007). In the second stage, the results of the first stage are used to obtain estimates of the autoregressive parameter for the lagged dependent variable, following a procedure analogue to that used in Kelejian and Prucha (1998). Each stage is divided into separate steps. A summary of the underlying mechanics of each stage

⁹ Alternatively, in the case of homoskedastic disturbances, one could use instead the feasible generalized spatial three-stage least squares (FGS3SLS) Kelejian and Prucha (2004) and estimate the food stamp participation and the (reduced form) food access equations simultaneously.

¹⁰ This approach differs from previous ones (Kelejian and Prucha, 1998; 1999), since the moment conditions are defined to allow for the presence of heteroskedastic disturbances.

and each step, following Arraiz *et al.* (2010) adaptation of Kelejian and Prucha (2010) are reported in Appendix I.

The elements of the weighting matrix W are obtained using the Dirichlet-Voronoi tessellation (Anselin 1988), accounting for the differences in county size and population density in different parts of the U.S., as it defines contiguity in a relative scale, based on variables such as county size and population density. Appendix II describes the Dirichlet-Voronoi tessellation in more detail. The estimation is executed in “R” using the “**sphet**” routine developed by Gianfranco Piras at Cornell University, illustrated in Piras (2010).

5. Econometric Results

The econometric results are presented in Table 3 and 4. Table 3 contains the estimated coefficients of the SARAR(1,1) GS2SLS estimator applied to the two cross sections of county-level observations (1998 and 2006, respectively), including the marginal effects for all the variables in the model. Table 4 presents estimates of three different specifications of the difference equation. The first specification includes state-level fixed effects, to capture changes in state-specific policies across states during the period in analysis; the second specification does not include the state-level fixed effects but it includes the log odds of food stamps at the beginning of period (1998); the third specification includes neither state-level fixed effects nor the beginning of the period log-odds of participation. For completeness the reader can find a summary of the estimated coefficients of equation (6) using the 1998 and 2006 cross-sections of continental U.S. counties, where the actual values of the food access variables are used in place of the instrumented ones, in Appendix III. Results of the first-stage IV equations are omitted for brevity and are available upon request by the authors.

Cross sectional estimates

In the first place, looking at magnitude and significance of the spatial parameters, one notices that the estimated spatial autocorrelation coefficient ρ is not significant in both models, while the spatial lag coefficient λ is positive and significant in both model although its magnitude is not large. Even though under these circumstances a spatial lag model would probably perform equally well (see Goetz *et al.* 2004), since a Wald tests for joint significance of λ and ρ rejects the parameters being jointly non-significant, we maintain the SARAR (1,1) structure of the model.

Before illustrating the impact of food access variables it should be noted that the coefficients associated with most of the socio-economic control variables show the expected signs and their behavior is consistent across cross-sectional samples, although some inconsistencies and divergences emerge. In the first place, among the variables used to capture county-level economic condition, unemployment rate impacts the log odds of program participation in a positive way as expected, while the log of low-skilled job earnings shows no statistically significant impact on program participation. In substance, this result points out that the likelihood of participation is higher among eligible individuals in counties economically depressed and where the likelihood of finding other sources of income is lower (i.e. unemployment is higher). It should be noted that the coefficient associated with unemployment rate using the 2006 cross-section of data is 2.5 times as large as the 1998 coefficient (0.1047 vs. 0.0390) suggesting that as economic condition worsen the response to lack of job opportunity becomes much more severe.

The likelihood of eligible individuals to participate in the program is impacted more by the gender and the ethnic composition of the population in 1998 than it is in 2006, while the age composition has a smaller impact in 1998 than in 2006. However, an overall trend of the result is that the rate of redemption appears higher in areas where there is more population being female, black or under 14 and over 65 of age, describing a pattern similar to other

county-level study (Goetz, *et al.* 2004). Lastly, the coefficient associated with the metro indicator is positive but only marginally significant for the 1998 cross-section indicating that, among eligible population, the likelihood of joining the program is only marginally higher in metro areas than in non-metro areas.

Moving to the food access results, the coefficient of small grocery stores is negative in both years although small and not statistically significant in 1998, and 4.5 times larger and significant in 2006. In 2006 the presence of smaller grocery stores seem to be a strong deterrent to the program participation: the estimated coefficient of -0.1844 generates a marginal effect of -0.043, suggesting that 1 small grocery store is associated with a decrease in -4.3% in the likelihood of participating in the FSP program. For both cross-sections, the presence of medium-sized grocery stores seems not to have an impact on the log-odds of program participation. Differently, the presence of large-sized traditional grocery stores is associated with positive and statistically significant coefficients in both cross-sectional estimates, those being 0.8430 in 1998 and 0.5135 in 2006. The estimated marginal effects show that one additional large grocery store per 1000 people increases the likelihood of participation by 11.94 and 16.53 %.

While the negative coefficients of small grocery stores can be best explained in terms of increased stigma, the lack of a statistically significant effect of medium grocery stores, may be due to the fact that such aggregate contains a variety of stores that tend to offer more variety, services but also higher prices (among traditional retailers service competition, which may drive size increases, leads to attract higher income consumers and charge higher prices (Bonanno and Lopez, 2009)). If on the one hand eligible individuals may have an incentive to join the program so that they could afford shopping in these stores with better assortment, on the other hand the stigma component may be important enough to partially discourage participation. Finally, the positive coefficient for large grocery stores support Feather's

(2005) findings that recipients' welfare increases if they have access to stores with larger varieties of products.

The behavior of convenience stores is somehow opposite to that of traditional grocery stores. Access to small convenience stores appears to be a catalyst of FSP participation, and, although its effect is only marginally significant in 1998, the estimated coefficients are similar in magnitude, being 0.1567 in 1998 and 0.1684 in 2006, respectively. The marginal effect are however one third larger in 2006 (increasing from 0.0307 to 0.0392) which suggests that in period of harsher economic conditions the presence of smaller/proximity stores may give incentives to join the program. As small convenience stores represent one of the typical store formats located in poor neighborhoods often small and offering lower quality of services and of products offered (King et al, 2004); such stores offer at times the only access to food for low income individuals who are often deprived of transportation, which may explain the positive coefficient associated with the small convenience stores in both cross sections.

The effect of other convenience stores is negative and significant in both years and show similar magnitude (-0.2751 in 1998 and -0.2687 in 2006). The resulting marginal effect is approximately 20% larger in magnitude in 2006 (-0.0539 and -0.0625). On the other hand, as convenience stores become larger and attached to gas stations they may not be as accessible without means of transportation to low income consumers, which causes an increase in transaction cost and makes this format a lot less appealing to FSP participants.

Lastly, the coefficients associated with Walmart supercenters are positive and significant in both cross sectional estimates, showing magnitudes of 0.0324 and 0.0107 respectively for the year 1998 and 2006, resulting in marginal effects of 0.0064 and 0.0025. These results suggest that, everything else equal, having one additional Walmart supercenter per 100,000 individuals, increases the likelihood of participating to the FSP respectively by 0.64 % and 0.25 % in the two years considered. These results indicate that having access to a low-price alternative may act as a catalyst for the effectiveness of the policy, as consumers

become able to buy more food with the same amount of subsistence, which increases the benefit coming from joining the FSP.

Difference Equations

One of the first results that emerge from the three specifications of the difference equation is that both the spatial lag and the spatial autoregressive coefficient (λ and ρ) are statistically significant. In particular in two specifications of the model λ is very close to 1, suggesting a considerable amount of spatial spillover in the evolution of the variation of participation over time.

The second striking result is that none of the variables capturing changes in food access have a statistically significant impact on the log-odds of program participation, with the exception of the small grocery stores, whose coefficients are statistically significant at the 10% level in all the models (although relatively small). As this result is consistent in different specifications of the model, one can state that, on average in the 8-year period 1998-2006, changes in the built environment (food access) did not contribute if not in a marginal way, to changes in the overall effectiveness of the FSP.

6. Concluding Remarks

As the public expenditure in the Food Stamps Program (FSP) increases, policymakers may be asked to improve the effectiveness of the program in lieu of increasing federal outlays. As transactions costs is one of the deterrents to joining the program and lack of food access is one of the determinants of transaction costs, this study presents an empirical assessment of the effect of store availability (i.e., food access) on FSP participation decision among the eligible population.

In order to assess such relationship we used two nationwide cross-sectional samples of county-level data spanning for the whole continental U.S., applying a novel estimation

technique, the spatial generalized two-stage least square (GS2SLS) estimator with heteroskedastic autoregressive disturbances of order (1, 1) or SARAR(1,1), developed by Kelejian and Prucha (2010), accounting also for the endogeneity of food stores' location.

Three different stores formats (grocery stores and convenience stores, divided by establishment size and a non-traditional, low-priced alternative, Wal-Mart Supercenters) are accounted for, discriminating also for the size of the different alternatives. Empirical results show that, among eligible individuals, the presence of small convenience stores, large grocery stores, and Walmart supercenters entice participation in the food stamp program. In sum, increasing the number of stores for which commuting by car is not strictly necessary (convenience stores) or the proximity to stores with wider assortment of low-priced items may act as catalysts to ability to the policy ability to reach the underprivileged.

The results of this paper could be useful to help policymakers decide whether to ease tax pressure on grocery stores located in low-income areas (Beherens, 2010) to improve food access in less affluent areas. Also, as Wal-Mart's expansion into food retailers has targeted areas where FSP redemption rate is larger (Bonanno, 2010) the FSP program may be acting as an indirect subsidy to the company's growth and profits.

The results of this study are, however, preliminary. Several issues of possible endogeneity of explanatory variables different than food access need to be addressed. Further analyses could expand the sample as to monitor more years of data and to implement different estimation techniques, perhaps the panel data spatial estimator developed by Kapoor, Kelejian, and Prucha (2007) exploiting fully the panel structure of the data, or to include some more detailed state- and time-varying indicator as to capture the impact of policy changes on policy effectiveness.

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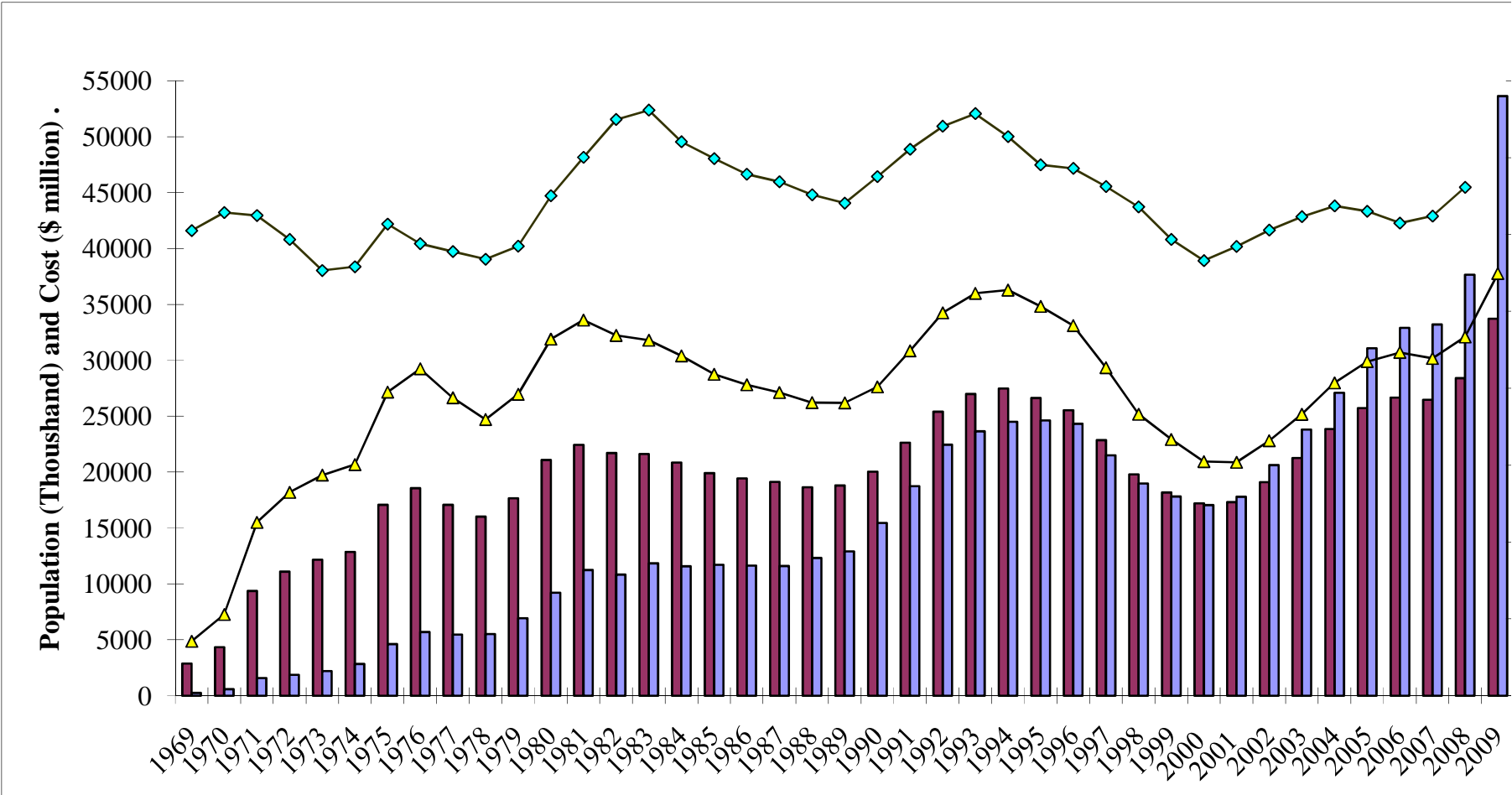
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Figure 1. FSP Participation rates, poverty and Total Cost of the Food Stamps Program



Source: Elaboration from USDA Supplemental Nutrition Assistance Program Participation and Costs, and U.S. Bureau of the Census, Current Population Survey, Annual Social and Economic Supplements.

Table 1. Variable description and data sources

Variable	Description	Source
<i>Dependent variable</i>		
Participation in FSP (Log-odds)	Ln(Participants)-Ln(Eligible non-participants)	Small Area Income and Poverty Estimates
<i>Food Access</i>		
Small Grocery	NAICS 445110 establishment (1 – 9 employees)/ 1000 people	County Business Pattern / Population Estimates Program
Medium Grocery	NAICS 445110 establishment (10 – 49 employees)/ 1000 people	County Business Pattern / Population Estimates Program
Large Grocery	NAICS 445110 establishment (more than 50 employees)/ 1000 people	County Business Pattern / Population Estimates Program
Small Convenience	[NAICS 445120 (1-4 employees) + NAICS 447110 (1-4 employees)] / 1000 people	County Business Pattern / Population Estimates Program
Other Convenience	[NAICS 445120 (> 4 employees) + NAICS 447110 (> 4 employees)] / 1000 people	County Business Pattern / Population Estimates Program
Walmart Supercenters	Walmart supercenters / 100,000 people	T. J. Holmes database / Population Estimates Program
<i>Control Variables</i>		
Unempl. Rate	Unemployment Rate	Local Area Unemployment Statistics
Log Wage	Per capita earnings of grocery stores + gas station + convenience stores	County Business Pattern
% Pop Female	Female population / total population	Population Estimates Program
% Pop Black	Black population / total population	Population Estimates Program
% Pop Hisp	Hispanic population / total population	Population Estimates Program
% Pop under 15	Population below 15 years of age / total population	Population Estimates Program
% Pop over 65	Population above 65 years of age / total population	Population Estimates Program
Met.dum	Metropolitan area dummy	U.S. Census Gazetteer of counties
Pop density	Population / Square miles of land	Population Estimates Program / U.S. Census Gazetteer of counties
<i>Instruments for Food Access Measures</i>		
Distance BC	Distance from Benton County (thousand miles)	Haversine formula on Census & U.S. Census Gazetteer of counties
Maximum corporate tax rate	Maximum corporate tax	U.S. Bureau of Census. The Tax Foundation
Minimum corporate tax rate	Minimum corporate tax	U.S. Bureau of Census. The Tax Foundation
Fas.t1950	Total Federal-Assisted Highways (1950)	Highway Statistics of the U.S. Department of Transportation,
Prop.park	Proportion of parkland out of total Land	ECS
Market size	Population	Population Estimates Program

Table 2. Summary Statistics

Variable	1998				2006			
	<i>Mean</i>	<i>St. Dev</i>	<i>Min</i>	<i>Max</i>	<i>Mean</i>	<i>St. Dev</i>	<i>Min</i>	<i>Max</i>
Participation Rate (% Participants /Eligible)	26.78	9.56	1.70	65.11	36.77	12.27	1.65	79.58
Small Grocery Establishments	13.29	53.14	0.00	1040.00	14.32	60.77	0.00	1253.00
Medium Grocery Establishments	12.57	32.84	0.00	934.00	11.37	32.03	0.00	933.00
Large Grocery Establishments	6.03	17.70	0.00	508.00	6.02	20.41	0.00	649.00
Small Convenience Establishments	13.12	35.51	0.00	917.00	16.54	45.75	0.00	1200.00
Other Convenience Establishments	23.51	43.92	0.00	814.00	24.30	45.36	0.00	929.00
Walmart Supercenters	0.22	0.58	0.00	6.00	0.83	1.69	0.00	41.00
Unemployment Rate	5.14	2.82	1.00	29.90	4.89	1.64	1.60	15.50
Log Wage	2.47	0.22	1.42	3.40	2.63	0.29	1.51	3.68
% Pop Female	50.68	1.84	33.37	56.92	50.36	1.90	33.01	56.06
% Pop Black	9.26	14.79	0.00	86.10	8.49	13.80	0.00	83.25
% Pop Hisp	4.56	8.46	0.00	50.24	7.25	12.73	0.14	97.43
% Pop under 15	21.85	3.04	7.19	39.22	19.12	2.79	8.30	34.64
% Pop over 65	14.40	4.05	3.17	34.72	15.02	3.94	4.04	34.54
Met.dum	0.36	0.48	0.00	1.00	0.36	0.48	0.00	1.00
Pop density	273.52	2128.79	0.30	87747.43	268.77	1801.31	0.27	70179.35

Tab. 3 – Estimation of equation (6) via GS2SLS-SARAR (1, 1): cross sections

Variables	1998 Cross-section				2006 Cross-section			
	<i>Estimate</i>	<i>Std. Error</i>	<i>t-stat</i>	<i>Marginal Effect</i>	<i>Estimate</i>	<i>Std. Error</i>	<i>t-stat</i>	<i>Marginal Effect</i>
Small Grocery	-0.0420	0.1065	-0.3945	-0.0082	-0.1844	0.0729	-2.5286	-0.0429
Medium Grocery	-0.0654	0.0841	-0.7780	-0.0128	0.0182	0.0606	0.2998	0.0042
Large Grocery	0.8430	0.1640	5.1395	0.1653	0.5135	0.1678	3.0596	0.1194
Small Convenience	0.1567	0.0834	1.8789	0.0307	0.1684	0.0470	3.5800	0.0392
Other Convenience	-0.2751	0.0508	-5.4116	-0.0539	-0.2687	0.0458	-5.8685	-0.0625
WM Supercenters	0.0324	0.0089	3.6432	0.0064	0.0107	0.0042	2.5456	0.0025
Unempl. Rate	0.0390	0.0045	8.7324	0.0077	0.1047	0.0086	12.1503	0.0244
Log Wage	-0.0046	0.0377	-0.1214	-0.0009	0.0448	0.0359	1.2458	0.0104
Metro Dummy	0.0300	0.0173	1.7356	0.0059	0.0301	0.0190	1.5815	0.0070
% Pop Female	2.4190	0.5409	4.4723	0.4743	1.2063	0.5512	2.1885	0.2805
% Pop Black	0.9066	0.0543	16.6832	0.1778	0.3777	0.0686	5.5094	0.0878
% Pop Hisp	0.2286	0.1237	1.8479	0.0448	-0.1857	0.1155	-1.6072	-0.0432
% Pop under 15	1.8974	0.4210	4.5066	0.3720	5.7808	0.5776	10.0081	1.3441
% Pop over 65	0.4948	0.2885	1.7150	0.0970	1.8730	0.3770	4.9676	0.4355
Pop. Density	0.0000	0.0000	1.3632	0.0000	0.0000	0.0000	-0.0959	0.0000
Constant	-2.6784	0.3069	-8.7267	-0.5252	-3.0340	0.2619	-11.5831	-0.7054
lambda	0.4152	0.0370	11.2097	0.0814	0.3588	0.0438	8.1897	0.0834
rho	0.0153	0.0548	0.2795	0.0030	-0.0530	0.0619	-0.8568	-0.0123
Wald test (joint sign. lambda and rho)	$\chi^2_{(1)}=148.99$ p-val = 0.0000				$\chi^2_{(1)}=59.674$ p-val=0.0000			
R-Squared (OLS)	0.6076				0.618			

State level fixed effects' coefficients are omitted for brevity.

Table 4 – Estimation of equation (6) via GS2SLS-SARAR (1,1): Difference sample.

Variables	State-level fixed effects*			Initial log-odds participation			Restricted specification		
	Estimate	Std. Error	t-stat	Estimate	Std. Error	t-stat	Estimate	Std. Error	t-stat
Small Grocery	-0.0002	0.0001	-1.8124	-0.0011	0.0006	-1.7732	-0.0012	0.0006	-1.7926
Medium Grocery	0.0004	0.0005	0.8091	0.0016	0.0012	1.3297	0.0017	0.0012	1.3571
Large Grocery	0.0000	0.0001	0.4808	0.0017	0.0015	1.1086	0.0016	0.0016	0.9925
Small Convenience	0.0001	0.0001	0.3812	-0.0009	0.0010	-0.8616	-0.0007	0.0011	-0.6506
Other Convenience	-0.0002	0.0002	-0.8932	-0.0099	0.0091	-1.0838	-0.0089	0.0095	-0.9395
WM Supercenters	0.0000	0.0000	0.3383	0.0000	0.0000	1.1669	0.0000	0.0000	0.9200
Unempl. Rate	0.0118	0.0037	3.1841	0.0033	0.0027	1.2294	0.0066	0.0028	2.3925
Log Wage	0.0774	0.0322	2.4040	0.0273	0.0236	1.1585	0.0391	0.0234	1.6683
Metro Dummy	0.0290	0.0135	2.1513	-0.0009	0.0106	-0.0849	0.0041	0.0106	0.3838
% Pop Female	-0.2685	0.4601	-0.5837	1.1138	0.3309	3.3660	0.6698	0.3460	1.9356
% Pop Black	-0.3457	0.0499	-6.9337	-0.0531	0.0285	-1.8657	-0.0960	0.0285	-3.3743
% Pop Hisp	-0.2928	0.0981	-2.9847	-0.1762	0.0574	-3.0704	-0.1945	0.0588	-3.3067
% Pop under 15	2.6902	0.3215	8.3671	0.8775	0.2163	4.0565	1.1045	0.2008	5.5004
% Pop over 65	1.0688	0.2276	4.6960	0.0840	0.1634	0.5141	0.3077	0.1424	2.1610
Pop. Density	0.0000	0.0000	-0.4109	0.0000	0.0000	0.4671	0.0000	0.0000	0.1798
Log odds 1998				-0.0441	0.0104	-4.2278			
Constant	-0.5141	0.2506	-2.0517	-0.8369	0.1920	-4.3581	-0.6688	0.2065	-3.2387
lambda	0.5719	0.0568	10.0666	0.9344	0.0350	26.7201	0.9275	0.0365	25.4359
rho	-0.3947	0.0831	-4.7528	-0.7217	0.0629	-11.4665	-0.6899	0.0630	-10.9492

* State level fixed effects' coefficients are omitted for brevity.

Appendix I - a 2-stage procedure to obtain the SARAR (1,1) GS2SLS.

The illustration of the 2-stage procedure to estimate the parameters of the SARAR (1,1) GS2SLS procedure that follows mirrors the discussion in Arraiz *et al.* (2010). For more details on the asymptotic properties of the SARAR (1, 1) GS2SLS estimator and its small- and large-sample properties as well as the technical details and assumptions underlining the estimation procedure are not include here; the interested reader should refer to Kelejian and Prucha (2007), Arraiz *et al.* (2010), Kelejian and Prucha (2010) and related works. Following Arraiz *et al.* (2010) one can define $\mathbf{Z}=[\mathbf{X}, \mathbf{W}Y]$, $\delta=[\beta, \lambda]'$ and rewrite equation (8) as:

$$(A-1) \quad Y = \mathbf{Z}\delta + \rho\mathbf{M}u + \varepsilon .$$

Let \mathbf{H} be the matrix of instruments described in the main text. Following Kelejian and Prucha (2010) and Arraiz *et al.* (2010), the population moment conditions that the GM estimator satisfies (in presence of heteroskedasticity) are defined as¹¹

$$(A-2) \quad \begin{aligned} n^{-1}E[\varepsilon' \mathbf{A}_1 \varepsilon] &= n^{-1}E[u - \rho\bar{u}] \mathbf{A}_1 [u - \rho\bar{u}] = 0 \\ n^{-1}E[\varepsilon' \mathbf{A}_2 \varepsilon] &= n^{-1}E[u - \rho\bar{u}] \mathbf{A}_2 [u - \rho\bar{u}] = 0 \end{aligned}$$

where $\bar{u} = \mathbf{M}u$, $\mathbf{A}_1 = \mathbf{M}'\mathbf{M} - \text{diag}(m'm)$ and $\mathbf{A}_2 = \mathbf{M}$.

Step 1a: 2SLS estimator

Define $\tilde{\mathbf{Z}}=[\mathbf{X}, \mathbf{H}(\mathbf{H}'\mathbf{H})^{-1}\mathbf{H}'\mathbf{W}Y]$; the two-stage least square estimator of δ , or δ_{2SLS} is:

$$(A-3) \quad \delta_{2SLS} = (\tilde{\mathbf{Z}}\tilde{\mathbf{Z}})^{-1}\tilde{\mathbf{Z}}'Y .$$

Step 1b: initial GMM estimator of ρ based on the 2SLS residuals

A first estimate of ρ , $\check{\rho}$, minimizes the following objective function:

$$(A-4) \quad \check{\rho} = \arg \min_{\rho \in [-1,1]} [m(\rho, \delta_{2SLS})' m(\rho, \delta_{2SLS})]$$

¹¹ In absence of heteroskedasticity, the moment conditions in equation (A-2) reduces to $n^{-1}E[\varepsilon' \mathbf{A}_1 \varepsilon] = n^{-1}\sigma^2 \text{tr}\{\mathbf{M}\mathbf{M}'\}$ where σ^2 is a finite variance term; under the null of homoskedasticity this quantity and that obtained of the sample analogue of (A-1) will converge to the same amount,. See Kelejian and Prucha (2007) and Kelejian and Prucha (2010) for more details.

where $m(\rho, \delta_{2SLS})$ is the sample analogue of the population moment condition in (A-2)

$$m(\rho, \delta_{2SLS}) = n^{-1} \begin{bmatrix} (\tilde{u} - \rho \tilde{u})' \mathbf{A}_1 (\tilde{u} - \rho \tilde{u}) \\ (\tilde{u} - \rho \tilde{u})' \mathbf{A}_2 (\tilde{u} - \rho \tilde{u}) \end{bmatrix}, \text{ where } \tilde{u} = \mathbf{M}\tilde{u} = \mathbf{M}[S - \mathbf{Z}\delta_{2SLS}] \text{ and } \tilde{\tilde{u}} = \mathbf{M}\tilde{\tilde{u}}.$$

Step 1c: Efficient GMM estimator of ρ

An efficient estimator of ρ , $\tilde{\rho}$, is obtained via non-linear weighted least squares, minimizing the following objective function:

$$(A-5) \quad \tilde{\rho} = \arg \min_{\rho \in [-1,1]} [m(\rho, \delta_{2SLS})' \tilde{\Psi}^{-1} m(\rho, \delta_{2SLS})]$$

where $\tilde{\Psi}^{-1}$ is a weighting matrix function of the 2SLS disturbances and $\tilde{\rho}$, or $\tilde{\Psi} = \tilde{\Psi}(\tilde{\rho})$. A detailed illustration of the structure of $\tilde{\Psi}$ can be found in Appendix B of Arraiz *et al.* (2010).

Step 2a: GS2SLS estimator.

Following Kelejian and Prucha (1998) the generalized spatial two-stage least squares (GS2SLS) estimator of δ is:

$$(A-6) \quad \hat{\delta}_{GS}(\tilde{\rho}) = [\hat{\mathbf{Z}}^*(\tilde{\rho})' \mathbf{Z}^*(\tilde{\rho})]^{-1} \hat{\mathbf{Z}}^*(\tilde{\rho})' Y^*(\tilde{\rho}),$$

where $Y^*(\tilde{\rho}) = Y - \tilde{\rho} \mathbf{M}Y$ and $\hat{\mathbf{Z}}^*(\tilde{\rho}) = \mathbf{H}(\mathbf{H}'\mathbf{H})^{-1} \mathbf{H}'[\mathbf{Z} - \tilde{\rho} \mathbf{M}\mathbf{Z}]$. This procedure consists in estimating a spatial Cochrane-Orcutt transformation of equation (A-2) via 2SLS.

Step 2b: Efficient GMM estimator of ρ using GS2SLS residuals

In the last step, the efficient GMM estimator of the autoregressive parameter, $\hat{\rho}$, is obtained.

$$(A-7) \quad \hat{\rho} = \arg \min_{\rho \in [-1,1]} [m(\rho, \hat{\delta}_{GS}(\tilde{\rho}))' \hat{\Psi}^{-1} m(\rho, \hat{\delta}_{GS}(\tilde{\rho}))]$$

where $\hat{\Psi}^{-1}$ is a weighting matrix function of the GS2SLS disturbances and, $\tilde{\rho}$ or $\hat{\Psi} = \hat{\Psi}(\tilde{\rho})$.

The structure of $\hat{\Psi}$ is illustrated in detail in Appendix B of Arraiz *et al.* (2010). The sample moments $m(\rho, \hat{\delta}_{GS}(\tilde{\rho}))$ are obtained replacing the 2SLS residuals with those from step 2a:

$$m(\rho, \hat{\delta}_{GS}(\tilde{\rho})) = n^{-1} \begin{bmatrix} (\hat{u} - \rho \hat{u})' \mathbf{A}_1 (\hat{u} - \rho \hat{u}) \\ (\hat{u} - \rho \hat{u})' \mathbf{A}_2 (\hat{u} - \rho \hat{u}) \end{bmatrix}, \text{ where } \hat{u} = Y - \hat{\mathbf{Z}} \hat{\delta}_{GS}(\tilde{\rho}) \text{ and } \hat{\tilde{u}} = \mathbf{M}\hat{u}.$$

Appendix II - Definition of the weighting matrix \mathbf{W}

A commonly used approach to obtain the elements of the spatial weighting matrix \mathbf{W} , defines any element w_{ij} of such a matrix as the inverse of a function of distance between two counties which are within a radius B or

$$w_{ij} = \begin{cases} \frac{1}{f(dist_{ij})} & \text{for } i \neq j \text{ and } dist_{ij} \leq B \\ 0 & \text{otherwise,} \end{cases}$$

Using such approach, all the counties within a distance of B from each other will be considered neighbors, which will result in a disproportionate number of neighboring units for more densely populated areas where counties are smaller. If neighbors are generated through distance-based methods, then the small northeastern counties will have many more neighbors than the large western counties. This could be inappropriate, in light of different driving habits and perceptions of distance in these regions. Since driving radii tend to be larger in the sparsely populated western regions, neighborhoods should be correspondingly larger. In order to avoid this problem our notion of neighboring counties uses the Dirichlet-Voronoi tessellation. This method accounts for the differences in county size and population density in different parts of the U.S., defining contiguity in a relative scale, based upon county size and population density.

To apply this method, we use the latitude, and longitude coordinates of each county in the U.S. to identify counties' centroids. Around each centroid, a Voronoi cell is obtained by identifying those points representing the minimum distance between centroids. Each county will therefore be neighbor of at least three other counties whose centroids are the closets. Each segment of the cell represents points in the plane (i.e. the US) that are equidistant to the two nearest centroids while vertices are points equidistant to the three (or more) nearest centroids. For a more thorough discussion of the use of Dirichlet-Voronoi tessellation and its advantages in neighborhood generation see Anselin (1988).

Appendix III - Econometric Results – estimation of equation (6) without assessing the endogeneity of food stores' location

Variables	1998 Cross-section			2006 Cross-section		
	<i>Estimate</i>	<i>Std. Error</i>	<i>t-Stat</i>	<i>Estimate</i>	<i>Std. Error</i>	<i>t-Stat</i>
Small Grocery	-0.0978	0.0631	-1.5507	-0.2274	0.0792	-2.8695
Medium Grocery	-0.3821	0.0605	-6.3175	-0.5270	0.0748	-7.0430
Large Grocery	-0.1938	0.1684	-1.1510	-0.4837	0.2566	-1.8852
Small Convenience	0.0828	0.0552	1.5019	0.0087	0.0538	0.1623
Other Convenience	0.1562	0.0493	3.1680	0.2246	0.0507	4.4334
WM Supercenters	0.0091	0.0028	3.2730	0.0106	0.0021	4.9540
Unempl. Rate	0.0382	0.0044	8.6458	0.0998	0.0084	11.9434
Log Wage	0.0342	0.0369	0.9249	0.0710	0.0346	2.0527
Metro Dummy	-0.0011	0.0153	-0.0721	0.0234	0.0174	1.3428
% Pop Female	3.1108	0.5255	5.9198	1.3078	0.5254	2.4891
% Pop Black	0.9810	0.0566	17.3200	0.4777	0.0661	7.2217
% Pop Hisp	0.2368	0.1249	1.8955	-0.2231	0.1083	-2.0593
% Pop under 15	1.3174	0.4067	3.2394	5.7982	0.5514	10.5162
% Pop over 65	0.0697	0.2805	0.2485	1.9558	0.3621	5.4015
Constant	-2.8959	0.3097	-9.3512	-3.0558	0.2492	-12.2601
lambda	0.4620	0.0378	12.2195	0.4439	0.0436	10.1778
rho	-0.0590	0.0587	-1.0039	-0.1760	0.0654	-2.6897