Dynamics of the Food Environment in the United States

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Abstract

State level data on food environment variables for the period 2000 through 2013, gathered from the *Food Environment Atlas* and various other government sources are used to model a panel VAR to capture specific state-level fixed and random effects. The set of food environment variables can be broadly classified into four major categories: food insecurity, food assistance, poverty and obesity. This will help explain interactions of innovations (new information) from food environment variables, which in turn help generate policy prescriptions dealing with the food environment in the United States

JEL Classification: C31, C32, C53, C54, E61, I38

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Background

There is increasing interest in understanding how a community's food environment influences food choices and diet quality (ERS/USDA, 2013). Important factors contributing to the food environment include indicators such as distance to the nearest grocery store, number of food stores and restaurants, expenditures on fast foods, participation in food and nutrition assistance programs, food prices, food taxes and availability of local foods. Also, there may be conventional community characteristics such as demographic composition, income, poverty status, and availability of recreation and fitness centers that may also have a substantial impact on diet and health outcomes. In addition to the aforementioned factors, other factors such as macroeconomic shocks (unemployment, interest rate, inflation, and mortgage crisis, etc), asset availability and liquidity, food prices and government support program for agricultural commodities also may also influence diet and health outcomes.

Food insecurity, adult and childhood obesity, and physical activity levels are key indicators of the health and wellbeing of a community. Several studies in the extant literature have investigated how these outcomes are associated with the "food environment" (to name a few, Nord *et al*, 2010; Gundersen *et al*, 2011a; Gundersen *et al*, 2011b; and Meyerhoefer and Yang, 2011, Dharmasena *et al*, 2013). However, these studies have either considered only a limited number of variables in piecemeal fashion or have mapped interactions between food environment variables in static or contemporaneous systems. Hence, a *true* dynamic picture of the "food environment" has not yet been put forward and our current understanding of the dynamics and complex interactions of characteristics of the food environment is limited. Public policies generated on the basis of static information may be sub optimal. Therefore, to improve policy-making, it is worthwhile to develop a more complete understanding of the dynamics of the food environment variables in the United States.

The specific objectives of this study are: (1) to estimate a panel vector autoregression (P-VAR) model to delineate the dynamic effects of factors affecting the food environment in the United States; (2) to perform innovation accounting using impulse response functions and error variance decompositions; (3) to develop causality patterns obtained through directed acyclic graphs applied to the innovations from P-VAR; (4) to identify structural breakpoints (if any) that affect the dynamic patterns of food environment variables; and (5) to perform policy analysis based on graphical causal structures obtained from objective 3.

Data and Methods

The study uses state level data on food environment variables for the period 2000 through 2013, gathered from the *Food Environment Atlas* and various other government sources (such as the Bureau of Labor Statistics (BLS), the United States Census Bureau, and the Federal Reserve System). A P-VAR model will be used to capture specific state-level fixed and random effects. The set of variables can be broadly classified into four major categories: food insecurity, food assistance, poverty and obesity. More specifically, the variables will include the following: proximity to a grocery store, number of food stores and restaurants, expenditures on fast foods, participation in food and nutrition assistance programs, food prices, food taxes, availability of local foods, food insecurity, presence of food deserts, adult and childhood obesity, demographic composition, income, and poverty status. Other macroeconomic factors such as unemployment rate; the debt-to- income ratio; the number of housing starts; median home prices; oil prices; interest rates, and various measures of the money supply are also considered. To account for the participation in USDA food assistance programs, we expect to use the number of eligible people and/or the average number of participants in the Supplemental Nutrition Assistance Program, the WIC Program, the National School Lunch Program and the School Breakfast Program.

The P-VAR model is described as:

(1) $X_{st} = \sum_{k=1}^{K} \Gamma_{ks} X_{st-k} + \beta u_s + \epsilon_{st}$ for $t = 1,2,\ldots,T$, and $s = 1,2,\ldots,S$,

where X corresponds to a vector of factors considered in the food environment, X_{st-k} is a vector of k lags of each of variables under consideration, Γ_{ks} is a matrix of parameters, β is an identity matrix, u_s is a vector of state level fixed effects and ϵ_{st} is a vector of orthogonal random innovations, i.e. $E(\epsilon_{st}) = 0$ and $cor(\epsilon_{st}|X_{st}, X_{st-k}, u_s) = 0$ (Greene, 2003). The P-VAR will be estimated following Holtz-Eakin, *et al*, (1988) and Vidangos (2009).

Once the VAR and P-VAR models are developed, we will perform innovation accounting to obtain the moving-average representation for either the general VAR or the panel VAR. Here the vector $\mathbf{X}_t$ can be written as a function of the infinite sum of past innovations as follows:

(2) $X_t = \sum_{i=0}^{\infty} H_k \epsilon_{t-k}$,

where H_k is a mxm matrix of moving average parameters which map current and historical innovations at lag k into the current position of the vector X_t. The key to performing this operation is the identification of contemporaneous causal flows among innovations. Bernanke (1986) used subjective information to accomplish such identification. We use the graph theoretical information following Swanson and Granger (1997) and Bessler and Akleman (1998).

The moving-average representation can be presented in three alternative forms to enlighten us on dynamic patterns of response to food environment factors: (1) the use of impulse response functions (how does each series respond, over time to a one-time-only shock in each series of the VAR?); (2) the use of forecast error variance decompositions (what percentage of the uncertainty (variance) at forecast horizon *h* is explained by current or earlier shocks in each series of the VAR?); and (3) the use of historical decomposition of each series (how does information emanating in each series contribute to the historical pattern in each series?). These three forms of presentation of the moving-average representation are standard offerings and are programmed in commercial software packages and have been applied in several studies (Bessler, 1984; Dharmasena and Bessler, 2004; Capps, Bessler, and Williams, 2012).

Breakpoint analysis in conjunction with the P-VAR makes it possible to objectively indentify time periods when macroeconomic variables went through structural changes that eventually affect the dynamics of food environment (variables) in the United States. Also, once P-VAR model is developed, we will perform innovation accounting to obtain the moving-average representation for P-VAR. The key to performing this operation is the identification of contemporaneous causal flows among innovations. To clarify the identification of the aforementioned contemporaneous causal flows, we will model causal structures (directed acyclic graphs or DAGs) among the innovations from each variable. Traditionally, the PC-Algorithm found in association with the TETRAD IV project (Sprites, Glymour and Scheines, 2000), was applied to achieve such identification. However, PC-algorithm assuming Gaussian distributions of innovations and conditional independence fails to identify equivalent causal graphs (could result bi-directional edges). Therefore, in our work, we use LiNGAM algorithm (Shimizu *et al.*, 2006), that takes into account non-Gaussian innovations based on functional composition, which results stronger identification of causal structures. Applications of LiNGAM algorithm can be found in Shimizu *et al.*, (2006).

Preliminary Results and Implications

Panel VAR helps identify dynamic effects on food environment variables and their implications on the aforementioned four outcomes (i.e. food insecurity, food assistance, poverty and obesity) taking into account specific state-level fixed and random effects. Structural breakpoints will help delineate effects of structural breaks on dynamics of food environment variables. A graphical directed acyclic graph structure on innovations from P-VAR will help explain interactions of innovations (new information) from food environment variables, which in turn help generate policy prescriptions dealing with the food environment in the United States.

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