

Evaluating the Contribution of Infrastructure to U.S. Agri–Food Sector Output

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ABSTRACT

The effect of infrastructure investment or capital on private sector output and productivity has been widely discussed over the past two decades. However, only limited studies have focused on the contribution of infrastructure to the output of U.S. agricultural and food sector. Considering the importance of agriculture in U.S. economy and its strong dependence on infrastructure, two empirical analyses were made in this thesis to evaluate the output impact associated with infrastructure in agricultural and food sector in the United States. The first study examines the spillover effect of two major transportation modes, roads and rails, on agricultural output across the United States. Applying a spatial econometric model that considers spatial dependence in both output and explanatory variables to agricultural output in 44 states from 1981 to 2004, the analysis suggests that spending on road system has significant and positive direct effect on agricultural output. However, the spillover effect of road infrastructure on agricultural output in the neighboring state varies along with the order of neighboring states considered in the model. No significant direct and spillover effect of rail infrastructure is observed. The second study estimates the dynamic effects of public infrastructure on the output of 34 U.S. food manufacturing industries during the period of 1958–2005. The contribution of public infrastructures to food industry output growth is assessed using heterogeneous dynamic methods. Results suggest a positive and significant contribution of public infrastructures to the output growth in food manufacturing industry. Also, a long-run relationship is confirmed between food manufacturing output, input use and public infrastructure. Moreover, the output effect of public infrastructure is homogeneous among the food manufacturing industries in the long run but varies in the short run. The findings of both studies in this thesis have several policy implications.

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Chapter 1: Introduction

Introduction

How important is infrastructure to economic growth? Do investments in infrastructure provide long-term returns to the economy? These questions have been at the center of policy maker and researcher debate in both developed and developing countries for the last two decades (Pereira and Andraz 2010). The answer to these questions, however, remains inconclusive. Due to the differences in assumptions and modeling setup, infrastructure definitions and measures, study periods, economic systems, and many other factors, research results include have found significant, insignificant and even negative effects of infrastructure on economic performance.

Starting in the 1970s, the U.S. economy experienced a severe decline in productivity. Aschauer (1989a, 1989b) initialized a series of empirical analyses exploring the effects of public infrastructure on aggregate economic productivity and found that core infrastructure including streets, highways, airports, and water system had a strong positive effect on economic growth. Therefore, he concluded that the decreasing public capital stock could be an important cause to the national productivity slowdown.

Aschauer's studies quickly caught policy makers' attention and have since influenced the plan of infrastructure investment in U.S. government proposals and policies. For example, President Clinton (1992), in his campaign document "Putting People First", proposed an \$80 billion dollar federal investment in a variety of infrastructure developments. President Bush (2005) then signed the Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU) into law, a funding and authorization bill with the goal of maintaining and improving the surface transportation infrastructure in the U.S. Most recently, President Obama (2011a) emphasized the importance of investment in infrastructure along with education and energy independence to help American win the future in his State of the Union speech in January

2011. In September 2011, President Obama (2011b) proposed a \$50 billion investment for highways, transit, rail and aviation in order to modernize the U.S. infrastructure system as well.

Aschauer's studies have also drawn considerable research attention to evaluating the economic return of public and transportation infrastructure development in both U.S. and other countries. A detailed review of those studies is summarized by several researchers, for instance, Bhatta and Drennan (2003), Romp and Haan (2007) and Pereira and Andrzej (2010), among others. Some studies suggested that infrastructure investment would increase economic output growth (Costa *et al.* 1987; Eberts 1990; Munnell 1992; Garcia-Mila and McGuire 1992; Pereira and Andrzej 2010), while a few studies found no significant effect or even negative effects of infrastructure at more disaggregated geographic level (Holtz-Eakin 1994; Evan and Karras 1994; Garcia-Mila *et al.* 1996).

More specifically, the effect of public and transportation infrastructure investment on agricultural output and productivity has come under scrutiny. Most studies in this regard find that infrastructure has a positive effect on agricultural output (e.g. Antle 1983, Craig *et al.* 1997, Felloni *et al.* 2001, Munisamy and Roe 1995). More recently, Onofri and Fulginiti (2008) evaluated the effect of public R&D and public infrastructure on the agricultural sector in the U.S. They found that public inputs are important for the smooth and rapid growth of agricultural economy.

Previous studies have provided a substantial knowledge base about the relationship between infrastructure capital and agricultural output and productivity; nevertheless, the spillover aspect of infrastructure has been usually overlooked, which means the infrastructure development could not only affect the economic growth within that region, but also affect the neighboring regions. Overlooking the spillover effect of infrastructure investment may lead to a

biased estimation and consequently inaccurate policy suggestions. Also, similar to productivity studies in agricultural sector (Heien 1983), most researchers have focused on the relationship between farm products and investment in public or transportation infrastructure. Of equal importance, however, is the output or productivity effect of infrastructure on the food manufacturing sector given the increased importance of the supply of processed food in the daily diet (Morrison *et al.* 2010).

This study aims to fill the gaps in the research of infrastructure capital and generate a more accurate evaluation of the output effect of infrastructure capital in the U.S. agricultural and food sector. Applying recently developed models in spatial analysis and panel data methods, this study has two specific objectives:

1. To estimate the spatial spillover effect of transportation infrastructure on state agricultural output across the United States, and
2. To evaluate the impact of public infrastructure on the output of food manufacturing industries.

The first objective will be addressed in the following chapter, while the second objective is covered in Chapter 3. The findings from those two analyses are summarized in the final chapter.

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Chapter 2: Evaluating the Spatial Spillover Effect of Transportation Infrastructure on Agricultural Output across the U.S.

Abstract

This study evaluates the effect of transportation infrastructure, including roads and railroads, on agricultural output across 44 states in the U.S. from 1981 to 2004. Applying a spatial Durbin model (SDM) considering four different weight matrices, the spillover effect of transportation infrastructure is analyzed. By catching spatial dependence in both dependent and explanatory variables, the results suggest that road disbursement in a state generally has positive direct effects on its own agricultural output. The spillover/indirect effect of road infrastructure on agricultural output in neighboring states varies with respect to the spatial weight matrix used in the model. Moreover, simulation analysis based on the results using the second order of contiguity weight matrix shows that enhancement in road infrastructure in the states in the central region of the U.S. has a larger spillover effect on agricultural output compared to coastal or border states. No significant direct effect or spillover effect from rail infrastructure is identified in this study.

Introduction

Research measuring the influence of transportation infrastructure to economic output and productivity in various geographical level, i.e. national, regional or less aggregated jurisdiction area, has been constantly conducted since the late 1980s (e.g., Aschauer 1989; Munnell and Cook 1990; Moomaw et al. 1995; Dalenberg and Partridge 1995; Fernald 1999; Stephan 2003). Most of those studies primarily focused on the impact of improved transportation infrastructure in a given jurisdiction unit on the output and productivity of private sectors within the area. Recently, the spillover effects of transportation infrastructure has received increasing attention in the literature in order to capture more comprehensive influence of transportation infrastructure in a spatial unit on the output and productivity within and outside the spatial unit (Kelejian and Robison 1997; Boarnet 1998; Cohen 2007; Pereira and Andr  z 2010).

As stated in Munnell (1992, p193-194), “As the geographic focus narrows, the estimated impact of public capital becomes smaller. The most obvious explanation is that, because of leakages, one cannot capture all of the payoff to an infrastructure investment by looking at a small geographic area.” As a result, when estimating the impact of transportation infrastructure in less aggregated geographic units, it is important to consider the spillover effect of transportation infrastructure. Specifically, it should be an integral part of the analysis based on the geographical circumstance (Kelejian and Prucha 2010, Cattaneo et al. 2011).

Presumably, transportation infrastructure in one jurisdiction area will not only affect the economic output within that area, but also link to the economic activities in neighboring regions. The construction of an interstate highway, for instance, could improve the network by efficiently connecting states. This construction would further lead to the redistribution of existing resources for production (Cohen 2007; Jiwattanakulpaisarn et al. 2009). Economic activities could be

reallocated from states with poor transportation infrastructure to states with more updated and maintained transportation systems. Thus, the construction or improvement of transportation infrastructure in one state could adversely affect the output of some private sectors in the neighboring states with less developed transportation infrastructure by drawing away their resources (Boarnet 1998). However, improved transportation network in a given state can potentially provide more efficient and integrated transportation network to a region, hence contributing to the economic activities in related states.

The development of transportation infrastructure is very important to U.S. agricultural activities since the main agricultural production states is primarily located in the north central U.S., which is distant from the major domestic markets and export ports (Yu et al. 2007). The agricultural producers heavily rely on transportation infrastructure to deliver their products to their domestic and international consumers. According to Casavant (2010), agriculture is the largest user of freight transportation in the United States, accounting for 31 percent of all ton-miles transported in the United States in 2007. Also, transportation costs usually account for a relative high share of delivered price of the relative low-value agricultural commodities (Park and Koo 2005). Therefore, it is important to better understand the full impact of transportation infrastructure on state's agricultural output if the spatial dependence of agricultural output among states exists.

To get a preliminary view of the spatial characteristics in U.S. agricultural output, Figure 1 illustrates state agricultural output index per million acres in 2004 based on the quantile classification. It shows that the major agricultural output was clustered in the Midwest. Moreover, applying a simple ordinary least square (OLS) regression to agricultural output and input factors and transportation infrastructure variables, the Moran's Index clearly presents the

spatial dependence in the residuals from the OLS model in Figure 2. This spatial dependence in the residuals suggests that spatial interaction should be taken into account when the complete impact of transportation infrastructure on agricultural output in a state is mandated.

As the level of U.S. farm output surged by 17 times between 1958 and 2009 (USDA-ERS 2012), the demand for getting efficient transportation infrastructure is even higher nowadays to the producers in many agricultural states. However, improvements in the deteriorating transportation infrastructure, primarily the road system, in the nation and many states have been long overdue and still under extensive debates due to budget deficits. Potentially, it will help policy makers and private sectors to allocate investment on transportation infrastructure if a better estimate on the output effect of transportation infrastructure in state's agricultural sector is made. Thus, the objective of this study is to provide an analysis of the contribution of transportation infrastructure and its spatial spillover effect to U.S. agricultural output. To accomplish the objective, it is hypothesized that transportation infrastructure investment within a state will have a statistically significant spillover effect on neighboring states. The hypothesis is empirically tested using a spatial modeling framework which considers the spatial interaction of both dependent and the explanatory variables (Lesage and Pace 2009).

Literature Review

Previous studies on agricultural transportation generally found positive effect of transportation infrastructure on agricultural output; however, those studies either used aggregated national data or neglected the spatial dependence of agricultural output and spillover effect of transportation infrastructure in less aggregated jurisdiction area. For example, Antle (1983) studied the effects of transportation and communication infrastructure on aggregate agricultural productivity in 47

less developed countries and 19 developed countries utilizing aggregate agricultural production data in 1965. The result indicated that a country's infrastructure services contribute positively to agricultural productivity. Craig et al. (1997) developed land and labor productivity measures for ninety-eight developed and developing countries using annual data over three decades, and found that publicly provided inputs, such as road density and public research, are important to agricultural productivity.

Felloni et al. (2001) assessed the effect of transportation infrastructure and electricity on agricultural production and productivity in 83 countries and 30 provinces in China, and confirmed the importance of infrastructure in agricultural development. Similarly, Benin et al. (2009) explored the agricultural productivity returns to different type of public expenditures in Ghana. Their results indicated that with one percent increase in public spending in agriculture, agricultural labor productivity will increase by 0.15 percent.

Onofri and Fulginiti (2008) evaluated the impact of public R&D and public infrastructure on U.S. agricultural sector at the aggregate national level and their results suggested that the rate of return of public infrastructure investment is approximately 1%. Zhang and Fan (2004) studied the effect of public infrastructure on agricultural productivity in rural India using a panel dataset for 290 districts in rural India from 1971 to 1994. Their findings suggested that roads and irrigation caused the growth in total factor productivity (TFP). Moreover, they found a large positive effect of infrastructure on agricultural productivity and suggested government should make more investment on infrastructure development.

Although the spillover effect of transportation infrastructure on output and productivity in agricultural sector has usually been neglected in the literature, the spillover effect of transportation or public infrastructure on output and productivity on national economy or private

sector economy has been discussed in the literature. Table 1 is a summary of infrastructure productivity studies incorporating spatial spillover effects.

Most of the previous studies supported the positive spillover effect of transportation infrastructure. Pereira and Roca-Sagales (2003) examined the possible existence of spatial spillover effect from public capital stocks in Spain and its 17 regions based on the vector autoregression (VAR) methods. They found that public capital has positive effect on the aggregate economy in Spain and most of the regions. To capture the spillover effect, they included both public capital within the region and public capital outside the region into the analysis. The results suggested that spillover effect is very important, which accounts for over half of the aggregate effect from public capital and the remaining effect comes from the public capital installed in the region itself.

Pereira and Andraz (2004) investigated the effects of investment in highway in the United States taking consideration of the presence of regional spillovers. They used VAR methods to estimate the effect and the result indicates that investment in highways affects private sector variables positively at national level as well as in most states. The result also suggested a positive spillover effects. Only 20% of the aggregate effect of public investment in highway came directly from the investment in state itself and the remaining 80% came from the public investment of highway in other states.

Cohen and Paul (2003) investigated the effect of air transport network on manufacturing cost of 48 United States from 1982 to 1996 and they found that a one percent increase in airport infrastructure in one state will not only reduce manufacturing cost within the state (-0.11), but also reduce cost for other states(-0.12). Cohen and Paul (2004) estimated the effect of public infrastructure investment on the costs and productivity of private enterprises. By analyzing U.S.

state level manufacturing data from 1982 to 1996, they found that enhancement in highway infrastructure within the state could lower production cost, augmented by cross-state spillovers. Specifically, a one percent increase in neighbors' highway infrastructure will reduce the own state cost by 0.01 percent.

Cantos et al. (2005) studied the impact of transport infrastructure on economic growth in Spain by constructing a variable including infrastructure capital stock both within the region and in close related regions. Their results identified the significant positive spillover effects associated with transport infrastructure. Jiwattanakulpaisarn et al. (2011) evaluated the relationship between highway infrastructure and employment in the United States at state level during the period 1984-1997. Their analysis revealed the evidence of positive effect from highway infrastructure within the state and outside the state in both short run and long run.

Some studies, however, found negative spillover effects of transportation infrastructure. For instance, Boarnet (1998) found that the economic output in one county is positively related to the increase of street-and-highway capital within it and negatively related to the change in nearby counties. Cohen and Monaco (2007) assessed the role of port and highway infrastructure in production cost in the manufacturing industry across 48 contiguous states. The results suggested that ports and highway infrastructure in a given state decreased manufacturing cost within the state, while it increased the cost of manufacturing firms in the neighboring states. Sloboda and Yao (2008) estimated the effect of public spending on transportation and non-transportation and private capital on economic production for 48 states in U.S. from 1989 to 2002. The results showed that public capital has a negative spillover effects on economic growth.

A few studies found mixed spillover effects of transportation or no spillover effects of transportation infrastructure. For instance, Holtz-Eakin and Schwartz (1995) examined how

highways effect economic growth beyond the states' border and found no evidence of spillover effects. Kelejian and Robinson (1997) evaluated the effect of different types of public capital on economic productivity across United States and could not find robust spillover effect in various model specifications. Moreover, Jiwattanakulpaisarn et al. (2010) explored the causal linkages between highways and employment in service, manufacturing, construction sectors, and overall private sectors based on 48 U.S. states from 1984 to 1997, and discovered the spillover effect of highway infrastructure across states varies among different sectors.

Those aforementioned studies usually considers the spatial spillover effect of transportation or public infrastructure on the neighboring states' output through spatial dependence in dependent variable , explanatory variable or error terms, none of them have taken into account the spatial correlation in both dependent and explanatory variables. The recent development of spatial Durbin model (SDM, LeSage and Pace 2009) includes spatial dependence in both dependent variable and independent variables. It not only shows the direct effect of explanatory variables within the spatial unit, but also calculates their indirect effect on neighboring units. According to LeSage and Pace (2009, p158-159), SDM model is the only model that produces unbiased estimator in all possible spatial data modeling process. Moreover, because of the inclusion of spatial dependence in the explanatory variables, the omitted variables problem is less likely observed in the SDM model.

Conceptual Framework

This study adopts the Cobb-Douglas production function approach: transportation infrastructure within the state is incorporated in the production function as an external factor to productivity (Boarnet 1998; Jiwattanakulpaisarn *et al.* 2011). The transportation infrastructure is treated as a

production function frontier “shifter”, which increases the efficiency of capital and labor and other inputs. In addition, transportation infrastructure is assumed to affect productivity directly as an input factor similar to capital and labor (Romp and Haan 2007). This relationship is elaborated by the following equation:

$$(1) y = A(h^w)f(k, l, im, la, h^w)$$

where A is the total factor productivity; y represents the output; k , l , im , and la represent capital, labor, intermediate, and land input factors; and h^w represents transportation infrastructure within the state.

Following Cohen (2010), the spatial spillover effect of transportation infrastructure from neighboring states is incorporated in equation (1) as follows:

$$(2) y = A(h^w, h^o)f(k, l, im, la, h^w)$$

where h^o represents transportation infrastructure from neighboring states. Under this framework, transportation infrastructure from both one’s own state and neighboring states could affect production by shifting the production function.

Methodology

Following Elhorst (2010), the SDM accommodating the spatial interaction effect from dependent and all the explanatory variables was applied in this study. A log linear transformation of a Cobb-Douglas production function in a SDM framework can be specified as follows:

$$(3) Y_{it} = \alpha + \beta X_{it} + \rho \sum_{j=1}^N W_{ij} Y_{jt} + \theta \sum_{j=1}^N W_{ij} X_{jt} + u_i + \lambda_t + e_{it}; \quad i = 1, 2, \dots, N; \quad t = 1, 2, \dots, T$$

The dependent variable Y_{it} represents the agricultural output for state i at time t . α is the constant term. $X_{it} = [K_{it}, L_{it}, LA_{it}, IM_{it}, ROAD_{it}, RAIL_{it}]$, which is a 1×6 vector of explanatory

variables containing capital input, labor input, land input, intermediate input, road disbursement and railway length while β is a corresponding 6×1 vector of parameters. W_{ij} is the i, j -th element of a $N \times N$ weight matrix describing the spatial arrangements of states. The variable $\sum_{j=1}^N W_{ij}Y_{jt}$ is called a spatial lag in dependent variable, which represents the spatially weighted average value of agricultural output from i 's neighboring states at time t . Its coefficient ρ represents the effect from neighbor states' agricultural output on i 's agricultural output. $\sum_{j=1}^N W_{ij}X_{jt}$ is the spatial lag in explanatory variables, and the corresponding coefficient θ represents the effect from neighboring states' input and transportation infrastructures on the own state's agricultural output. e_{it} is the residual with a zero mean and constant variance.

Spatial specific effects (u_i) and time period specific effects (λ_t) can be included in order to account for spatial and temporal heterogeneity. Spatial specific effects control for all space-specific time-invariant variables, while time period specific effects control for time-specific space-invariant variables. These specific effects can be treated as fixed effects or random effects. In the fixed effect model, each spatial unit and time period unit is represented by a dummy variable. In the random effect model, u_i and λ_t are treated as random variables with a zero mean and constant variance (Elhorst 2011).

Some specification tests were conducted before applying the SDM. First, a likelihood ratio (LR) test was implemented to examine the joint significance of spatial and/or time period effects based on an OLS regression without considering spatial interaction effects. Based on the test results, a decision was made in regard to the inclusion of spatial fixed effects, temporal fixed effects, or both in spatial model estimations. Second, a Lagrange Multiplier test (Burrige 1980) was conducted to determine whether spatial lag dependence or spatial error dependence exists in state's agricultural output. Rejection of the null hypothesis indicates that certain spatial

interaction effects tested should be included in the model. If the LM test rejects the null hypothesis of the non-spatial model in favor of a spatial lag model or spatial error model, the SDM is then recommended (Elhorst 2010; LeSage and Pace 2009).

To further confirm that the SDM is appropriate for the analysis, two hypotheses of $H_0: \theta = 0$ and $H_0: \theta + \rho\beta = 0$ were tested by the Wald test to evaluate that if the SDM could be simplified to a spatial lag model or spatial error model. If both null hypotheses are rejected by Wald tests, the SDM is preferred over the spatial lag model (SAR) and the spatial error model (SEM). If the Wald test result contradicts previous LM test results, the SDM should still be adopted since it is a more general framework (Elhorst 2010). In addition, a ϕ parameter was estimated to test the random effects model against the fixed effect model. If ϕ is not different from zero, it suggests that a fixed effect model fits the data better, while the value of ϕ equating one indicates that random effect model is more appropriate.

The choice of an appropriate weight matrix to reflect the intensity of the geographic relationship between observations is important to the spatial analysis (Cho *et al.* 2011). However, there is no consensus about which weight matrix is the best for analysis (Anselin 1988). Four queen's continuity weight matrixes from the order of one to four (W1-W4) were estimated for the sensitivity analysis¹. The first order queen continuity spatial weight matrix was constructed to assign the off-diagonal elements of the matrix to be one, i.e. $W_{ij} = 1$, if state i and state j share the same border or vertex or $W_{ij} = 0$ otherwise. The diagonal elements of the matrix have a value of 0. The second order queen continuity weight matrix was constructed in a similar way but it also takes the neighbors of neighbors into account (Haandrikman *et al.* 2011). The third and fourth order of the queen continuity matrices were constructed following the same logic. All

¹ The order stops at four since a queen continuity weight matrix of the order four treats most of the states as neighbors.

weight matrices were row-standardized to avoid the singular matrix problem (Kelejian and Prucha 2010).

In the SDM, the inclusion of a spatial lagged dependent variable as an explanatory variable produce endogeneity problem because of the correlation between the regressor (WY) and residual (e). As a result, traditional OLS estimation may be biased and inconsistent. To prevent this endogeneity issue, this study applied the maximum likelihood estimation method based on the conditional log-likelihood function of the model (Anselin 1988). In addition, this study adopted the bias-correction procedure proposed by Lee and Yu (2010) to obtain unbiased estimators in the presence of spatial and time period fixed effects.

Direct and indirect effects

In models with spatial effects such as in this study, the estimated parameters, i.e., ρ and θ in equation (3), cannot be simply explained as a partial derivative of a dependent variable with respect to an explanatory variable (Lesage and Pace 2009). Lesage and Pace (2009) provided an approach to decompose the total marginal effect into direct and indirect effects to better capture and explain marginal effects in the presence of spatial interaction effects. Specifically, direct effect includes the initial effect of a change in an explanatory variable on a dependent variable within a spatial unit and the feedback effect from dependent variables of neighboring states. The feedback effect measures the effect of passing through the neighboring units and back to the original unit that triggered a change. Indirect effect (or spillover effect) measures the impact of change in an explanatory variable of one spatial unit on a dependent variable in all other units.

In order to better explain the derivation of the marginal effects of explanatory variables in a spatial panel data setting, equation (3) can be rewritten in the vector form (Lesage and Pace 2009; Elhorst 2010):

$$(4) Y_t = (I - \rho W)^{-1} \alpha l_N + (I - \rho W)^{-1} (X_t \beta + W X_t \theta) + (I - \rho W)^{-1} \varepsilon$$

where l_N denotes an $n \times 1$ vector of ones, ε includes e_t , and possible spatial and/or time period fixed effects. Taking a partial derivative of Y with respect to the k_{th} explanatory variable from unit 1 to unit N at a given time, we get the following $N \times N$ matrix representing the marginal effects:

$$(5) \frac{\partial Y}{\partial X_k} = (I - \rho W)^{-1} (\beta_k I + W \theta_k)$$

where β_k and θ_k are the coefficient estimates associated with the k_{th} explanatory variables. This $N \times N$ matrix in equation (5) denotes the effect of a one unit change of a particular explanatory variable in one state on a dependent variable of all the states. Lesage and Pace (2009) calculated the direct and indirect effect based on an average of the main diagonal and off-diagonal elements of the matrix. Specifically, the direct effect is generated from dividing the sum of the diagonal elements of the matrix by N , while the indirect effect is calculated by dividing the sum of the off diagonal elements of the matrix by N .

Based on the $N \times N$ matrix of equation (5), the impact pattern of a one percent change in a particular explanatory variable² in a given state on all other states was explored. Specifically, the i^{th} element in the i^{th} column of this matrix represents the direct effect of the change in a particular variable (increase by one percent) in state i , while the sum of the remaining elements in the i^{th} column represents the indirect/spillover effect of this increase on all other states. Based

² Since X and Y in equation (5) are in natural logarithm, the marginal effect represented by the $N \times N$ matrix in equation (5) can be explained as elasticity.

on this $N \times N$ matrix, this study conducted a simulation analysis in order to better understand how a one percent increase in transportation infrastructure, e.g. expenditure on road, in one state would affect the agricultural output in all states. Using the estimated parameters of equation (3) (e.g., ρ , β_{ROAD} , and θ_{ROAD}), the matrix in equation (5) was obtained. Based on this matrix, the spillover effect of a one percent increase in road disbursement in each state was calculated. In addition, the spreading path of the spillover effect associated with the changes in road disbursement was illustrated through two states based on the dominance of their agricultural sector: one is a primarily agricultural state (Iowa in this study), whereas the other is not an agricultural proficient state (Massachusetts as an example in this paper).

Data

This analysis covered panel data for 44 U.S. states³ during the period from 1981 to 2004. Agricultural input and output data for each state were obtained from the Economic Research Service (ERS), U.S. Department of Agriculture (USDA) (USDA-ERS 2012). The index of agricultural output data (Y) is generated by physical quantities and market prices of crops and livestock. The index of capital input ($CAPITAL$) is estimated from the state level capital stock and rental price for each asset type, while the index of labor input ($LABOR$) is constructed using data of working hours and compensation per hour. The index of intermediate input ($INTERMEDIATE$) mainly includes energy input, agricultural chemical input, pesticide consumption, and fertilizer consumption. The index of land input ($LAND$) measures the stock of land in farms by state, which is constructed as the ratio of the value of land in farms to the intertemporal price index of the land.

³ Only 44 (see following notes) states are included because the railroad mileage data used in this study are unavailable for six states, including Alaska, Hawaii, Vermont, Rhode Island, New Hampshire, and Maine.

Data on transportation infrastructure includes road disbursement (*ROAD*) and railroad mileage (*RAIL*)⁴. Road disbursement data were generated from the Highway Statistics series published by the U.S. Federal Highway Administration (FHWA) annually, mainly includes the capital outlay on interstate highway systems, other federal-aid systems, other roads and streets, and maintenance and traffic services. The road disbursement data were deflated by a GDP deflator by setting 1996 value equal to one in order to match input and output data. Railroad mileage data were found in the *Railroad Facts* series published annually by the Association of American Railroads (AAR). The total miles of railway line in each state is represented by mileage operated by Class I roads.

Empirical Results

Table 2 presents the results of (1) a pooled OLS model, (2) an OLS model with spatial fixed effects, (3) an OLS model incorporating temporal fixed effects and (4) an OLS model considering both fixed effects (referred to as “Model (4)” here and below), respectively. In this study, statistical significance at the 5% level is denoted with one asterisk in the tables; those variables and test statistics are henceforth referred to as “significant” in the discussion below. The null hypothesis of the LR test for joint significance of spatial fixed effects is rejected, indicating that spatial fixed effects should be included in the model. Similarly, the hypothesis that time period fixed effects are not significant is also rejected. As a result, the model should include both spatial and time period fixed effects, also called a two-way fixed effects model (i.e. Model (4)).

⁴ Rail mileage, instead of investment in rail infrastructure, is used as a proxy for rail infrastructure each state due to lack of rail capital investment data at state level.

The result of Model (4) in Table 2 shows labor and intermediate input have positive impact on state's agricultural output while land input contributes negatively to the agricultural output. Increase in road disbursement and rail mileage has no significant effect on agricultural output. However, Model (4) does not capture the spatial interaction effects among variables, which may produce biased estimations. In addition, LM tests on the residuals from four models using the four weight matrices (W1-W4) generally reject the null hypothesis of no spatial lag and spatial error, implying the existence of spatial dependence in the dependent variable and error term. Note that when W4 is considered, the LM tests could not reject the null hypothesis. However, the Wald test result presented later shows the SDM is preferred. According to Elhorst (2010), if there is a contradiction between the LM and Wald tests, the SDM should still be adopted since it incorporates the functions of both the SAR and SEM models.

Table 3 shows the results of the SDM based on four different weight matrices. A higher order weight matrix means more states are treated as neighbors. Instead of imposing a cutoff number for neighbors to be included, this study tests if the spatial interaction effects dissipate as the order of weight matrix increases. Only the estimation of the bias-corrected fixed effect model is presented here since the value of the ϕ parameter is not different from zero in all cases, suggesting the fixed effect model is preferred. In all specifications, the hypothesis that the SDM can be simplified to an SAR model is rejected by a Wald spatial lag test. Similarly, the hypothesis that the SDM can be simplified to an SEM model is also rejected by a Wald spatial error test. As a result, the SDM is preferred to SAR and SEM models in all cases.

In Table 3, the coefficients of road infrastructure (*ROAD*) are significant under W3 and W4, while the coefficients of rail mileage are not significant under any of the models. Both the spatial lag of road infrastructure (*WROAD*) and rail mileage (*WRAIL*) are significantly positive

only when W2 was considered. However, the positive sign associated with *WROAD* and *WRAIL* does not necessarily suggest that a higher level of neighbors' transportation infrastructure is beneficial to the agricultural output within the state (Ozyurt and Daumal 2011).

These coefficients cannot simply be interpreted as a partial derivative of a dependent variable with respect to explanatory variables because of the inclusion of spatial interaction effects (Lesage and Pace 2009). The direct and indirect effects of the parameters using the decomposition approach discussed in the Methodology section were estimated. The estimates of the direct and indirect effects using W1 to W4 are reported in Table 4. In general, the direct marginal effects of capital and land on agricultural output are both negative. This negative impact may result from productivity growth, hence less amount of capital and land are needed to enhance agricultural production (Ball *et al.* 1997). Table 4 also shows that a one percent increase in intermediate input in a state increases agricultural output in the same state by 0.44 to 0.47 percent. Labor input has a positive effect on agricultural output using W3 and W4, with an elasticity of 0.04.

Disbursement in road system is found to have a positive direct effect on agricultural output using W2, W3, and W4. A one percent increase in disbursement on road systems in a state will increase output by 0.02 to 0.03 percent. In contrast, no significant direct effect of rail infrastructure on agricultural output is found in the model under any weight matrix. This result may be related to the modes of U.S. grain transportation over the past thirty years: the truck share of grain shipment almost doubled between 1978 (30%) and 2010 (58%), while rail share declined from 48% to less than one-quarter over the same period (USDA 2012).

The indirect effects that are also equivalent to, and referred to as the spillover effects of transportation variables, i.e., *ROAD* and *RAIL*, are primarily discussed as the focus of this study.

As hypothesized, this study does find a statistically significant spillover effect of road infrastructure. However, the significance of the spillover effects of road infrastructure on a state's agricultural output is not consistent over the four models. When using a weight matrix considering only the first layer of adjacent states (W1), neither the spillover effect of road disbursement nor railway mileage is significant. However, when the neighbor states are extended by including one more layer of adjacent states in the weight matrix (W2), the spillover effect of road disbursement becomes significant. Specifically, a one percent increase in road disbursement in one state will increase the agricultural output in all other states by an average of 0.24 percent under W2. The positive and significant direct and indirect effects of road disbursement contribute to the positive and significant total effect under W2. A one percent increase in road disbursement in a particular state increases the agricultural output of across the states by 0.27 percent. No significant indirect or total effect of transportation infrastructures on a state's agricultural output is found when further adjacent layers were considered as neighbor states (i.e., W3 and W4).

The simulation of the spatial spillover effect with a one percent increase in road disbursement in a given state based on the estimated parameters using the W2 matrix is displayed in Figure 3. The spillover effects of Missouri and Tennessee are the largest (0.40-0.45), suggesting an improvement in the road disbursement in these two states would/could have higher spillover effects on the agricultural output of other states. In contrast, the spillover effects of seven border or coastal states, including North Dakota, Washington, Louisiana, Florida, South Carolina, Connecticut, and Massachusetts, have relatively small spillover effects on the agricultural output of other states (0.10-0.15).

In addition, Figure 4 shows the spillover effects pattern associated with a one percent increase in road disbursement in Iowa and Massachusetts, respectively. Figure 4a displays the pattern in Iowa. The spillover effects diminish as the order of neighbor increases and reach the border states. Figure 4b shows the spatial spillover effects given a one percent increase in road disbursement in Massachusetts. The spillover effects are much smaller comparing to Iowa. Also, the spillover effects extend toward west and diminish quickly.

The results in Figures 3 and 4 indicate that the magnitude and structure of spatial spillover effects with the increase in road infrastructure mainly depends on a neighboring state's structure and the path available for a spillover effect. The effect of the road disbursement increase in states in the central part of the U.S. spread out in all directions, starting from first order neighbors, then second, third and continuously⁵. Missouri, for instance, has 8 first order neighbors, 24 second order neighbors, and 34 third order neighbors. By the fourth order, the spillover effect has covered 41 of the 44 states (including lower orders) considered in this study. As a result, the spillover effects reach the border before getting trivial. Conversely, given an improvement in road infrastructure in Massachusetts, which only has 2 first order neighbors, 4 second order neighbors, 8 third order neighbors, and 12 fourth order neighbors (include lower orders), the spillover effects shrink quickly and become almost zero before it could reach further states in higher order neighbors. Thus, the spillover effects of the changes in central U.S., which are also the major agricultural states, are relatively large, whereas the spillover effects of the shock in coastal or border states, which are generally the modestly agricultural production region (particularly in the East coast), are constrained to paths limited by fewer neighbors.

⁵ The spillover effect calculation is based on the infinite series $(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \dots$, in which matrix W represents first order contiguous neighbors, matrix W^2 represents second order contiguous neighbors, and so on (Lesage and Pace 2009). As a result, the spillover effect will cover all 44 states included.

Conclusion and Discussions

This study evaluates the effect of transportation infrastructure on agricultural output for 44 continuous states in the U.S. during the period of 1981 to 2004. The SDM based on four different weight matrices is employed to accommodate spatial dependence in both dependent variable and independence variables. Findings based on the model estimates suggest that road disbursement has a significant positive direct effect on a state's agricultural output. A one percent increase in the investment and maintenance in road system in one state will increase agricultural output within the same state by 0.02 to 0.03 percent. This positive effect is consistent with many previous studies (Costa *et al.* 1987; Munnell and Cook 1990; Moomaw *et al.* 1995; Felloni *et al.* 2001; Pereira and Andraz 2010).

The positive and significant impacts of spillover effect of road disbursement find under W2, but not find under W1, W3, and W4, can be linked to the nature of U.S. agriculture. For example, improvements in road systems in coastal or mountain states, which are far from the heart of U.S. agriculture in the Midwest and South-Central states, results in a limited impact on agricultural output in the first layer of adjacent neighbor states (W1), which may not be proficient in agricultural production. Alternatively, the insignificant spatial spillover effect of road disbursement under W1 may be explained by already well-established highway linkages between neighbor states. On the other hand, the spatial spillover effect of road disbursement on agriculture output captured by W2 links road disbursement in coastal or mountain states to agricultural output in the Midwest and South-Central regions. Eventually, the same spatial spillover effect dissipates when neighbor states are extended further by W3 and W4, probably because the road disbursement and agricultural output linkage dissipates as the distance between them becomes too great.

In contrast, no significant direct effect or spillover effect from rail infrastructure to a state's agricultural output is identified in this study. This finding may be related to the declining dependence of the agricultural sector on railway. The U.S. rail industry experienced significant structure change because of the deregulation introduced in the 1980 Staggers Rail Act (1980). A significant number of mergers and integration occurred in rail industry between 1980 and 1996: the number of Class I railroad companies operating in the U.S. has dropped from 132 in 1990 to only seven at present. Because of the acquisition and integration of railroad companies, many agricultural product shippers lost their access to rail transportation. According to a report from the USDA (Klindworth 1988), 87 crop reporting districts in main grain production states were served by less than 3 railroads in 1996. Concurrently, the access to railroads by farmers, particularly the smaller ones, had decreased significantly.

This study has important policy implications. Agriculture is an important sector of the U.S. economy, and the development of agriculture depends heavily on transportation infrastructure. The findings in this study indicate that investment in road infrastructure is not only imperative to the agricultural development within a state but also beneficial to the agricultural development in other states. As a result, more resources should be allocated to the construction and maintenance of road infrastructure to enhance the growth in the agricultural economy. Our findings also suggest that, given the U.S. budget deficit situation, the investment decision in road infrastructure investment for the sake of agriculture output may be prioritized based on state location because road infrastructure investment in central U.S. states was found to produce larger spatial spillover effect.

A limitation of this study is the construction of weight matrix that was used in the SDM. Presumably, it would be better to create a weight matrix that captures the linkage of the

transportation network across states. In this study, the variable representing road infrastructure includes interstate highway and local roads since both of them are very important to the transportation of agricultural products. Due to the complexity of local roads within and across states, the construction of weight matrix capturing the road system linkages requires further investigation.

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Appendix

Table 1. Summary of studies about the economic impact of infrastructure with spatial spillover effects

Author (Year)	Data	Public Capital Measure	Conclusions
Positive spillover effects			
Pereira and Rocs-Sagales (2003)	Spain; T.S. 1970-1995; 17 regions	Transports and communications	Positive spillover effect. Spillover effect accounts for 57% of the total effect
Cohen and Paul (2003)	U.S. P.D. 1982-1996; 48 states	Airport infrastructure	Neighbors' public capital elasticity is -0.12
Cohen and Paul (2004)	U.S.; P.D. 1982-1996; 48 states	Highway infrastructure	Neighbors' public capital elasticity is -0.01
Pereira and Andraz (2004)	U.S.; T.S. 1977-1999; 48 states	Highway infrastructure	Positive spillover effect. Spillover effect accounts for 80% of the total effects
Cantos <i>et al.</i> (2005)	Spain; P.D. 1965-1995; 17 regions	Transportation infrastructure	Significant positive spillover effect
Jiwattanakulpaisarn <i>et al.</i> (2011)	U.S. P.D. 1984-1997; 48 states	Highway infrastructure	Positive spillover effect in both short run and long run
Negative spillover effects			
Boarnet (1998)	U.S.; P.D. 1969-1988; California counties	Street and highway	Negative spillover effect of -0.02
Cohen and Monaco (2007)	U.S. P.D. 1984-1996; 48 states	Port and highway infrastructure	Port infrastructure in neighboring states will increase own state's manufacturing costs
Sloboda and Yao (2008)	U.S. P.D. 1989-2002; 48 states	Transportation and non-transportation	Significant negative spillover effect of public expenditure
No or mixed spillover effects			
Holtz-Eakin and Schwartz (1995)	U.S.; P.D. 1969-1986; 48 states	State highways	No spillover effect
Kelejian and Robinson (1997)	U.S. P.D. 1969-1986; 48 states	Total, highway, water and sewer, and other public capital stock	Estimation varies according to model specifications
Jiwattanakulpaisarn <i>et al.</i> (2010)	U.S.; P.D. 1984-1997; 48 states	Highway infrastructure	Both positive and negative spillover effect on employment across states

Table 2. Estimation results of panel data without spatial interaction effects

	(1) Pooled OLS	(2) Spatial fixed effects	(3) Time period fixed effects	(4) Spatial and time period fixed effects
CAPITAL	-0.13(0.00)*	-0.25(0.00)*	-0.11(0.00)*	0.02(0.55)
LABOR	0.24(0.00)*	0.03(0.05)*	0.26(0.00)*	0.04(0.01)*
INTERMEDIATE	0.91(0.00)*	0.57(0.00)*	0.88(0.00)*	0.45(0.00)*
LAND	-0.02(0.00)*	-0.14(0.00)*	-0.02(0.00)*	-0.14(0.00)*
ROAD	0.09(0.00)*	0.07(0.00)*	0.08(0.00)*	0.01(0.28)
RAIL	-0.05(0.00)*	-0.01(0.42)	-0.05(0.00)*	-0.02(0.12)
LM Spatial lag test				
W1	0.23(0.64)	311.60(0.00)*	7.85(0.01)*	66.80(0.00)*
W2	7.91(0.01)*	419.91(0.00)*	32.48(0.00)*	60.26(0.00)*
W3	3.74(0.05)	445.72(0.00)*	23.76(0.00)*	21.09(0.00)*
W4	39.97(0.00)*	438.40(0.00)*	4.96(0.03)*	1.42(0.23)
LM Spatial error test				
W1	177.80(0.00)*	386.74(0.00)*	113.50(0.00)*	116.56(0.00)*
W2	146.55(0.00)*	579.62(0.00)*	55.53(0.00)*	86.46(0.00)*
W3	69.11(0.00)*	714.17(0.00)*	3.26(0.07)	27.31(0.00)*
W4	65.94(0.00)*	765.02(0.00)*	0.01(0.92)	1.37(0.24)
LR Spatial fixed effects test	1936.35(0.00)*			
LR Time period fixed effects test	305.09(0.00)*			

Note: P-value is in parentheses.

Table 3. SDM results with different weight matrices (bias-corrected fixed effects)

	W1	W2	W3	W4
CAPITAL	-0.14(0.00)*	-0.10(0.02)*	-0.09(0.06)	-0.07(0.12)
LABOR	0.02(0.21)	0.03(0.09)	0.04(0.03)*	0.04(0.03)*
INTERMEDIATE	0.49(0.00)*	0.45(0.00)*	0.45(0.00)*	0.44(0.00)*
LAND	-0.14(0.00)*	-0.16(0.00)*	-0.15(0.00)*	-0.14(0.00)*
ROAD	0.02(0.08)	0.02(0.06)	0.02(0.05)*	0.03(0.04)*
RAIL	-0.02(0.15)	-0.02(0.06)	-0.02(0.17)	-0.02(0.20)
WCAPITAL	0.30(0.00)*	0.34(0.00)*	0.51(0.00)*	0.73(0.00)*
WLABOR	0.04(0.20)	-0.00(0.94)	0.07(0.39)	-0.02(0.87)
WINTERMEDIATE	-0.34(0.00)*	-0.28(0.00)*	-0.11(0.43)	-0.30(0.18)
WLAND	0.16(0.00)*	0.29(0.01)*	0.34(0.07)	0.40(0.23)
WROAD	-0.01(0.78)	0.11(0.01)*	0.07(0.34)	0.02(0.86)
WRAIL	0.02(0.37)	0.08(0.03)*	0.05(0.40)	0.02(0.82)
WY	0.43(0.00)*	0.51(0.00)*	-0.00(0.97)	0.27(0.00)*
WALD Spatial Lag test	92.43(0.00)*	47.70(0.00)*	32.82(0.00)*	27.40(0.00)*
WALD Spatial Error test	30.63(0.00)*	25.89(0.00)*	30.80(0.00)*	25.85(0.00)*

Note: P-value is in parentheses.

Table 4. Direct and indirect effects of SDM results with different weight matrices (bias-corrected fixed effects)

	W1	W2	W3	W4
DIRECT EFFECTS				
CAPITAL	-0.11(0.01)*	-0.09(0.06)*	-0.09(0.07)*	-0.06(0.19)
LABOR	0.02(0.13)	0.03(0.08)	0.04(0.03)*	0.04(0.04)*
INTERMEDIATE	0.47(0.00)*	0.45(0.00)*	0.45(0.00)*	0.44(0.00)*
LAND	-0.13(0.00)*	-0.14(0.00)*	-0.15(0.00)*	-0.14(0.00)*
ROAD	0.02(0.12)	0.03(0.02)*	0.02(0.05)*	0.03(0.05)*
RAIL	-0.02(0.18)	-0.02(0.14)	-0.02(0.18)	-0.02(0.20)
INDIRECT EFFECTS				
CAPITAL	0.39(0.00)*	0.55(0.00)*	0.51(0.00)*	0.96(0.01)*
LABOR	0.07(0.12)	0.02(0.82)	0.07(0.42)	-0.01(0.96)
INTERMEDIATE	-0.21(0.00)*	-0.10(0.51)	-0.11(0.42)	-0.24(0.43)
LAND	0.17(0.10)	0.41(0.07)	0.34(0.07)	0.50(0.31)
ROAD	0.00(0.91)	0.24(0.01)*	0.07(0.34)	0.03(0.82)
RAIL	0.02(0.56)	0.12(0.07)	0.05(0.41)	0.02(0.87)
TOTAL EFFECTS				
CAPITAL	0.27 (0.03) *	0.48 (0.01) *	0.42 (0.00) *	0.91 (0.01) *
LABOR	0.10 (0.06)	0.05 (0.64)	0.11 (0.20)	0.02 (0.89)
INTERMEDIATE	0.26 (0.00) *	0.34 (0.03) *	0.33 (0.02) *	0.21 (0.51)
LAND	0.04 (0.76)	0.27 (0.28)	0.19 (0.32)	0.35 (0.46)
ROAD	0.02 (0.62)	0.27 (0.01) *	0.09 (0.21)	0.06 (0.67)
RAIL	0.00 (0.99)	0.11 (0.13)	0.03 (0.58)	0.00 (0.98)

Note: P-value is in parentheses.

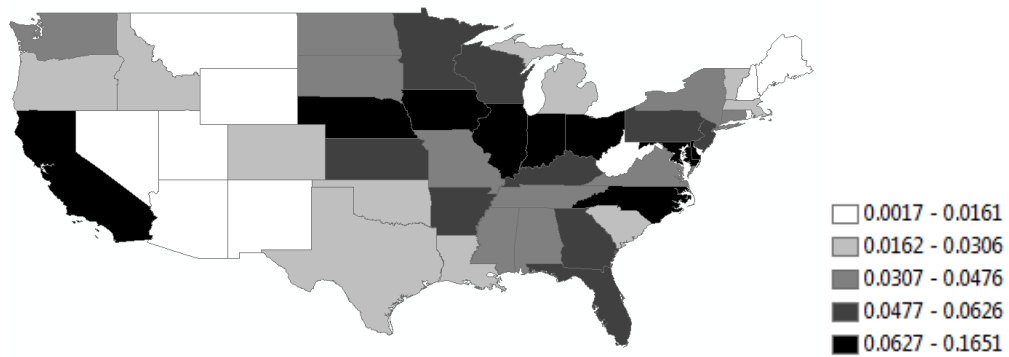


Figure 1. Agricultural output index per million acres in the U.S. (2004)

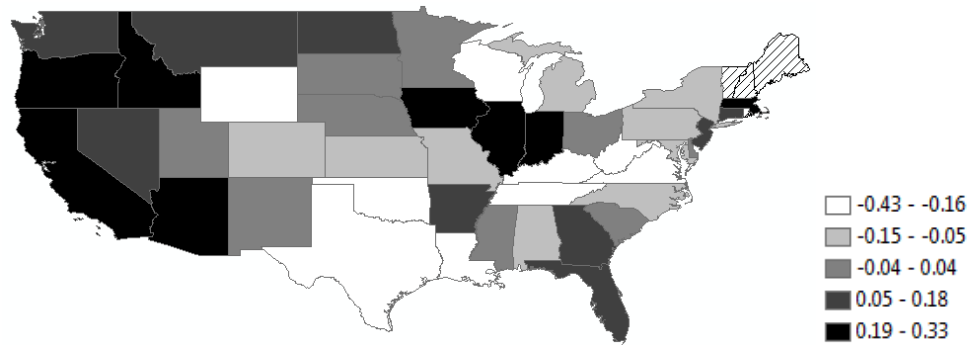


Figure 2. Spatial dependence of residuals (2004) (Moran's I =0.29, P-value=0.005)

Note: Four states, including Vermont, Rhode Island, New Hampshire, and Maine (marked in lines), were excluded due to data availability.

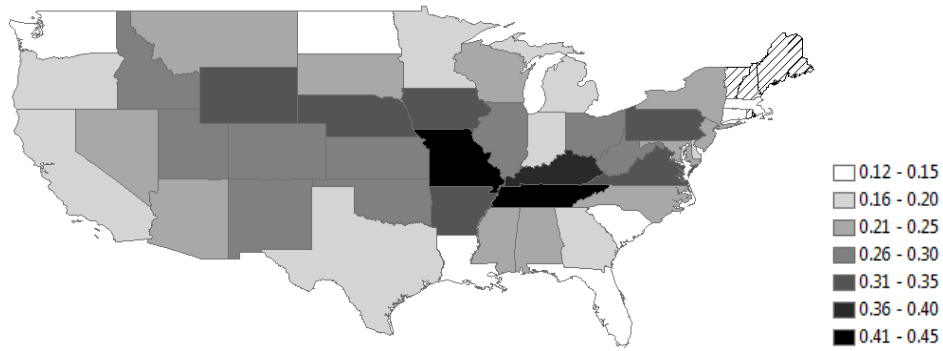


Figure 3. Spillover effect of each state with increase in road disbursement within the state

Note: Four states, including Vermont, Rhode Island, New Hampshire, and Maine (marked in lines), were excluded due to data availability.

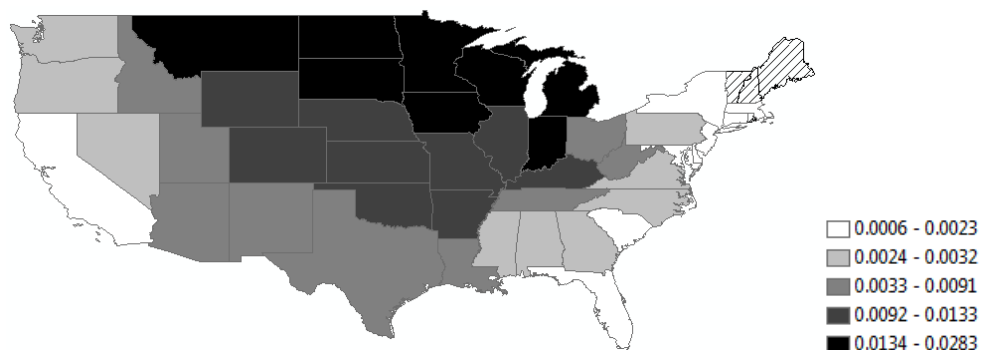


Figure 4a. The pattern of spillover effect with road disbursement increases in Iowa

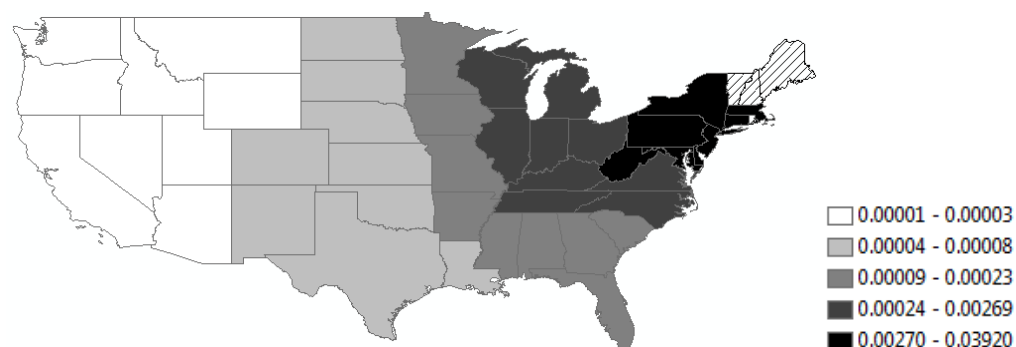


Figure 4b. The pattern of spillover effect with road disbursement increases in Massachusetts

Note: Four states, including Vermont, Rhode Island, New Hampshire, and Maine (marked in lines), were excluded due to data availability.

**Chapter 3: Assessing the Impact of Public Infrastructure on Output Growth in U.S. Food
Manufacturing Industries: A Heterogeneous Dynamic Panel Approach**

Abstract

This study analyses the effects of public infrastructure on the output growth in the U.S. food manufacturing industries during 1958–2005. Specifically, this study identifies a long-run relationship between output, input factors and public infrastructure in food manufacturing industries utilizing a panel unit root test and a panel cointegration test. Also, this study estimates both the long-run and short-run impacts of public infrastructure using dynamic heterogeneous panel methods, including pooled mean group (PMG) and mean group (MG). The results suggest that public infrastructure has a homogeneous long term output impact across 34 food manufacturing industries. Precisely, a one percent increase in public infrastructure enhances the U.S. food manufacturing industry output by 0.33 percent in the long run. Conversely, only eight of the evaluated food industries are affected by changes in public infrastructure in the short run. The long-run positive impact of public infrastructure on food output suggests the importance of continuous public infrastructure investment on the output growth of the food manufacturing industry.

Introduction

The impact of public infrastructure on private sector performance has been thoroughly discussed over the last two decades. However, no clear conclusion has yet been reached. Theoretically, public infrastructure, such as highway, sewer, and water systems, could raise the marginal productivity of private capital, therefore crowd in private investment and extending output. However, public expenditure may crowd out private capital if higher public expenditure accumulation raised the national rate of capital accumulation above the level chosen by the private sectors as private sectors would have to reduce private savings to reestablish an optimal level of resource use (Aschauer 1989b). Thus, while most numerous empirical studies in this area supported the finding that public infrastructure has positive effect on private sector performance (e.g. Costa *et al.* 1987; Conrad and Seitz 1992; Kim and Lee 2002; Pereira and Andraz 2003), other researchers could not find any significant effect of public infrastructure or even found a negative consequent impact on private sector performance (e.g. Hulten and Schwab 1992; Evans and Karras 1994; Nadiri and Mamuneas 1994; Greenstein and Spiller 1995).

Despite the great number of studies evaluating the effect of public infrastructure on output and productivity in the private sector, the importance of public infrastructure on food manufacturing industries in the U.S. specifically has received much less attention. The food manufacturing industry plays a significant role in the U.S. economy, accounting for more than 10 percent of all manufacturing shipments in 2006 (U.S. Department of Commerce 2008). Also, the sector provides great employment opportunities. In 2008, the U.S. food manufacturing industry provided 1.5 million jobs (United States Department of Labor 2011). Moreover, the products of the food manufacturing industry fulfill a fundamental need in everyone's daily life. According to Morrison *et al.* (2010), inclusion of processed food, such as cheese, sugar, processed meat,

processed eggs, processed fruit, etc., in American's diet has increased significantly between 1909 and 2008. Thus, an economical and reliable supply of products from various food industries is crucial to the health and security of the nation.

Within the context of the food manufacturing industry, the increasing prices of agricultural products have become a challenge over the past few years. For instance, the price of corn has more than doubled from \$2.23 per bushel in 2005 to \$5.30 per bushel in 2010 (USDA 2012). Also, increasing costs of other input such as labor, energy, and transportation together with stricter regulation in environmental sustainability and food safety requirements have influenced costs in the food manufacturing industry. As a result, the productivity and efficiency of the food manufacturing industry have become increasingly important to the bottom line of all parties involved, such as food produces, consumers, and input suppliers (Paul 2000). Investment in public infrastructure, e.g. transportation system, can potentially enhance the productivity and efficiency of the food production since such investment can improve procuring, processing, packaging, and marketing processes by hastening the speed of the circulation of capital, labor, and other inputs, hence enhancing productivity and efficiency (Bernstein and Mamuneas 2008). Also, public infrastructure availability is important to the decision on the location of food industry (Lopez and Henderson 1989; Lambert and McNamara 2009).

Given the social and economic benefit of the food manufacturing industry to consumers and food producers, and the influence of public infrastructure to this industry, exploring the impact of public infrastructure on food manufacturing output is timely and necessary. Particularly, the deteriorating U.S. public infrastructure has drawn considerable concern lately since it may affect private sectors' productivity and the nation's economy (Obama 2011). Thus, the object of this study is to analyze the impact of public infrastructure on the output growth of

the disaggregated food manufacturing industries in the U.S. It is hypothesized that increases in public infrastructure can increase the output growth in the food manufacturing industry.

Furthermore, this study anticipates providing more insights about the dynamic output impact of public infrastructure on U.S. food manufacturing industry through application of the recently developed heterogeneous dynamic panel estimation method (Pesaran *et al.* 1999).

Literature Review

Starting from a series of empirical analyses on the economic impact of public infrastructure investment by Aschauer (1989a; 1989b; 1990), this subject has been scrutinized for the national economy or private sectors performance of the United States and other countries in the literature. A detailed survey of those studies can be found in Bhatta and Drennan (2003), Romp and Haan (2007), and Pereira and Andrzej (2010). A brief summary of the literature focusing on the impact of public infrastructure on the output and productivity in the private sectors including food manufacturing industry is offered below in this section.

Most of the previous studies supported the positive role of public infrastructure on the U.S.'s private sector performance. Costa *et al.* (1987) evaluated the economic impact of public infrastructure on different sectors in the U.S. and found that, at the state level, the output elasticities of public capital were 0.19, 0.20, and 0.26 for manufacturing, all sectors, and nonagricultural sectors, respectively. Deno (1988) examined the effect of public infrastructure on the production of U.S. manufacturing industries in 36 regions from 1970 through 1978 and concluded that, among all the evaluated public capital, including highway, sewer, water, and total public capital, the aggregate stock of public capital had the biggest effect on the input demand and output supply of manufacturing industries. Kim and Lee (2002) investigated the

relationship between public capital and the production efficiency of U.S. manufacturing industries during the period of 1969-1986. The authors found that (i) public capital increases technological efficiency, hence enhancing the private sector's output and (ii) improvements in technological efficiency diverged spatially and temporally, primarily due to variations in public capital. The positive impact of public infrastructure on private sector output and productivity was also found in case studies in other countries (Lynde and Richmond 1993; Kim *et al.* 1999; Karadag *et al.* 2004).

Some studies, however, could not find any significant impact of public infrastructure on private sector output and productivity. For instance, Hulten and Schwab (1992) found the link between public infrastructure and economic performance in manufacturing industries in the U.S. from 1951 to 1986 weak. Evans and Karras (1994) estimated the effect of government capital on the aggregate economy as well as on the manufacturing sectors of seven countries, including Belgium, Canada, Finland, Germany, Greece, the United Kingdom, and the U.S. from 1963 to 1988 and found that the effect of government capital was not significant in terms of real value added to manufacturing in the countries evaluated. Greenstein and Spiller (1995) assessed the impact of telecommunication infrastructure on the sectors of fire, insurance, and real estate as well as the manufacturing industry in the U.S. and showed that the modernization of the telephone network was not related to activities in the manufacturing sector.

Relatively little literature exists considering the effect of public infrastructure on food manufacturing industries. A summary of related studies is listed in Table 5, categorized by the analytical approach. Studies using the production function approach usually, but not always, found positive effects of public infrastructure on food manufacturing industries. Bernstein and Mamuneas (2008) evaluated the effect of public infrastructure capital on the production

techniques, cost of production, and productivity growth for Canadian food processors. Their results indicated that a one percent increase in infrastructure capital reduced production cost by 0.16 percent. Also, public infrastructure capital contributed 0.50 percentage points to annual productivity. Ku and Yoo (2011) found that the output elasticities of the food, beverage and tobacco industries with respect to industrial water was about 0.01 in South Korea. Moreover, Mitra *et al.* (2012) estimated that elasticity of total factor productivity (TFP) with respect to the core infrastructure index in the food and beverage industry in India and found that a one percent increase in core infrastructure index enhanced the TFP of the food and beverage industries by 0.24 percent. On the other hand, Castaneda *et al.* (2000) studied the impact of highway and electricity infrastructure on Mexican manufacturing output growth. Unlike other studies, the authors did not find significant output effect of infrastructure on food, beverage and tobacco industries.

Other studies adopted the cost function approach to evaluate the contribution of public infrastructure on the food and beverage industries, with mixed results. Nadiri and Mamuneas (1994) examined the effect of public infrastructure and R&D capital on the cost and productivity of 12 manufacturing industries in the U.S. Their results suggested that a one percent increase in R&D capital lowered cost by 0.05 percent; however, a one percent increase in public infrastructure investment increased cost by 0.02 percent. Harchaoui and Tarkhani (2003) evaluated the effect of public infrastructure on 37 industries in Canada and found that cost elasticity of food industry with respect to public infrastructure is -0.04. Recently, Mamatzakis (2007) conducted a study in Greek manufacturing industries and concluded that a one percent increase in public infrastructure reduced cost in the long-run food industry by 0.10 percent.

A few scholars employed the multivariate time series analysis method to address the potential reverse impact of industry output to public infrastructure development. Pereira and Andraz (2007) analyzed the effect of transportation infrastructure on 18 industries in Portugal using the Vector AutoRegression (VAR) approach. At the aggregate level, their results suggested that there was a positive effect of public investment on private input, private output, and labor productivity. However, the effect of public infrastructure varied across different industries. For the food industry, the long-run accumulated output elasticity with respect to public investment was found to be 0.10.

Although the aforementioned studies have provided rich knowledge about the impact of public infrastructure on food industry output and productivity in various contexts, most of them, except for Pereira and Andraz (2007), did not explicitly identified the dynamic impact of public infrastructure. This study, therefore, contributes to the literature by evaluating both the short-run and long-run effects of public infrastructure on U.S. food manufacturing industries using recently developed heterogeneous dynamic models.

Empirical Models

This study evaluated the effect of public infrastructure on the food manufacturing industry using a Cobb-Douglas production function framework (Cobb and Douglas 1928).

$$(1) y = Af(l, k, e),$$

where y represents the gross output; A represents multifactor productivity; and l, k , and e represent capital, labor, and energy use, respectively. Public infrastructure not only affects private output directly as an input factor similar to capital and labor but also the multifactor productivity (A). By shifting the production function frontier upward, investment in public

infrastructure improves the marginal output of other input factors, thus increasing private output indirectly. As a result, by following Romp and Haan (2007), the effect of public infrastructure on private output can be expressed as:

$$(2) y = A(g)f(l, k, e, g),$$

where g represents public infrastructure.

Assuming that A has an exponential form ($A = g^\beta$), equation (2) can be written as:

$$(3) y = g^\beta l^\gamma k^\delta e^\varepsilon g^\theta.$$

Take logarithms of both sides. Equation (3) can be presented as:

$$(4) Y = \alpha + (\beta + \theta)G + \gamma L + \delta K + \varepsilon E + \mu,$$

where each variable is presented in natural form. The economic impact of public infrastructure is derived as the derivative of Y with respect to G :

$$(5) \partial Y / \partial G = \beta + \theta.$$

Methodology

1. The fixed effects model (FE) and the random effects model (RE)

This study first employs the fixed effects (FE) model and the random effects (RE) models to evaluate the effect of public infrastructure on the output of the food manufacturing industry.

Both the FE and RE models are based the on unobserved effects model (UEM) (Wooldridge 2002, p251):

$$(6) y_{it} = \beta_i X_{it} + a_i + u_{it}; t = 1, \dots, T; i = 1, \dots, N,$$

where t represents time period and i represents panel units; y is dependent variable; X_{it} is a

$1 \times K$ matrix containing independent variables with β_i as the corresponding coefficient matrix;

a_i is the unobserved effects, which can be also called as unobserved heterogeneity, individual

effects, or individual heterogeneity. It can be treated as a fixed effect or a random effect; and u_{it} is the error term.

The crucial difference between FE and RE models is whether they assume individual effects are correlated with explanatory variables in the model. According to Stock and Watson (2007), the key insight of the FE model is that changes in dependent variables are due to influences other than individual fixed characteristics since they do not change over time. Its main advantage is to remove the time-invariant individual characteristics from the independent variable to determine the net effect of the predictor variables. Alternatively, the RE model assumes that variation across panels is random and uncorrelated with the predictor; thus, it can include time invariant variables as an explanatory variable.

The analysis in this study is based on the following equation:

$$(7) Y_{it} = \beta_1 L_{it} + \beta_2 K_{it} + \beta_3 E_{it} + \beta_4 G_{it} + a_i + u_{it}; \quad t = 1, \dots, T; i = 1, \dots, N,$$

where t represents the time period from 1958 to 2000; i represents 34 food manufacturing industries; Y_{it} is the total value added by industry i at time t ; L_{it} , K_{it} , and E_{it} are respective labor, capital, and energy inputs used by the food manufacturing industry; G_{it} represents public infrastructure; a_i is the individual effect; and u_{it} is error term. A statistically significant coefficient β_i indicates the effect of the explanatory variables on the output of food manufacturing industry.

Several tests are conducted before estimating the panel FE and RE models. First, a Lagrange multiplier (LM) test (Breusch and Pagan 1980) is performed to determine if a panel effect exists. If the null hypothesis is rejected, the test suggests the existence of panel effect. The Hausman test (Hausman 1978) has been suggested in previous studies to test for fixed or random effects (Stuart et al. 2010). However, according to Wooldridge (2002, p. 289), the Hausman test

is not valid when the residuals are heteroskedastic and/or serially correlated. Accordingly, this study performs a likelihood ratio (LR) test for heteroskedasticity (Wiggins and Poi 2003)⁶ and a Wooldridge test for autocorrelation (Wooldridge 2002) in any panel data. If these two tests reject the null of no heteroskedasticity and autocorrelation in residuals from the models, the Hausman test may produce biased results⁷.

As an alternative, an overidentification test (Schaffer and Stillman 2006) is adopted to test between the fixed and random effects. The FE estimator uses the orthogonality condition that independent variables are uncorrelated with the idiosyncratic error. In addition, the RE estimator uses additional orthogonality conditions that require that the independent variables are uncorrelated with individual effects, also called overidentification restriction. The null hypothesis of the test is that RE estimator is consistent. The rejection of the null hypothesis indicates that the FE is preferred over the RE model.

Recently, there has been increasing concern about the power of traditional FE and RE models, especially when there is a large T . According to Baltagi (2001), the current focus on panel data analysis is the non-stationarity of the data series and the heterogeneity among individuals. Apart from the panel data with small T , the non-stationarity or unit root of the data needs to be evaluated and addressed prior to further analysis in the large T panel data. Also, ignoring the heterogeneity among individuals in the large N panel may generate a misleading estimate when the individual varies significantly. To address these issues and provide a more comprehensive estimation, this study first conducted unit root tests for each data series followed by a panel cointegration test to examine if a long-run relationship among data series existed.

⁶ Wiggins and Poi (2003) pointed out that the easiest way to test for heteroskedasticity is to compare two panel generalized least squares models, one with heteroskedasticity and one without, and then compare their likelihoods using a likelihood ratio test.

⁷ A robust Hausman test, suggested by Wooldridge (2002) to fix the caveats of Hausman test, is not applicable since infrastructure variables change across t but not i in the model.

Based on the output in those two tests, heterogeneous dynamic panel estimations and post sample predictions were made. The details of each procedure are presented in following subsections.

2. Unit root tests

The presence of a unit root in time series or panel data implies that the current value of a variable is correlated to its value in previous periods, which makes the data series non-stationary or integrated. A non-stationary series can lead to a spurious regression and biased estimates if the ordinary least square (OLS) is used. For this reason, unit root tests were conducted before taking the panel data analysis. Since the public infrastructure variable in this study is industry-invariant (i.e., time-series data), the conventional unit root test methods for time series data were used, which include the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller 1979), Philips-Perron (PP) (Phillips and Perron 1988) and the Kwiatkowski, Phillips, Schmidt, and Shin test (KPSS) (Kwiatkowski *et al.* 1992).

Panel unit root test methods have been applied to other food manufacturing industry data series as the panel unit root test method is generally recognized a higher test power than the conventional unit root test for individual series (Oh 1996; Macdonald 1996; Levin *et al.* 2002). This study first applied the panel unit root test developed by Levin *et al.* (2002) (hereafter referred to as the “LLC”), which assumes that there is a common unit root process across the industries. It is based on ADF test:

$$(8) \Delta y_{it} = \alpha y_{it-1} + X'_{it}\theta + \sum_{j=1}^{p_i} \beta_{it} \Delta y_{it-j} + \epsilon_t$$

where α is common for all panels, whereas p can be different. The null hypothesis of the LLC is $\alpha = 0$, which indicates the existence of unit root.

Different from the LLC, two alternative panel unit root tests allowing for heterogeneity in the autoregressive coefficient, the test developed by Im *et al.* (2003) (hereafter referred to as the “IPS”) and the Fisher type test (Fisher 1932), were also performed. The IPS test statistics can be written as follows:

$$(9) \quad \bar{t} = \frac{1}{N} \sum_{i=1}^N t_{iT}$$

where t_{iT} is the ADF t-statistic for industry i based on the industry-specific ADF regression. The Fisher-ADF and Fisher-PP statistics combine the p -value of individual unit root tests with a Chi-squared distribution with $2N$ degrees of freedom:

$$(10) \quad -2 \ln \pi_i \sim \chi_{2N}^2$$

where π_i is the p -value of the individual unit root test.

The aforementioned panel unit root tests, referred to as *first generation unit root tests*, have a strong assumption of no cross-section dependence among industries. However, cross-section dependence may exist due to unobserved common effects, economic relationships among units, and residual interdependence (Bangake and Eggoh 2011). Several alternative tests aim to solve the cross-section dependence issue, referred to as *second generation unit root tests*. This study employed the cross-sectionally augmented IPS (CIPS) test, which is a commonly used second generation test developed by Pesaran (2007). This test augmented the standard ADF test with the cross-section averages of lagged levels and first-differences of the individual series. The test statistics are based on the average of individual cross-sectionally augmented ADF statistics (Pesaran 2007).

3. Panel cointegration test

Based on the unit root test, the data series can be identified as stationary or integrated. If more than one of the evaluated variables are integrated, a panel cointegration test needs to be conducted to determine if the linear combination of those variables is stationary (Jonathan 2006). As long as none of the evaluated variables is integrated of order two $I(2)$, or a higher order, the panel cointegration analysis used in this study is valid.

This study adopted the panel cointegration technique from Pedroni (1999), which takes heterogeneity into account by using specific parameters varied across the sample industries. According to Pedroni (1999), traditional tests based on a moderate length time period have low test power, while pooling the data across panels can provide more information about the long-run relationship. Therefore, panel cointegration techniques allow researchers to selectively pool information across panels to get long-run relationships while allowing heterogeneity across different panel members. The method developed by Pedroni (1999) is based on the following equation:

$$(11) \quad Y_{it} = \alpha_i + \delta_i t + \beta_{1i} L_{it} + \beta_{2i} K_{it} + \beta_{3i} E_{it} + \beta_{4i} I_{it} + u_{it}; \quad t = 1, \dots, T; i = 1, \dots, N,$$

where α_i is the individual effects; $\delta_i t$ represents the trend; u_{it} is the residuals representative deviation from the long-run relationship.

The null hypothesis of the Pedroni cointegration test is that there is no cointegration relationship, which means the residual u_{it} is $I(1)$. The following unit root test is applied on the residuals from equation (11):

$$(12) \quad u_{it} = \rho_i u_{it-1} + e_{it}.$$

Based on the above equation, Pedroni (1999) developed seven different statistics to test the null hypothesis of no panel cointegration ($\rho_i = 1$). Four of those statistics evaluate cointegration

within dimensions, which include panel ν , panel ρ , panel PP, and the panel ADF statistics. These statistics are based on estimators that effectively pool the autoregressive coefficient across different members for the unit root tests on the estimated residuals. Another three test statistics examine cointegration between dimensions, including group ρ , group PP, and group ADF. These tests are based on the simple average of the individually estimated coefficients for each industry i . If the test results show evidence of cointegration, the panel cointegration method can be used to estimate the long-run relationship between the dependent and explanatory variables.

4. *Heterogeneous dynamic panel estimation*

This study considered two heterogeneous dynamic panel methods, the mean-group (MG) and pooled mean group (PMG) methods developed by Pesaran *et al.* (1999), to estimate the output effect of public infrastructure. The PMG and MG methods are two important techniques to estimate non-stationary and heterogeneous panels. An important feature of the PMG method is that it allows short-run coefficients and error variances vary across different groups while assuming a homogeneous long-run relationship between dependent and explanatory variables. The MG estimator is generated by estimating N time-series regressions and averaging the coefficients among the N series. In contrast to the PMG method, the MG method allows the slopes, intercepts, and residuals to be heterogeneous across individuals (Blackburne and Frank 2007).

The PMG method is an application of the autoregressive distributed model (ARDL) and the coefficients are calculated following the maximum likelihood method developed by Pesaran *et al.* (1999). The choice of lag order in the ARDL framework is of crucial importance (O'Mahony and Vecchi 2005). According to Loayza and Ranciere (2006), if the main research

interest is in the long-run estimators, the lag order of the ARDL model should vary across the individuals. However, if short-run relationships are also of study interest, the imposition of a common lag structure across individuals is recommended, as adopted in this study. In order to preserve the degree of freedom while allowing for reasonable dynamics, this study imposed a common ARDL(1,1,1,1,1) structure to all industries.

Assume the following long-run relationship:

$$(13) \quad Y_{it} = \theta_{0i} + \theta_{1i}L_{it} + \theta_{2i}K_{it} + \theta_{3i}E_{it} + \theta_{4i}G_{it} + u_{it}; \quad i = 1, 2, \dots, N; t = 1, 2, \dots, T,$$

where each variable is presented in natural logarithm. Equation (13) can be presented in an ARDL(1,1,1,1,1) dynamic panel model:

$$(14) \quad Y_{it} = u_i + \delta_{10i}L_{it} + \delta_{11i}L_{it-1} + \delta_{20i}K_{it} + \delta_{21i}K_{it-1} + \delta_{30i}E_{it} + \delta_{31i}E_{it-1} + \delta_{40i}G_{it} + \delta_{41i}G_{it-1} + \lambda_i Y_{it-1} + e_{it}.$$

The error correction model of equation (14) becomes:

$$(15) \quad \Delta Y_{it} = \phi_i(Y_{it-1} - \theta_{0i} - \theta_{1i}L_{it} - \theta_{2i}K_{it} - \theta_{3i}E_{it} - \theta_{4i}G_{it}) - \delta_{11i}\Delta L_{it} - \delta_{21i}\Delta K_{it} - \delta_{31i}\Delta E_{it} - \delta_{41i}\Delta G_{it} + e_{it},$$

where $\phi_i = -(1 - \lambda_i)$, $\theta_{0i} = \frac{u_i}{1-\lambda_i}$, $\theta_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1-\lambda_i}$, $\theta_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1-\lambda_i}$, $\theta_{3i} = \frac{\delta_{30i} + \delta_{31i}}{1-\lambda_i}$, and $\theta_{4i} =$

$\frac{\delta_{40i} + \delta_{41i}}{1-\lambda_i}$. ϕ_i is the error correction coefficient to reflect how fast an industry responds to a shock

and reaches to a new equilibrium. θ_{1i} , θ_{2i} , θ_{3i} , and θ_{4i} are long-run coefficients. δ_{11i} , δ_{21i} , δ_{31i} , and δ_{41i} reflect the short-run effects of changes in input factors and infrastructures on industry output.

A potential problem of estimating a production function is the endogeneity of explanatory variables. In the PMG model, the error term is assumed to be independently and identically distributed across panel units and uncorrelated with right hand variables (Pesaran *et al.* 1999). However, as long as the order of the ARDL model is approximately augmented, the long-run

estimator in the PMG method is immune to the endogeneity problems (Pesaran and Shin 1999; Favara 2003). Moreover, since all explanatory variables enter the regression with lags in the ARDL structure, contemporaneous feedback and reverse causality from output growth to public infrastructure was mitigated (Catao and Solomou 2005; Kim *et al.* 2010b).

The Hausman test (1978) was performed to compare the PMG and MG models. According to Pesaran *et al.* (1999), the MG estimator provides consistent estimates by taking means of long-run coefficients, which are inefficient when long-run homogeneity holds. Alternatively, the PMG estimator provides both consistent and efficient estimators when there is long run homogeneity. Thus, the Hausman test was used to check if long-run homogeneity holds also to determine which method is preferable in this study.

Based on the results of the Hausman test, several robustness checks of the long-run impact of public infrastructure on food industry output growth and on the error correction coefficient in the preferred method (referred to as the baseline case) were proposed. Three robustness analyses were made in this study: we first evaluated the alternative lag length in the ARDL model that was chosen based on the Schwarz Bayesian criterion (SBC) for each industry, subject to a maximum lag of 2. In addition, the robustness check was applied to a sub-category of public infrastructure. The core public infrastructure, which has received considerable attention in the literature on this subject (e.g. Aschauer 1989a; Munnell 1990; Gramlich 1994), was selected to estimate its output growth impact in the food manufacturing industry. Following Gramlich (1994), the core public infrastructure in this study included government fixed assets in highways and streets, and sewer and water infrastructures. Finally, the coefficients for a subcategory of food manufacturing industry, the processed crop category, were evaluated, as this

sub-group had the largest output growth among four processed food categories (meat, dairy, grain and crops) between 1959 and 1991 (Gopinath *et al.* 1996).

5. *Post sample prediction*

To further compare the quality of these two panel cointegration models, post sample tests were conducted. Post sample is defined as the S time periods following the sample (Granger and Huang 1997). The post sample test was conducted following Granger and Huang (1997) and Freeman (2000). First, the long- and short-run coefficients in equation (15) were estimated for each industry using both the PMG and MG methods. These estimated coefficients were used with actual values of independent variables and lagged predicted values of dependent variables for upcoming periods to assess predicted values. The prediction error is the difference between the predicted values and the actual values. Second, the overall mean square prediction error (MSPE) was calculated as the sum of the squared prediction errors divided by the product of the predicted time period and the number of industries. The MSPE was also calculated for 34 industries separately under both estimation methods and then the number of industries with lower MSPE was summarized.

Data

This study utilized a panel data set of 34 food manufacturing industries over the period of 1958–2005 based on the North American Industry Classification System (NAICS) six-digit code. The first 43 years (1958–2000) were used in model estimation while the remaining five years (2001–2005) were used for post sample prediction. A list of 34 food manufacturing industries is provided in Table 6. Input data, output data, and the related deflators were taken from NBER-

CES Manufacturing productivity database (NBER-CES 2009), which is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES). Output data (Y) is the total value added divided by the shipment deflator. Three input factors were included in this study: capital, labor, and energy. Capital (K) is the total real capital stock; labor (L) is represented by production worker hours; and energy (E) is the energy cost of electric and fuels divided by the energy deflator.

Public infrastructure data (G) were obtained from the U.S. Bureau of Economic Analysis (USBEA 2012) and represents a stock of government fixed assets excluding national defense, mainly including government fixed assets in highways and streets, sewer and water infrastructures, residential and office buildings, and educational infrastructure. Public infrastructure data were deflated by the GDP deflator with 1997 as the base year, which is consistent with the input and output deflators. All data used in the empirical model were in logarithms.

Empirical Results

1. *Fixed effects (FE) and random effects (RE) models*

Table 7 shows the results of the FE and RE models and the related tests. The LM test results reject the null hypothesis at 5% significance level, which indicates the existence of the panel effect. In this study, statistical significance at the 5% level is denoted with one asterisk in the tables; thus, those variables and test statistics are henceforth referred to as “statistically significant” in the discussion below. Moreover, the LR and Wooldridge tests also reject the null hypotheses, which indicates that there likely heteroskedasticity and autocorrelation in the residuals. So the Hausman test is not appropriate in this study. As an alternative, this study

applies the overidentification test (Schaffer and Stillman 2006). The test rejects the null hypothesis, showing that the FE is preferable to the RE model. Moreover, according to Asteriou and Hall (2011), the RE model is built under strong assumptions that the fixed effects are uncorrelated with explanatory variables, which creates strict limitations when doing the panel data analysis. As a result, the FE model is more suitable to this study than RE model.

From Table 7, the FE model shows that all input variables and the public infrastructure variable have a significant and positive effect on industry output. A one percent increase in public infrastructure will increase industry output by 0.61 percent. However, those elasticities might be biased if unit roots are observed in the data series.

2. Unit roots and panel cointegration tests

The output of the ADF, PP, and KPSS unit root tests for the public infrastructure variable is summarized in Table 8. Both the ADF and PP tests failed to reject the null hypothesis of the existence of unit root in levels. The KPSS test rejected the null hypothesis (no unit root) in levels, indicating the existence of a unit root. After taking first difference, both the ADF and PP tests suggested that the variable is stationary and the KPSS test could not reject the null hypothesis, which suggested that public infrastructure variable is integrated of order one, $I(1)$.

Table 9 displays the panel unit root test results of the LLC and first generation tests for the input and output variables of the food manufacturing industry. For variable Y , the LLC test rejects the null hypothesis for the existence of a unit root in levels without trend. When the trend is included, all four tests reject the null hypothesis, implying that Y is stationary in levels. For variables L , K , and E , the null of integration cannot be rejected for the data in levels but is rejected in first difference, suggesting that those three variables were $I(1)$.

The result of the panel unit root test considering cross-section dependence is presented in Table 10. Considering a lag length up to three, Y is stationary in levels as the null hypothesis is rejected generally, regardless of the number of lags. Both L and K are $I(1)$ since the null hypothesis of unit root, though not rejected in levels, is rejected after taking first difference in most cases. For E in levels, the CIPS test shows that the series does not contain a unit root only when no lag was chosen. After taking the first difference, the existence of a unit root is rejected in all cases.

Given that at least two variables were found non-stationary and none of them is integrated of order two or higher, the result of Pedroni panel cointegration test is presented in Table 11. Most statistics reject the null hypothesis of no cointegration among evaluated variables in both cases with or without time trend. Therefore, we assume that the cointegration relationship exists between dependent and explanatory variables in this study.

3. *Heterogeneous dynamic panel estimation and post sample tests*

Table 12 displays the results of the MG and PMG methods. The statistically significant and negative error correction coefficients in both methods further confirmed the existence of a long-run cointegration relationship (Iwata *et al.* 2011; Kim *et al.* 2010a). In the output of the MG method, the error correction coefficient of -0.50 indicates that 50% of the deviation from long-run equilibrium is eliminated in one year through the change in public infrastructure and other input factors (Li and Leung 2012). This suggested that food manufacturing industries generally take about two years to reach to a new equilibrium after a shock in public infrastructure or other input variables. In the long run, only K is found to affect the output growth in food manufacturing industries, with output elasticities of 0.50. In the short run, L is the sole force

sustaining the output growth in food output growth; a one percent increase in L generates growth in food output by 0.37 percent.

In the PMG output, the error correction coefficient is -0.23, suggesting it takes at least four years for the food manufacturing industries to adjust their output to reach to a new equilibrium after a perturbation occurs in input factors or public infrastructure. The PMG output suggests a positive impact of public infrastructure on food manufacturing industry output. A one percent increase in G enhances growth in output by 0.33 percent. Both L and K also have positive effects on industry output growth in the long run. Specifically, the food manufacturing industry output grows by 0.26 percent and 0.50 percent, respectively, along with a one percent increase in L and K . In the short run, labor, capital, and energy use make positive impacts on food industry output growth; however, no statistically significant effect is observed from G on food industry output growth. The food output elasticities of L , K , and E are 0.47, 0.29, and 0.10, respectively.

Although a long-run homogeneous relationship is suggested among food industries, the PMG method can still identify heterogeneity in the short-run coefficients. The number of industries affected by public infrastructure in the short-run by subcategory of food manufacturing industries is summarized in Table 13. The output growth in a total of 8 industries under five subcategories of the food manufacturing industry (grain and oilseed milling, sugar and confectionery product manufacturing, fruit and vegetable preserving and specialty food manufacturing, animal slaughtering and processing, and bakeries and tortilla manufacturing) are found to be affected by changes in public infrastructure in the short-run at the 5% level. The output growth of the other 26 food industries is not affected by a shock in public infrastructure in the prior period.

The Hausman test failed to reject the null hypothesis of homogeneity at the 5% significance level, suggesting PMG estimators are preferable to MG estimators. Moreover, Figure 5 shows the long run elasticity of the infrastructure variable across industries. It is obvious that there are significant differences of long-run coefficients among industries, so the simple average estimation proposed by the MG method could produce severely biased results (Freeman 2000). Both results indicated that the homogeneity is held in the long run relationships between output growth and input variables as well as public infrastructure among 34 food manufacturing industries, which is sensible given the similarity and connection between those industries.

Table 14 presents the robustness analysis associated with the PMG estimators of the error correction coefficient and the positive impact of public infrastructure on the output of the food manufacturing industries. The alternative setups to the baseline estimation are listed on the left panel of Table 14. By releasing the lag length assumption in the baseline case, the ARDL(1,1,1,1), to the SBC-determined optimal length, the long-run output growth elasticities of public infrastructure among food manufacturing industries (0.37) is similar to the baseline case (0.33). The error correction coefficient also remains close to the baseline estimation (-0.23).

Core infrastructure is a major component in public infrastructure in the U.S. In 2010, core infrastructure accounted for nearly 45% of the total fixed government assets excluding national defense (USBEA 2012). The results in Table 14 show both the long-run coefficients and the error correction coefficients are statistically significant. The estimated long-run output elasticity of the core public infrastructure in food industries is 0.23, which is relatively lower than the impact of overall public infrastructure on the baseline estimation. In addition, the estimation suggests that it takes about four to five years for food industries to adjust their output to respond

the shock in the core public infrastructure and other input factors, given the estimated error correction efficient of -0.22, which is in line to the baseline estimation.

For the output of category of processed crops food, the long-run impact of public infrastructure on food output growth is statistically significant and slightly higher than the baseline estimation (0.39 vs. 0.33). Interestingly, the statistically significant error correction coefficient associated with the group of processed crops industries, -0.29, indicates that this particular food manufacturing industry group adjusts output to the shocks in public infrastructure and other inputs within 3.5 years, which is faster than the average adjustment speed in all food industries (~4.3 years). The relatively higher long-run impact of public infrastructure and faster adjustment pace in the preprocess crop group to changes in inputs and public infrastructure may help this particular food manufacturing industry group gain a higher growth in output than other food industry groups, as found in Gopinath *et al.* (1996).

The three cases of robustness analysis confirm the goodness of baseline estimation given similar magnitude and identical sign of coefficients. The long-run impact of public infrastructure on food manufacturing industry output in all cases is statistically significant and ranges between 0.23 and 0.39. The error correction coefficient is also statistically significant with the elasticities ranging from -0.22 to -0.29.

In terms of the post sample prediction performance, the PMG method was also found to outperform the MG method in terms of the MSPE values. The overall MSPE of the panel data generated from the PMG method is 0.11, while the overall MSPE of the MG is 4.34, suggesting that the prediction error from the PMG method is much lower than that of the MG method. Moreover, the prediction power of an individual industry using the PMG method also dominated the prediction performance of the MG method. The number of industries with a minimal MSPE

using the PMG method is much higher than that of the MG method: 31 out of 34 industries show a lower MSPE using the PMG method. This finding further confirms that the PMG method is more appropriate in this study.

Conclusions and Discussions

The impact of public infrastructure on private sector output and productivity has been examined in the literature since the late 1980s. However, very little attention has been allocated to the food manufacturing sector in the U.S., despite its fundamental role in terms of providing for consumer's daily needs. This study investigates the contribution of public infrastructure to 34 U.S. food manufacturing industries output growth from 1958 to 2005. By applying a recently developed panel unit root test as well as panel cointegration analysis, this study identifies a long-run relationship between output, input factors, and public infrastructure in the food manufacturing industries. In addition, this study contributes to the literature by estimating both the short- and long-run impact of public infrastructure on the U.S. food manufacturing industry through the dynamic panel method, with the advantage of allowing heterogeneity in panel estimators and by addressing unit roots in a long panel data.

Results generated from the PMG method suggest that food manufacturing industries generally need 4–5 years to adjust output and reach a new equilibrium status in response to a shock in public infrastructure or other input factors. The short-run effect of public infrastructure on food manufacturing industries varies. Specifically, the short-run output growth in most of food manufacturing industries is not affected by changes in public infrastructure. However, public infrastructure has a positive long-run effect on output growth in food manufacturing industries. Specifically, a one percent increase in public infrastructure enhances industry total

value added by 0.33 percent in the long run. Similar positive output effects of public infrastructure in the food manufacturing industry were also found in the case studies of other countries (e.g. Bernstein and Mamuneas 2008 and Mitra *et al.* 2012).

The positive long-run impact of public infrastructure on the food manufacturing industry, verified by several robustness analyses, has important policy implications. The price spike of agricultural materials since 2005 has created significant challenges to food manufacturing industries. According to Morrison and MacDonald (2003), a one percent increase in the price of agricultural materials causes the costs for food manufacturing industries to increase by 0.25 percent. It is crucial for the food manufacturing industry to improve efficiency and increase output under the current high input costs. The findings in this study indicate that the role of public infrastructure is imperative to help the industries encounter the pressure yet continue to meet consumers' need.

As President Obama pointed out in the State Union Speech (Obama 2011), the leading role of the U.S. in terms public infrastructure has slipped over the past decades. The deteriorating infrastructure in the U.S. has received a rank of "D" based on the evaluation of domestic experts. Although an investment of \$105.3 billion has been allocated to U.S. infrastructure through the American Recovery and Reinvestment Act in 2009 (ARRA 2009), the demand for the enhancement of U.S. public infrastructure still remains high. However, due to the current budget restrictions, the policy debate on the whether the government should allocate more resources to public infrastructure has been drawn out for months, e.g. the H.R.7 (American Energy and Infrastructure Jobs Act of 2012). Based on the findings in this study, it is clear that investment in public infrastructure needs to be maintained in order to enhance growth in many sectors such as the food manufacturing industries so closely related to the basic needs of human life. Similarly,

because of the ongoing importance of public infrastructure investment on the output growth of the vital food manufacturing industry, this study also suggests that the investment decision in public infrastructure investment should be considered more in terms of long-run impact instead of short-run impact.

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Appendix

Table 5. Summary of studies about food manufacturing industries

Author (Year)	Data	Public Capital Measure	Conclusions
Production function approach			
Bernstein and Mamuneas (2008)	Canada; T.S. 1963-1997 Food processing industry	Infrastructure capital stock	One percent increase in infrastructure investment will reduce cost by 0.16 percent; increase productivity by 0.5 percent
Castaneda <i>et al.</i> (2000)	Mexican; P.D. 1970-1991 Manufacturing	Highways and electricity	Highways and electricity do not have significant effect on food and beverage and tobacco industry
Ku and Yoo (2011)	Korean; C.S. 2003 Manufacturing	Industrial water	Output elasticity of food, beverage and tobacco industry for water is 0.008.
Mitra <i>et al.</i> (2012)	India; P.D. 1994-2008 Manufacturing	Core infrastructure index	Elasticity of TFP with respect to core infrastructure index is 0.2423 in food and beverage industry.
Cost function approach			
Harchaoui and Tarkhani (2003)	Canada; T.S. 1961-2000 37 industries	Public capital stock	Cost elasticity of food industry with respect to public capital is -0.04
Mamatzakis (2007)	Greek; P.D. 1959-2000 Manufacturing	Public capital stock	One percent increase in public infrastructure reduces cost of food industry by 0.101 percent
Nadiri and Mamuneas (1994)	U.S.; P.D. 1955-1986 Manufacturing	Publicly financed infrastructure and R&D capitals	Cost elasticity of food industry (SIC=20) for public capital is 0.0234; for R&D capital is -0.0487
VAR approach			
Pereira and Andraz (2007)	Portugal; T.S. 1976-1998 18 industries	Transportation	Elasticity of private output with respect to public investment in food industry is 0.10.

Table 6. A list of food processing industries

NAICS	Industry
3112	Grain and Oilseed Milling
311211	Flour Milling
311212	Rice Milling
311213	Malt Manufacturing
311221	Wet Corn Milling
311222	Soybean Processing
311223	Other Oilseed Processing
311225	Fats and Oils Refining and Blending
311230	Breakfast Cereal Manufacturing
3113	Sugar and Confectionery Product Manufacturing
311311	Sugarcane Mills
311312	Cane Sugar Refining
311313	Beet Sugar Manufacturing
311320	Chocolate and Confectionery Manufacturing from Cacao Beans
311340	Nonchocolate Confectionery Manufacturing
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
311411	Frozen Fruit, Juice, and Vegetable Manufacturing
311412	Frozen Specialty Food Manufacturing
311421	Fruit and Vegetable Canning
311422	Specialty Canning
311423	Dried and Dehydrated Food Manufacturing
3115	Dairy Product Manufacturing
311511	Fluid Milk Manufacturing
311512	Creamery Butter Manufacturing
311513	Cheese Manufacturing
311514	Dry, Condensed, and Evaporated Dairy Product Manufacturing
311520	Ice Cream and Frozen Dessert Manufacturing
3116	Animal Slaughtering and Processing
311611	Animal (except Poultry) Slaughtering
311613	Rendering and Meat Byproduct Processing
311615	Poultry Processing
3117	Seafood Product Preparation and Packaging
311711	Seafood Canning
311712	Fresh and Frozen Seafood Processing
3118	Bakeries and Tortilla Manufacturing
311812	Commercial Bakeries
311813	Frozen Cakes, Pies, and Other Pastries Manufacturing

Table 6. Continued.

311821	Cookie and Cracker Manufacturing
311822	Flour Mixes and Dough Manufacturing from Purchased Flour
311823	Dry Pasta Manufacturing
311830	Tortilla Manufacturing

Table 7. FE and RE model results

	FE	RE
L	0.65(0.00)*	0.66(0.00)*
K	0.06(0.03)*	0.07(0.01)*
E	0.19(0.00)*	0.18(0.00)*
I	0.61(0.00)*	0.60(0.00)*
Cons	-5.12(0.00)*	-5.11(0.00)*
R-sq	0.83	0.83
LM test	15208.07(0.00)*	
LR test	847.86(0.00)*	
Wooldridge test	15.13(0.00)*	
Overidentification test	7.74(0.05)*	

Table 8. Unit root tests results for public infrastructure variable

	ADF	PP	KPSS
	Levels		
Intercept	-2.44(0.14)	-2.44(0.14)	0.78*
Intercept &Trend	-1.91(0.63)	-1.38(0.85)	0.19*
	First Difference		
Intercept	-3.97(0.00)*	-3.97(0.00)*	0.40
Intercept &Trend	-4.30(0.01)*	-4.19(0.01)*	0.14

The optimal lag length is determined by the Schwarz Bayesian criterion (SBC)

Table 9. Panel unit root test results (LLC and first generation tests)

		LLC	IPS	Fisher-ADF	Fisher-PP
		Levels			
Intercept	Y	-2.44(0.01)*	1.02(0.85)	73.00(0.32)	83.84(0.09)
	L	3.77(0.00)*	1.13(0.87)	58.29(0.79)	83.51(0.10)
	K	-1.72(0.04)*	3.01(1.00)	90.61(0.03)*	225.69(0.00)*
	E	-7.00(0.00)*	-1.45(0.07)	82.59(0.11)	139.13(0.00)*
Intercept &Trend	Y	-5.27(0.00)*	-4.28(0.00)*	135.87(0.00)*	140.49(0.00)*
	L	-0.37(0.36)	1.99(0.98)	47.53(0.97)	46.18(0.98)
	K	-4.59(0.00)*	-0.85(0.20)	111.07(0.00)*	222.08(0.00)*
	E	-2.53(0.01)*	0.09(0.54)	71.06(0.38)	66.83(0.52)
		First Difference			
Intercept	Y	-38.35(0.00)*	-38.05(0.00)*	1001.77(0.00)*	1111.70(0.00)*
	L	-33.43(0.00)*	-30.65(0.00)*	819.58(0.00)*	888.83(0.00)*
	K	-9.86(0.00)*	-10.78(0.00)*	263.56(0.00)*	268.40(0.00)*
	E	-35.56(0.00)*	-36.44(0.00)*	1044.73(0.00)*	2419.69(0.00)*
Intercept &Trend	Y	-35.56(0.00)*	-36.44(0.00)*	1044.73(0.00)*	2419.69(0.00)*
	L	-33.90(0.00)*	-31.18(0.00)*	790.06(0.00)*	1428.49(0.00)*
	K	-9.51(0.00)*	-7.48(0.00)*	203.76(0.00)*	205.54(0.00)*
	E	-34.45(0.00)*	-33.33(0.00)*	893.20(0.00)*	1773.41(0.00)*

The optimal lag length is determined by the Schwarz Bayesian criterion (SBC)

Table 10. Panel unit root test results (Second generation-CIPS)

		q=0	q=1	q=2	q=3
		Levels			
Intercept	Y	-6.58(0.00)*	-4.32(0.00)*	-2.14(0.02)*	-2.64(0.00)*
	L	1.03(0.85)	1.32(0.91)	2.71(1.00)	3.74(1.00)
	K	1.17(0.88)	-0.41(0.34)	1.57(0.94)	1.27(0.90)
	E	-3.00(0.00)*	-0.95(0.17)	-0.39(0.35)	0.26(0.60)
Intercept &Trend	Y	-4.04(0.00)*	-2.03(0.02)*	0.31(0.62)	-0.48(0.32)
	L	3.13(1.00)	3.56(1.00)	5.12(1.00)	6.59(1.00)
	K	3.09(1.00)	-0.048(0.48)	1.74(0.96)	1.00(0.84)
	E	-2.33(0.01)*	-0.18(0.43)	0.16(0.56)	1.44(0.92)
		First Difference			
Intercept	Y	-26.76(0.00)*	-20.09(0.00)*	-13.08(0.00)*	-8.93(0.00)*
	L	-25.22(0.00)*	-17.18(0.00)*	-11.77(0.00)	-8.52(0.00)*
	K	-11.65(0.00)*	-8.58(0.00)*	-5.44(0.00)*	-3.89(0.00)*
	E	-26.01(0.00)*	-17.86(0.00)*	-12.13(0.00)*	-7.79(0.00)*
Intercept &Trend	Y	-25.87(0.00)*	-18.25(0.00)*	-11.13(0.00)*	-6.53(0.00)*
	L	-24.75(0.00)*	-16.46(0.00)*	-11.30(0.00)*	-8.84(0.00)*
	K	-10.48(0.00)*	-6.76(0.00)*	-2.24(0.01)*	-0.60(0.28)
	E	-25.08(0.00)*	-15.79(0.00)*	-10.15(0.00)*	-5.35(0.00)*

Table 11. Panel cointegration test results

	Intercept	Intercept & Trend
Panel v -statistic	0.89(0.19)	-0.21(0.58)
Panel ρ -statistics	-3.89(0.00)*	-3.33(0.00)*
Panel PP-statistics	-7.27(0.00)*	-9.61(0.00)*
Panel ADF-statistics	-7.49(0.00)*	-10.14(0.00)*
Group ρ -statistics	-0.96(0.17)	0.12(0.55)
Group PP-statistics	-5.95(0.00)*	-7.79(0.00)*
Group ADF-statistic	-7.22(0.00)*	-8.97(0.00)*

The optimal lag length is determined by the Schwarz Bayesian criterion (SBC)

Table 12. PMG and MG estimation results based on ARDL

	MG	PMG
<i>Dependent variable Y</i>		
<i>Long run coefficients</i>		
L	0.18(0.35)	0.26(0.00)*
K	0.50(0.03)*	0.50(0.00)*
E	0.19(0.11)	-0.00(0.77)
G	-0.07(0.64)	0.33(0.00)*
<i>Short-run coefficients</i>		
L	0.37(0.00)*	0.47(0.00)*
K	-0.01(0.96)	0.29(0.04)*
E	0.05(0.29)	0.10(0.00)*
G	-0.14(0.44)	-0.27(0.06)
Constant	0.60(0.51)	-0.51(0.00)*
Error correction coefficient	-0.50(0.00)*	-0.23(0.00)*
Hausman test	7.96(0.09)	

Table 13. Number of industries affected by public infrastructure in the short-run in each category

NAICS	Industries	TOTAL
3112	Grain and Oilseed Milling	2(8)
3113	Sugar and Confectionery Product Manufacturing	1(5)
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	2(5)
3116	Animal Slaughtering and Processing	1(3)
3118	Bakeries and Tortilla Manufacturing	2(6)

Number outside of the parenthesis represents industries affected by public infrastructure in the short-run in each category.

Number inside of the parenthesis is the number of industries per category.

Table 14. PMG estimates of alternative models

Model	Elasticity	Error correction coefficient
SBC	0.37(0.00)*	-0.23(0.00)*
Core infrastructure	0.23(0.00)*	-0.22(0.00)*
Processed crops	0.39(0.00)*	-0.29(0.00)*

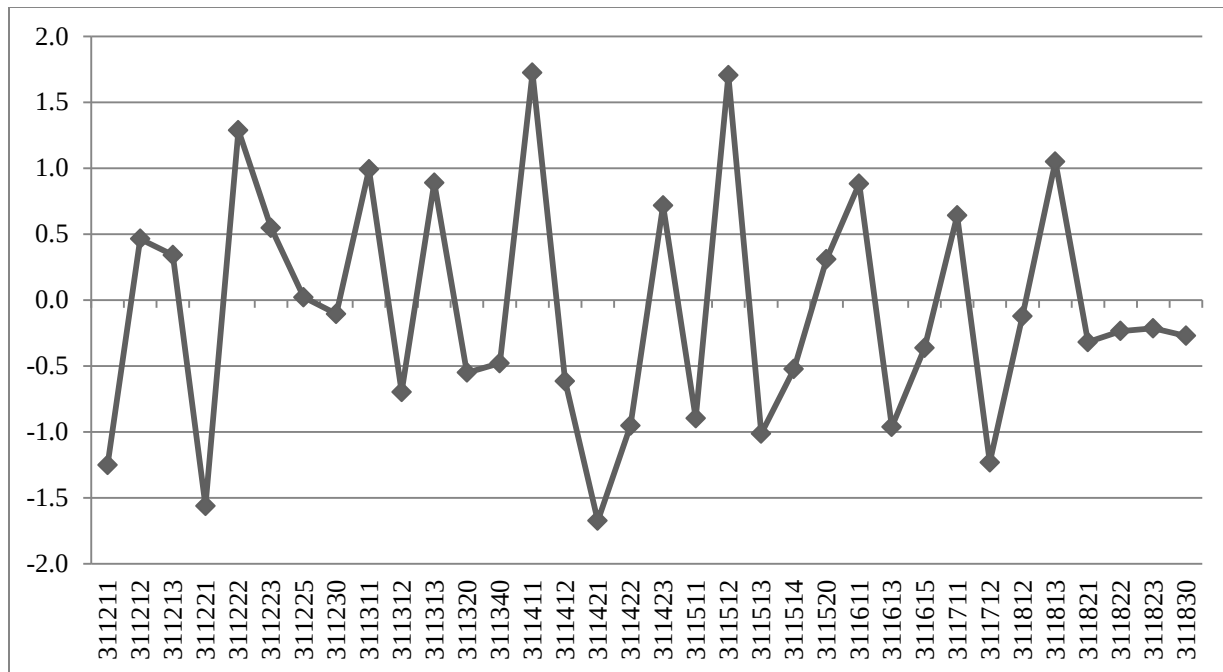


Figure 5. Long run elasticity of infrastructure variable across industries (MG)

Chapter 4: Summary

Summary

This study evaluates the effect of infrastructure investment on the output in agricultural sector in the United States. The first study examines the effect of transportation infrastructure on agricultural output across states in the United States. Different from previous spatial studies, which generally consider spatial interaction effects in dependent variable or in residuals, this study incorporates spatial dependence in both dependent and independent variables. By adopting a spatial Durbin model (SDM) in a panel data framework, this study provides estimation for both direct and indirect effects of explanatory variables. Also, four continuity weight matrices from order one to four (W1-W4) are constructed in order to better evaluate the spillover effect of transportation infrastructure.

The empirical results in this study indicate that road disbursement has a significant and positive effect on agricultural output growth across states and this effect is robust to the order of weight matrix. A one percent increase in road disbursement will increase the own state agricultural growth by 0.02 to 0.03 percent. Also, this study found positive and significant spillover effect from road disbursement under W2 but not under W1, W3, and W4. In contrast, no significant direct and spillover effect from rail infrastructure was identified in this study. The positive and significant direct and spillover effects of road infrastructure investment found in this study suggest that investment in road infrastructure is not only important to the development within the state, but also beneficial to the neighboring states. Also, the states located in the central parts of U.S. generate larger spillover effects on agricultural output.

The second part of this research focuses on the effect of public infrastructure on the U.S. food manufacturing industries. This study adopts heterogeneous dynamic panel cointegration methods with the advantages of allowing heterogeneity in cross-sectional estimators and

addressing unit roots in a long panel data. Through the heterogeneous dynamic panel methods, both the long-run and short-run impacts of public infrastructure on the output are estimated for 34 food industries over the period of 1958–2005. The analysis results in this study suggest that there exists a long run relationship between output, input factors, and public infrastructure in the food manufacturing industries. Specifically, a one percent increase in public infrastructure enhances industry total value added by 0.33 percent in the long run. In the short run, the output growth in most of the food manufacturing industries is not affected by the change in public infrastructure. The long-run positive impact of public infrastructure on food output suggests the importance of continuous public infrastructure investment on the output growth of the food manufacturing industry.

The deteriorating U.S. public infrastructure has drawn considerable concern lately since it may affect private sectors' productivity and the nation's economy. However, due to the current budget restrictions, the policy debate on the whether the government should allocate more resources to public infrastructure has lasted for a lengthy period. Results in both studies suggest the crucial impact of public infrastructure on the output in U.S. agri-food sector. Based on the findings, it is clear that investment in public infrastructure needs to be maintained in order to enhance growth in many sectors, including the agri-food sector that is so closely related to the basic needs of human life. Similarly, because of the ongoing importance of public infrastructure investment on the output of agricultural and food manufacturing industry, this study also suggests that the investment decision in public infrastructure investment should be considered more in terms of long-run impact instead of short-run impact.

Vita

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