Essays on Spatial Analysis of Policy Impacts

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I am submitting herewith a thesis written by Daegoon Lee entitled "Essays on Spatial Analysis of Policy Impacts." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

Seong-Hoon Cho, Major Professor

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Essays on Spatial Analysis of Policy Impacts

A Thesis
Presented for the
Masters of Science Degree
The University of Tennessee, Knoxville

Daegoon Lee
August 2012
Abstract

This thesis is composed of two essays under the theme of spatial analysis of policy impacts. The objective of the first essay was to analyse how population dynamics affect greenhouse gas (GHG) emissions. The effects of population redistribution resulting from the South Korean government’s decentralization efforts on GHG emissions were assessed. Simulation results suggest that the direction of change in total GHG emissions depends on the share of the population redistributed from higher to lower population density regions. If the entire redistributed population of 877,000 persons expected from the government’s decentralization project were from the Seoul Area, annual CO$_2$e [carbon dioxide equivalent] would increase by 1.72%-2.26% compared to benchmark levels. Alternatively, more balanced migration between higher and lower population density regions, i.e., 65% of the 877,000 persons from higher-density locations to lower-density destinations and 35% from lower-density to higher-density regions, decreases CO$_2$e [carbon dioxide equivalent] by 1.49%-2.42%.

The second essay evaluated the impact of highway disbursement under the American Recovery and Reinvestment Act (ARRA) on highway demand in the frame of cost and benefit analysis. Highway demand equation was estimated by employing a spatial Durbin model and panel data for the 48 contiguous US states during 1994-2008. The estimates from the equation were used to validate the hypothesis that the different highway disbursements caused different upwards shifts in the highway demand curves. The different shifts in demand curves resulted in a wide range of consumer surplus increases across states. The consumer surplus estimates, along with explicit and implicit costs associated with additional highway usage, were used to estimate the total net benefit of ARRA highway disbursement and the net benefits per dollar spent for each state. Estimated total net benefits for the 48 states as a result of the $27.2 billion in ARRA
highway disbursements were $4.6 billion in, which yield an average net benefit of $0.17 per dollar spent.
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Chapter 1: Introduction
Introduction

The importance of spatial analysis in modeling of ecological and economic systems is well recognized with the advancement of geographic information system, spatial statistics, and spatial econometrics. The main objective of two essays in this thesis was to develop spatial econometrics frameworks to test the hypotheses about the impact of policies involved with population redistribution on climate change and cost and benefit of highway disbursement.

The first study analyzed the effects of the South Korean government’s decentralization efforts on greenhouse gas (GHG) emissions, focusing on how population redistribution affects national GHG emissions. South Korea was used as a case study because the government aims to achieve a 30% reduction in GHG emissions by 2020 and is in the process of executing a comprehensive decentralization strategy that expects to redistribute population throughout the country. To achieve the objective, the effects of the South Korean government’s decentralization efforts on GHG emissions were assessed. In particular, the hypothesis that outmigration reduces national GHG emissions was tested because the decrease in GHG emissions of outmigration locations outweighs the increase in GHG emissions of in-migration destinations.

The key contribution of the first essay is to provide the first empirical evaluation of population redistribution on national GHG emissions. A number of studies have shown that population growth positively influences GHG emissions (e.g., Newell and Marcus 1987; Bongaarts 1992; Dietz and Rosa 1997; Laurance 1999; Hamilton and Turton 2002). However, the relationship found in the previous literature does not directly address how a rearrangement of population within a society affects GHG emissions when total population does not change. Because previous studies focused on the relationship between population growth and GHG
emissions using macro-level data (e.g., national- and/or international-level data), they inherently
did not explore the question of how population redistribution affects national GHG emissions.

The second essay evaluated the impact of highway disbursement under the American
Recovery and Reinvestment Act (ARRA) on highway demand in the frame of cost and benefit
analysis. The highway disbursement under the ARRA (hereafter, referred to as “ARRA highway
disbursement”) is intended to satisfy increasing need for highway, to maintain aging facilities, to
improve security and safety, and to release traffic congestion (US Department of Transportation
2012). The ARRA highway disbursement is expected to increase highway usage differently by
state, based on its purpose (e.g., construction, maintenance, and extension) and the scale of
investment. The resulting state-level increases of highway demand are expected to increase the
benefits and cost (negative externalities —air pollution and traffic congestion) of highway usage
differently by state emphasizing the need for a cost-benefit analysis of the ARRA highway
disbursement at the state level.

The second essay contributes to the literature by estimating state-level highway
demand curves for use in evaluating nationwide investments such as the ARRA highway
disbursement. Several highway computer simulation models have been developed to perform cost-
benefit analysis of highway development, starting with COst-Benefit Analysis (COBA)
developed by UK government (Department of Transport, UK, 2012) and followed by other
computer simulation models, such as the Highway Investment Analysis Program (HIAP),
Highway Economic Requirements Model (HERS), Micro-computer Benefit Cost Analysis
Model (MicroBENCOST), and the Stratgeic Benefit Cost Analysis Model (StratBENCOST)
(McElroy and Huheey 1992; Lee 2000; Snarr and Axelsen 2007). However, because those
computer simulation models have focused on utilizing micro-level data for a specific highway-
project (e.g., I-70 Hyper Fix Project in Indianapolis), they cannot be used for the macro-scale analysis needed to evaluate the benefits and costs of the ARRA highway disbursement at the state level.
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Chapter 2: Effects of Population Redistribution on Greenhouse Gas Emissions
Abstract

The objective of this research was to analyse how population dynamics affect greenhouse gas (GHG) emissions. I assessed the effects of population redistribution resulting from the South Korean government’s decentralization efforts on GHG emissions. Simulation results suggest that the direction of change in total GHG emissions depends on the share of the population redistributed from higher to lower population density regions. If the entire redistributed population of 877,000 persons expected from the government’s decentralization project were from the Seoul Area, annual CO₂e [carbon dioxide equivalent] would increase by 1.72%-2.26% compared to benchmark levels. Alternatively, more balanced migration between higher and lower population density regions, i.e., 65% of the 877,000 persons from higher-density locations to lower-density destinations and 35% from lower-density to higher-density regions, decreases CO₂e [carbon dioxide equivalent] by 1.49%-2.42%.
Introduction

Ever since the Kyoto Protocol agreement of 1997, mitigation of greenhouse gas (GHG) emissions has been at the center of climate change debates. The main focus has been on who should bear the responsibility for reduction and how to reduce emissions. The general consensus resulting from earlier debates is that developed countries carry more of the burden in reducing emissions than developing countries. However, the seriousness of climate change and the issue of political equity between developed and developing countries call for shifting more of the burden to developing countries in the foreseeable future (Brown 2008; Lomborg 2009). These pressures for emissions reductions are expected to create economic problems that may slow economic growth and further exacerbate the unequal balance among global economies (Mendelsohn 2009). Thus, identifying emission reduction strategies that minimize interference with economic growth has become an important task for governments trying to achieve emission-reduction goals.

A part of this dilemma lies in the relationship between population dynamics and GHG emissions. Previous studies reflect two conflicting views regarding the relationship. One view is that as population density increases, energy use per capita increases, leading to increased emissions per capita. This perspective assumes that population growth requires the exploitation of lower quality resources, which in turn requires more energy consumption per unit of value added and creates increased demand for energy-intensive services (Malthus 1778; Holdren 2000) (referred to as “Malthusian view”). The other view is that proximity and agglomeration in high population density areas provide more energy-efficient infrastructure and services that help lower per capita emissions. For example, enforcing environmental legislation may be less costly in more densely developed areas. In addition, the relative proximity of residential and
commercial areas tends to encourage mass transit, walking and cycling, which may help lower emissions per person (Boserup 1965; Boserup 1981; Dodman 2009) (referred to as “Boserupian view”).

Both views highlight the importance of population dynamics as a factor determining GHG emissions. As a result, this relationship depends on various factors that may be important in developing emission-mitigation strategies (i.e., economic development, trade, technology, infrastructure and income) (Fan et al. 2006).¹ The objective of this study is to analyze how population dynamics affect GHG emissions. South Korea is used as a case study because the government aims to achieve a 30% reduction in GHG emissions by 2020 and is in the process of executing a comprehensive decentralization strategy that expects to redistribute population throughout the country. To achieve the objective, I assess the effects of the South Korean government’s decentralization efforts on GHG emissions. In particular, I test the hypothesis that outmigration reduces national GHG emissions because the decrease in GHG emissions of outmigration locations outweighs the increase in GHG emissions of in-migration destinations.

The key contribution of this research is to provide the first empirical evaluation of population redistribution on national GHG emissions. A number of studies have shown that population growth positively influences GHG emissions (e.g., Newell and Marcus 1987; Bongaarts 1992; Dietz and Rosa 1997; Laurance 1999; Hamilton and Turton 2002). However, the relationship found in the previous literature does not directly address how a rearrangement of population within a society affects GHG emissions when total population does not change. Because previous studies focused on the relationship between population growth and GHG

¹ Previous literature on CO₂ emissions has empirically evaluated the validity of the Environmental Kuznets Curve (EKC) that shows a quadratic relationship between income per capita and per capita emissions.
emissions using macro-level data (e.g., national- and/or international-level data), they inherently did not explore the question of how population redistribution affects national GHG emissions.

**Study Area and Data**

South Korea has undergone rapid industrialization since the 1960s (Park 2001). Economic development has brought with it higher living standards, but also many new challenges. Challenges include rising GHG emissions and densely concentrated population in urban areas. Rising GHG emissions have become a particularly serious concern. The country’s emissions almost doubled between 1990 and 2005 (OECD 2010). South Korea emitted 509 million metric tons of carbon dioxide (CO₂) in 2008, which ranked tenth in the world (UNSD 2011). Like most countries, high emissions are concentrated in large metropolitan areas. For example, Seoul has the highest concentrations of GHG emissions and population. The Seoul Metropolitan Statistical Area (hereafter referred to as the “Seoul Area”) comprised 12% of the country’s total land area, and contained 36% of the nation’s 48 million residents in 2005 (Kim 2009; KOSIS 2010). The Seoul Area’s population has grown continuously since the beginning of industrialization in the 1960’s even as national population growth has slowed since 1970 with the declining national birth rate (Hwang 2010; Statistics Korea 2010). Population in the Seoul Area grew 8.6% from 2001 to 2007, more than twice the national growth rate of 3.6% (Statistics Korea 2010).

High population density and pollution intensity have been blamed for negative effects on human well-being (e.g., respiratory disease caused by air pollution, traffic congestion and injuries, and low affordability of housing) (Kang 2011). In 2006, particulate matter in the air was measured at 58 micrograms per cubic meter (µg/m³), which was considerably higher than in major cities of developed countries (e.g., 20µg/m³ in London, 21µg/m³ in New York, 22µg/m³ in
Paris, and 37µg/m³ in Tokyo) (Cho 2006). The number of automobiles in the Seoul Area increased from 1.19 million to 2.98 million (a 150% increase) between 1990 and 2010 whereas the extension of the road system only increased from 7,300 to 8,100 km (a 10% increase) during the same period. The social costs of traffic congestion in the Seoul Area were estimated at about $7 billion in 2008, which accounts for lost time, air pollution, accidents and psychological anxiety (Jung 2011). Furthermore, high population density has led to an overheated of the real estate market. In 2008, the housing price-to-income ratio in Seoul was 9.7 (median personal annual income: $30,700 and median house price: $298,300), which was higher than cities such as San Francisco, New York and Tokyo whose housing price-to-income ratios were 9.5 and 9.3 in 2007 and 9.1 in 2008, respectively (Jang 2009).

The South Korean government has begun to take action to address the Seoul Area’s densely clustered population and high pollution intensity. An example is the government’s recent plan to build a multifunctional administrative city called Sejong Special Autonomous City (hereafter referred to as “Sejong City”), which is about 120 kilometers south of Seoul and located in the geographical center of the country (MACCA 2011). Despite numerous political disputes over the plan, the special law for construction of Sejong City has been enacted and construction is currently underway. The law’s purpose is to mitigate the effects Seoul Area’s large population through decentralization and achieve balanced development throughout the country. The government plans to reallocate 10,440 government employees from 35 central governmental organizations and to construct supporting infrastructure including roads, schools, libraries and parks. The plan is projected to attract a population of half a million to Sejong City (MACCA 2011). In addition to Sejong City, the government plans to relocate 113 government

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2 The housing price-to-income ratio indicates the ratio of median annual income to median housing price in a region and the exchange rate of 1,173.48 Won for $1 (Jan. 1st 2012) was used here and throughout the paper.
institutes (e.g., government funded research institutes) from Seoul to 11 cities and counties outside of Seoul, which constitutes the transfer of 37,344 jobs (KRIHS 2006). The comprehensive decentralization strategy calls for the South Korean government to invest a total of $25.1 billion (Kim 2011).

The data for this analysis pertains to 7 metropolitan cities (i.e., Seoul Teukbyeolsi and Busan, Daegu, Incheon, Kwangju, Daejeon, and Ulsan Gwangyoksi) and 155 counties (i.e., 84 Si and 71 Gun depending on types of counties) after excluding Jeju, Ongjin and Ulleung islands (see Figure 2.1 for the study area). Each of the 7 metropolitan cities contains multiple Gun and Gu. The Gun and Gu under each metropolitan area are merged as one observational unit because (1) the resolution of the GHG emissions data (approximately 11 kilometers in latitude × 9 kilometers in longitude = 99 square kilometers) used for the regression is relatively large compared to the size of the Gun and Gu in each metropolitan area, mainly in Seoul (e.g., average size of Gu in Seoul: 39 square kilometers), and (2) gross regional domestic product (GRDP) data used in the regression are not available at the Gun and Gu levels for Seoul and Incheon metropolitan cities.3

This study used four datasets (i.e., census, environmental, geographical, and GHG emission data) for 7 cities and 155 counties. Seven metropolitan regions were considered equivalent to cities. The 2005 census data, including population, employment share in non-service sector, housing vacancy ratio, seniority ratio (equal to or over 65), share of at least bachelor degree holder, GRDP share in service sector were obtained from Korean Statistical Information Service (KOSIS 2010). GRDP data for 2005 were collected from the GRDP division

3 Seoul contains 25 Gus and the other metropolitan cities have 8 Gus and Gus on average.
of each local government, metropolitan cities and provinces, except Jeollanam province.\textsuperscript{4} The raw GRDP data and employment data were reported in sectors. Based on the categories, data for shares of GRDP in the service and of employment in non-service sectors were obtained by aggregating the sectors. Sectors, logistics, storehouse, telecommunication, sanitation, social welfare, wholesale and retail businesses, restaurants, lodging, education, public service, national defense, real estate, business service, finance, and other services were included in the service sector. The agriculture and forestry, electricity and gas, mining and manufacture, and construction sectors were included in the non-service sector.

Annual average temperature may affect energy use for heating and cooling systems. Data for annual average temperature in 2005 were acquired from Korean Meteorological Administration (KMA 2012). The geographical data for the location map of the 7 cities and 155 counties were acquired from Korean Statistical Geographic Information Service (SGIS 2010). CO\textsubscript{2}e data that represent GHG emissions were obtained from the Emission Database for Global Atmospheric Research (EDGAR) (Janssens-Maenhout et al. 2010). EDGAR provides annual data for atmospheric components. The emissions data cover the entire spectrum of emission sources (e.g., agriculture, transportation, fuel production, and industry combustion) and thus consist of all anthropogenic greenhouse gases (EDGAR 2010).

CO\textsubscript{2}e was calculated by summing the weighted values of CO\textsubscript{2}, CH\textsubscript{4}, and N\textsubscript{2}O based on values of global warming potential reported by the Intergovernmental Panel on Climate Change (IPCC). Using ArcGIS 9.3, the values of CO\textsubscript{2}e at the county or city (referred to as “regional”) levels were obtained by following a three-step interpolation procedure: (1) the points containing emission values were distributed in geographic latitude and longitude coordinates, (2) \begin{footnote}{Because 2005 data were not available for Jeollanam province, 2007 GRDP data were used as a proxy.}

\textsuperscript{4}Because 2005 data were not available for Jeollanam province, 2007 GRDP data were used as a proxy.
polygons were created based on the points and the values of CO$_2$e from the points were assigned to the corresponding Theissen polygons, and (3) the weighted sums of CO$_2$e were obtained based on regional boundaries. (See Figure 2.2 for visual presentation of the three-step procedure.) Definitions of the variables used in the regressions and descriptive statistics are reported in Table 2.1.

**Empirical Model**

*Model specification*

The empirical framework begins with the IPAT$^5$ model frequently used in ecological studies. The classic IPAT identity ($I = PAT$) assumes the human impact on the environment ($I$) is the product of three driving factors, namely population size ($P$), a society’s affluence ($A$), and a technology index ($T$) (Ehrlich and Holdren 1971; Holdren 2000). This identity has often been reexpressed as $T = I / GDP$, where $A$ is represented by gross domest product (GDP) per capita ($A = GDP / P$) and thus $PA = P \times (GDP / P) = GDP$. This relationship has been used to identify $T$, which represents the human impacts required to generate a unit of GDP and is assumed to contain all the drivers other than population size and a society’s affluence using the obtainable values of $I$, $P$, and $A$ (Commoner 1971; Ehrlich and Holdren 1972; Ehrlich and Ehrlich 1990; Harrison 1993; Raskin 1995; York et al 2003). $T$ is often referred to as the “technology multiplier” (Dietz and Rosa 1997). This identity has also provided the conceptual framework for previous literature in forecasting GHG emissions and impacts of human activities on the environment (e.g., Stern et al. 1992; Harrison and Pearce 2000; Auffhammer and Carson 2008). Despite its contribution, the IPAT identity has two limitations (York et al. 2003). First,

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$^5$ IPAT represents impact ($I$) is a function of population ($P$), affluence ($A$), and technology ($T$).
the identity assumes the three driving factors have proportional contributions (Dietz and Rosa 1997). For example, the model implicitly assumes a unitary elasticity of GHG emissions with respect to population growth under the *ceteris paribus* assumption, which may not be the case in reality. Second, the identity does not allow for hypothetical testing because it is an accounting identity where known values of some terms determine the value of an unknown term.

Addressing these limitations, Dietz and Rosa (1994) developed a stochastic version of the IPAT identity (referred to as STIRPAT). The STIRPAT is expressed as: \( I_i = aP_i^bA_i^cT_i^d \varepsilon_i \), where subscript \( i \) denotes the \( i \)th region, \( a, b, c, \) and \( d \) are parameters to be estimated by regression and \( e \) is an error term. In the traditional STIRPAT model, \( T \) represents all factors that impact the environment, other than \( P \) and \( A \), in the same sense as IPAT. If these factors are not explicitly included in the model, then \( T \) becomes part of the error term. The advantage of the STIRPAT model is that it allows empirical testing of the human impacts on environments.

Based on the IPAT conceptual framework, an empirical model that explains GHG emissions at the regional level is established. First, I hypothesize that GHG emissions for region \( i \) are determined by population (\( P \)), GRDP per capita reflecting affluence (\( GRDP \)), percentage of employment from the non-service sector (\( E \)), and annual average temperature (\( M \)) representing the drivers other than population size and a society’s affluence (referred to as “Model 1”):

\[
\ln(GHG_i) = \alpha_1 + \alpha_2 \ln(P_i) + \alpha_3 \ln(GRDP_i) + \alpha_4 \ln(E_i) + \alpha_5 \ln(M_i) + \varepsilon_i,
\]

where \( \alpha \) denotes parameters, and \( \varepsilon_i \) is the error term.

The potential endogeneity of \( P \) and \( GRDP \) in Model 1 was tested for the need to control biases that may result from simultaneity. Endogeneity of \( P \) and \( GRDP \) was presumed because population and regional development reflected in \( GRDP \) may affect each other interdependently. All possible combinations of the four available variables as instruments (i.e., housing vacancy
rate, seniority rate, share of at least bachelor degree holder, and share of GRDP in service sector) were used for the test. The endogeneity test statistic that is defined as the difference of two Sargan-Hansen statistics: one for the equation with suspect regressors being treated as endogenous and one for the equation with those being treated as exogenous, ranged between 0.205 and 4.043 for all possible combinations of the four instruments (corresponding p-values were 0.9024 - 0.1324) used in the Model 1 indicated failure to reject the null hypotheses of P and GRDP being exogenous variables at the 5% level.

Like any other endogeneity test, choice of instruments may be challenging (Ebbes 2007) and thus validity of the instruments was tested by three identification tests, i.e., under-, weak-, and over-identification tests. Anderson (1951) large range multiplier statistic for whether the equation is identified ranged between 23.064 and 67.304, suggesting that the instruments are identified at the 5% level for ten of eleven sets of instruments. Cragg-Donald’s (1993) Wald statistics suggested by Stock and Yogo (2005) ranged between 9.942 and 42.627 suggesting that the instruments are not weakly identified at the 5% level for ten of eleven sets of instruments. Sargan’s (1958) statistics ranged between 0.088 and 2.742 suggesting the null hypothesis that the instruments are uncorrelated with the error term for all five sets of any combination of three or four instruments cannot be rejected. These identification tests provide some confidence that the instruments are appropriate for this analysis.

Spatial dependence of GHG measured by CO2e at the regional level was tested. Moran’s indices for the 2005 CO2e data were significant at the 5% level and ranged between 0.26 and

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6 Given the constraint that number of instruments has to be greater than two (the number of variables with potential endogeneity) for the over-identification tests (Wooldridge 2009), only five sets (instead of eleven) of three or four instruments were used.
The cluster map of the Local Indices of Spatial Association (LISA, Anselin 1995) reaffirms significant spatial clustering of CO$_2$e. The cluster map shows a pattern of high-high clusters (i.e., high CO$_2$e surrounded by high CO$_2$e) in and around the Seoul Area. Low-low clusters appear in Gangwon province, which is the most mountainous area in the country (see Figure 2.3). Significant spatial dependence was also identified in the residuals of the aspatial model, *Model 1*. Using 7 different weight matrices including inverse distance weight matrix, 3 queen contiguity weight matrices (first-, second-, and third- order queen contiguity), and their corresponding hybrids of inverse distance and 3 queen contiguity weight matrices, the spatial lagrange multiplier statistics of the residual from the aspatial model ranged between 3.78 and 6.17 and all are significant at the 5% level, except for the third-order queen contiguity weight matrix.

The cost of ignoring the spatial lag dependence in GHG measured by CO$_2$e is biased parameter estimates. The cost of ignoring spatial dependence of errors from the aspatial model is a loss of efficiency (LeSage and Pace 2009). A region-specific spatially lagged dependent variable and a spatial autoregressive error term were incorporated in the spatial general model to accommodate such potential problems (referred to as “*Model 2*”):

\[
\ln(GHG_i) = \beta_0 + \rho_s \sum_{j=1}^{n} w_{i,j} \ln(GHG_j) + \beta_2 \ln(P_i) + \beta_5 \ln(GRDP) + \beta_6 E + \beta_7 M + u_i;
\]

(2)

\[
u_i = \lambda \sum_{j=1}^{n} w_{i,j} u_i + \epsilon_i
\]

where $w_{i,j}$ is a $(i, j)$ element of a spatial weight matrix $W$ that captures the spatial lagged effect of $GHG$, $\beta$ denote parameters of the other explanatory variables, $\rho_s$ is parameter of spatial lag

---

5 Five spatial weight matrices (i.e., inverse distance, inverse distance squared, fixed distance band, zone of indifference, and polygon contiguity first order) were used to calculate the Moran’s indices. All the spatial weight matrices used in the paper are row-standardized, that is, each row of a weight matrix is made to be summed up to one.
term, and \( u \) is a disturbance. Including \( \sum_{j=1}^{n} w_{i,j} \ln(GHG_j) \) as an explanatory variable allows for a region’s \( GHG \) to influence \( GHG \) in its neighbourhood, defined by \( W \).

Alternatively, I hypothesize a spatially lagged dependent variable and spatial lagged explanatory variables in the spatial Durbin model following Anselin (1988) (referred to as “Model 3”):

\[
(3) \quad \ln(GHG_i) = \delta_i + \rho_d \sum_{j=1}^{n} w_{i,j} \ln(GHG_j) + X_i \delta_2 + \sum_{j=1}^{n} w_{i,j} X_j \delta_3 + \nu_i;
\]

where \( X_i \) is a \( 1 \times 4 \) vector of explanatory variables including \( P, GRDP, E \) and \( M \); \( \delta \) and \( \delta \) are respectively, parameter scalars and conformable vectors, \( \rho_d \) denotes the parameter of spatial lag term, and \( \nu \) is the error term.

**Direct and indirect effects**

In the spatial models, i.e., Models 2 and 3, the marginal effect of an explanatory variable can be decomposed into direct and indirect effects based on the spatial dependence structure (see LeSage and Pace 2009 for a more detailed description). The direct effect refers to the combination of (1) the effect of an explanatory variable for \( i \)th region on GHG emissions in the \( i \)th region (i.e., equivalent to the parameter itself in Models 2 and 3) and (2) an effect passing through neighboring regions that exerts a feedback influence on the GHG emissions of the \( i \)th region (referred to as “feedback effect”). The indirect effect refers to the sum of effects of an explanatory variable for \( i \)th region on the GHG emissions of the other regions (-i). The total effect is the sum of the direct and indirect effects which denotes the effect of one unit change in an explanatory variable in the entire region.
Based on these definitions, average direct, average indirect, and average total effects are computed for each explanatory variable. For example, with regards to population size \( P \) in Model 2, the average total effect is

\[
n^{-1}I_n'(I_n - \rho_s W)^{-1}I_n \beta_2 = n^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n} v_{i,j} \beta_2,
\]

which denotes the sum of all element of \((I_n - \rho_s W)^{-1}I_n \beta_2\) divided by \(n\) where \(v_{i,j}\) is the \((i,j)\) element of \((I_n - \rho_s W)^{-1}\). The average direct effect is

\[
n^{-1}tr((I_n - \rho_s W)^{-1}I_n \beta_2) = n^{-1} \sum_{i=1}^{n} v_{i,i} \beta_2,
\]

which is equivalent to the sum of diagonal elements of \((I_n - \rho_s W)^{-1}I_n \beta_2\) divided by \(n\). The average indirect effect is

\[
n^{-1} \sum_{i=1}^{n} \sum_{j=1}^{n} v_{i,j} \beta_2, \quad (i \neq j),
\]

which is the sum of off-diagonal elements of \((I_n - \rho_s W)^{-1}I_n \beta_2\) divided by \(n\), which is simply the average direct effect subtracted from the average total effect, \(n^{-1} \left( \sum_{i=1}^{n} \sum_{j=1}^{n} v_{i,j} \beta_2 - \sum_{i=1}^{n} v_{i,i} \beta_2 \right)\).

The decomposition of average direct and average indirect effects for Model 3 is equivalent to the Model 2 except that the lagged terms of explanatory variable \(WX\) are added in the calculation. To illustrate the details, the marginal effect of an explanatory variable, say \(P\), for the Model 3 is expressed as the \(n \times n\) matrix:

\[
\begin{bmatrix}
v_{1,1} & v_{1,2} & \cdots & v_{1,n} \\
v_{2,1} & v_{2,2} & \cdots & v_{2,n} \\
\vdots & \vdots & \ddots & \vdots \\
v_{n,1} & v_{n,2} & \cdots & v_{n,n}
\end{bmatrix},
\]

when \(\text{abs}(\rho_s) < 1\).

---

8 By the Taylor’s expansion, \((I_n - \rho_s W)^{-1} = 1 + \rho_s W + \rho_s^2 W^2 + \rho_s^3 W^3 + \ldots\) assuming \(\text{abs}(\rho_s) < 1\).
where $\delta_{2,p}$ and $\delta_{3,p}$ denote the parameters of $P$ and $WP$, respectively. Through analogous decomposition for Model 2, the sum of all elements of the resulting $n \times n$ matrix divided by $n$ denotes the average total effect of a 1% change in $P$ where each row sum represents the total effect of each observation, the average of diagonal elements denotes the average direct effect, and the average of off diagonal elements represents the indirect effect (Brown et al. 2009).

**Forecasting GHG emissions based on hypothetical population redistribution scenarios**

Hypothetical population redistribution scenarios are based on the comprehensive decentralization strategy of the South Korean government. The scenarios were simulated under the assumption that the government’s decentralization efforts are effective in redistributing the population as anticipated by the government. According to the Korea Research Institute for Human Settlements (KRIHS 2006) and the Ministry of Land, Maritime and Transport (MLMT 2006), populations of 377,000 and 500,000 are estimated to be reallocated to 11 cities due to the transfer of 113 institutes and to Sejong City, respectively, for a total of 877,000. While detailed migration information about Sejong City is limited, the plan from MLMT projects population migration of 133,000 from Seoul to 11 cities and the anticipated migration is projected to attract additional population of 244,000 from other regions.

Three scenarios were constructed based on the limited migration information, assuming a population of 877,000 is redistributed. Scenario (1) assumes that the entire 877,000 population migrates from the Seoul Area, scenario (2) assumes that 176,000 migrate from the Seoul Area to Sejong City and 133,000 migrate from the Seoul Area to the 11 cities, while the remainder of the
migrating population (324,000 to Sejong City and 244,000 to the 11 cities) comes from other South Korean regions proportional to their 2005 populations, and scenario (3) is the same as the scenario (2) except the 244,000 migrate from non-Seoul regions to the 11 cities in the ascending order of the populations within the provinces of the 11 destination cities.\footnote{The migration of the 133,000 population from Seoul associated with the planned movement of 113 institutes was calculated using the multipliers provided by MLMT and the migration of the 176,000 population from Seoul to Sejong city was proxied by applying the same multiplier.}

Once hypothetical population redistribution scenarios were established, corresponding GHG emissions were predicted using the parameters estimated from the spatial models (i.e., \textit{Models 2} and \textit{3}). Forecasting for \textit{Model 2} relies on the spatial autoregressive predictor (LeSage and Pace 2009) expressed as, \( \hat{y} = (I_n - \hat{\rho}_s W)^{-1} X \hat{\beta} \) where \( \hat{y} \) denotes an \( n \times 1 \) vector of predicted values of \( \ln(GHG) \), \( \hat{\rho}_s \) is estimated parameter of spatial lag term, \( X \) is an \( n \times 5 \) matrix of regressors, \( X = \begin{bmatrix} i_n & \ln(P) & \ln(\text{GRDP}) & \ln(E) & \ln(T) \end{bmatrix} \), and \( \hat{\beta} \) a \( 5 \times 1 \) vector of estimated parameters, \( \hat{\beta} = \begin{bmatrix} \hat{\beta}_1 & \hat{\beta}_2 & \hat{\beta}_3 & \hat{\beta}_4 & \hat{\beta}_5 \end{bmatrix}' \). The predictor of \textit{Model 3} takes the form of the spatial autoregressive predictor with spatially lagged explanatory variables, \( \hat{y} = (I_n - \hat{\rho}_s W)^{-1} (i_n \hat{\delta}_1 + X \hat{\delta}_2 + W X \hat{\delta}_3) \), where \( X = \begin{bmatrix} \ln(P) & \ln(\text{GRDP}) & \ln(E) & \ln(M) \end{bmatrix} \).

\textbf{Empirical Results}

Table 2.2 presents the parameter estimates for \textit{Models 1}, \textit{2} and \textit{3}, with estimates using two different weight matrices presented for \textit{Models 2} and \textit{3}. Among the 6 weight matrices used in \textit{Models 2} and \textit{3}, the results using two weight matrices were chosen for each model through performance-wise comparison based on Akaike Information Criteria (AIC). The first-order and third-order queen contiguity weight matrices were chosen for \textit{Model 2}. Likewise, the first-order...
queen contiguity weight matrix and its hybrid form with the inverse distance weight matrix were chosen for Model 3.

The AIC scores in the range of -48.989 to -45.686 for Models 2 and 3 and -43.551 for Model 1 suggest the goodness of the fit is slightly better for the spatial models than for the aspatial model. The control of spatial dependences in GHG and residuals is revealed by the positive and significant spatial lag parameter ($\rho$) in Model 3 and spatial error parameter ($\lambda$) in Model 2 across the weight matrices. The variables that are significant at the 5% level are denoted with asterisks in Table 2.2, and those variables are referred to as “significant” in the discussion below.

The aspatial variables (i.e., population, GRDP per capita, and employment share in non-service sector) demonstrate robustness across the five models. All five models consistently suggest that regions with higher population, higher GRDP per capita, and higher employment in non-service sector have higher GHG emissions. These results confirm the IPAT conceptual framework where GHG emissions is determined by population size $P$, affluence $A$ reflected by GRDP per capita, and technology $T$ reflected by share of economy in non-service sector. Temperature $M$, included to capture the effect of energy use on heating and cooling system, is consistently insignificant, which is likely due to small variation of temperature across the country because of its relatively small size (approximately the size of State of Indiana). Spatially lagged GRDP per capita using the hybrid weight matrix is negative and significant whereas it is not significant using the first-order queen contiguity weight matrix. These results imply that the affluence, reflected in GRDP per capita, of neighboring regions might have negative effects on GHG emissions, but the effects depend on how neighborhoods are structured.
The direct, indirect, and total effects of the four explanatory variables in Models 2 and 3 are presented in Table 2.3. The interpretation of the direct and indirect effects is unique in that it reveals the spatial structure of the relationship between dependent and explanatory variables. For example, Models 2 and 3 suggest that a 1% increase in the population of a given region (i) increases GHG emissions in that region by 0.862% to 0.873% as the direct effect, (ii) increases GHG emissions outside that region by 0.073% to 0.103% as the indirect effect, and (iii) increases total GHG emissions by 0.941% to 0.965% as the total effect. The inelastic relationship between population and GHG emissions implies an inverse relationship between per capita GHG emissions and population. This relationship suggests that greater population density leads to lower per capita emissions, given the fixed areas of the outmigration locations and destinations, which reaffirms the Boserupian view.

It is worth noting that, while a group of neighbors was specified by choosing spatial weight matrices, the indirect effects are not limited to their own neighbors. For example, an increase in population in a given region causes changes in GHG emissions in its immediate neighbors, which in turn causes changes in GHG emissions in its immediate neighbors’ neighbors. These neighborhood spillover effects continue throughout the entire country. The spatial lag parameter less than 1 implies a decay pattern of spillover effects. The total effects of population, GRDP per capita, and employment share in non-service sector on GHG emissions, after taking into account of the spatial interactions, are higher than the same effects estimated with OLS. The differences come from both the feedback and indirect effects, generated through spillover effects in the spatial models.

Another point worth noting is the negative and significant indirect effect of GRDP per capita derived from Model 3, which suggests that an increase in GRDP per capita in a region
decreases GHG emissions outside that region. This finding may be associated with more concentrated development in big cities, reflected in higher GRDP per capita, that has left other regions less-developed, which in turn has led to lower emissions in those regions. For example, as Seoul has expanded, it has absorbed a great deal of energy-using economic activity that has led to declining GHG emissions in its neighboring regions. Thus, the negative indirect effect cancels out the positive direct effect to produce an insignificant total effect of GRDP per capita.

The GHG emissions under the three hypothetical scenarios are compared in Table 2.4 with baseline (status quo) GHG emissions across the four spatial models. Scenario (1) increases CO$_2$e between 5.14 and 6.63 million tons, a 1.72% to 2.26% increase compared to the baseline, which provides the highest increase among the scenarios. Scenario (2) increases CO$_2$e by 3.37 to 4.21 million tons, a 1.13% to 1.44% increase compared to the baseline, providing a more moderate increase in emissions than scenario (1). In contrast to scenarios (1) and (2), scenario (3) decreases CO$_2$e between 4.36 and 6.38 million tons, a 1.49% to 2.42% decrease compared to the baseline. Thus, only scenario (3) mitigates GHG emissions, while scenarios (1) and (2) exacerbate GHG emissions.

To explore the simulation results in more detail, the consequences of population redistribution on GHG emissions in terms of population densities between in-migration destinations and outmigration locations are compared. I do this comparison because redistribution of population reshuffles population densities when total population remains unchanged, which result in higher and lower total emissions depending on the relationship between population density and energy use per person.

Scenario (1) triggers population migration from outmigration locations of higher density to in-migration destinations of lower density (referred to as “H→L migration”) of the entire
877,000, which increases GHG emissions compared to the baseline more than the other two scenarios. Scenario (2) triggers \( H \rightarrow L \) migration of 731,000 of the 877,000 population (or 83%) and population migration from outmigration locations of lower density to in-migration destinations of higher density (referred to as “\( L \rightarrow H \) migration”) of the rest of population (or 17%), which increases GHG emissions compared to the baseline more moderately than scenario (1). Scenario (3) triggers \( H \rightarrow L \) migration of 570,000 of the 877,000 population (or 65%) and \( L \rightarrow H \) migration of the rest of population (or 35%), which decreases GHG emissions compared to the baseline. The simulation results show that the sum of the positive effects of \( H \rightarrow L \) migration on GHG emissions exceeds the sum of the negative effects of \( L \rightarrow H \) migration on GHG emissions for Scenarios (1) and (2), while the opposite is the case for Scenario (3). The inelastic relationship between population and GHG emissions that leads to the Boserupian view, dictates the general pattern of a larger share of \( L \rightarrow H \) migration leading to lower total GHG emissions. The net effect on total GHG emissions compared to the baseline depends on existing size of the population in each region, the percentage of the moving from one region to another, and spatial structure of each region.

Conclusions

This study was motivated by global interest on GHG emissions associated with climate change, concentration of high emissions in large metropolitan areas, and potential impacts of decentralization efforts on GHG emissions. A case study pertaining to South Korea was developed to test the hypothesis that outmigration mitigates national GHG emissions by increasing the GHG emissions of in-migration destinations by less than GHG emissions are
reduced in outmigration locations. Using parameter estimates from models with different assumptions about spatial structure, three hypothetical population redistribution scenarios were simulated under the assumption that the South Korean government’s decentralization efforts are effective in redistributing the population as anticipated by the government.

Simulation results suggest that the net outcome of the positive effect of H→L migration on GHG emissions and the negative effect of L→H migration on GHG emissions depends on the ratio of H→L to L→H migration. A clear pattern emerges from the results: as the share of L→H migration becomes larger relative to the share of H→L migration, total GHG emissions increase less compared to the baseline (in going from scenario (1) to (2)), and eventually GHG emissions decrease compared to the baseline (in going from scenario (2) to (3)) as the share of L→H migration becomes further larger relative to the share of H→L migration.

The decentralization efforts in South Korea make sense considering the high cost of the overly-concentrated population in Seoul (e.g., traffic congestion and overheating of the real estate market); however, the results of this study highlight a potential major cost that has not yet been considered, the effects on GHG emissions. The contrast in the simulated effects of population redistribution between scenarios (1) and (3) suggests that the decentralization plan can be implemented to not only achieve the goal of decentralization but also the goal of mitigating national GHG emissions.

A caveat for future study is worthy of mention. Although our study accounts for spatial dependences, temporal dynamics of the relationship between population and GHG emissions was not considered in the model. A future research direction could include spatial-dynamic modeling
based on a time-series of changes in GHG emissions with appropriate time-varying variables under the spatial econometric framework using spatial-panel data.
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Appendix
<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greenhouse gas emissions</td>
<td>Total carbon dioxide equivalent in 2005 (tons of CO$_2$e)</td>
<td>13.891</td>
<td>1.216</td>
</tr>
<tr>
<td>Population</td>
<td>Total population in 2005</td>
<td>11.580</td>
<td>1.177</td>
</tr>
<tr>
<td>Gross regional domestic product per capita</td>
<td>Gross regional domestic product in 2005 (million Won per capita)</td>
<td>2.819</td>
<td>0.360</td>
</tr>
<tr>
<td>Employment share in non-service sector</td>
<td>Number of employees in the non-service sector divided by total employment in 2005</td>
<td>3.958</td>
<td>0.337</td>
</tr>
<tr>
<td>Temperature</td>
<td>Annual average temperature in 2005 (0.1 Celsius)</td>
<td>4.78</td>
<td>0.087</td>
</tr>
<tr>
<td>Housing vacancy ratio</td>
<td>Number of vacant houses divided by total number of houses in 2005 (%)</td>
<td>2.121</td>
<td>0.520</td>
</tr>
<tr>
<td>Seniority rate</td>
<td>Number of people 65 or older divided by total population in 2005 (%)</td>
<td>2.695</td>
<td>0.561</td>
</tr>
<tr>
<td>Share of at least bachelor degree holder</td>
<td>Number of people with at least bachelor degree divided by total population in 2005 (%)</td>
<td>1.931</td>
<td>0.504</td>
</tr>
<tr>
<td>Share of gross regional domestic product in service sector</td>
<td>Gross regional domestic product in service sector divided by total gross regional domestic product in 2005 (%)</td>
<td>3.768</td>
<td>0.379</td>
</tr>
</tbody>
</table>

†Natural log is taken for all variables.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First-order Queen contiguity</td>
<td>Third-order Queen contiguity</td>
<td>First-order Queen contiguity</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.785</td>
<td>0.133</td>
<td>0.809</td>
</tr>
<tr>
<td></td>
<td>(3.739)</td>
<td>(3.504)</td>
<td>(3.670)</td>
</tr>
<tr>
<td>Population</td>
<td>0.890*</td>
<td>0.860*</td>
<td>0.860*</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.084)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Gross regional</td>
<td>0.643*</td>
<td>0.671*</td>
<td>0.625*</td>
</tr>
<tr>
<td>domestic product per capita</td>
<td>(0.204)</td>
<td>(0.199)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Employment share in non-service sector</td>
<td>1.018*</td>
<td>1.071*</td>
<td>1.183*</td>
</tr>
<tr>
<td></td>
<td>(0.307)</td>
<td>(0.310)</td>
<td>(0.331)</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.001</td>
<td>-0.720</td>
<td>-0.928</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.834)</td>
<td>(0.842)</td>
</tr>
<tr>
<td>Spatial lag</td>
<td>0.079</td>
<td>0.082</td>
<td>0.209*</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.049)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>Spatial error</td>
<td>0.137*</td>
<td>-0.221*</td>
<td>-0.099</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.017)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>Spatially lagged Population</td>
<td></td>
<td>-0.924*</td>
<td>-0.683*</td>
</tr>
<tr>
<td>Spatially lagged Population</td>
<td></td>
<td>(0.347)</td>
<td>(0.339)</td>
</tr>
<tr>
<td>Spatially lagged Gross regional</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>spatially lagged Gross regional</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spatially lagged Temperature</td>
<td></td>
<td>0.718</td>
<td>0.581</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.716)</td>
<td>(0.598)</td>
</tr>
<tr>
<td>AIC</td>
<td>-43.551</td>
<td>-48.528</td>
<td>-48.989</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-47.818</td>
<td>-45.686</td>
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* represents: \( p < 0.05 \)
<table>
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<tr>
<th>Variable</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First-order Queen contiguity</td>
<td>Third-order Queen contiguity</td>
</tr>
<tr>
<td><strong>Direct Effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0.868*</td>
<td>0.873*</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Gross regional domestic product per capita</td>
<td>0.676*</td>
<td>0.610*</td>
</tr>
<tr>
<td></td>
<td>(0.202)</td>
<td>(0.195)</td>
</tr>
<tr>
<td>Employment share in non-service sector</td>
<td>1.087*</td>
<td>1.050*</td>
</tr>
<tr>
<td></td>
<td>(0.308)</td>
<td>(0.295)</td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.747</td>
<td>-0.598</td>
</tr>
<tr>
<td></td>
<td>(0.406)</td>
<td>(0.395)</td>
</tr>
<tr>
<td><strong>Indirect Effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0.073*</td>
<td>0.078*</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Gross regional domestic product per capita</td>
<td>0.057*</td>
<td>0.054*</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Employment share in non-service sector</td>
<td>0.092*</td>
<td>0.095*</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.066</td>
<td>-0.057</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.050)</td>
</tr>
<tr>
<td><strong>Total Effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0.941*</td>
<td>0.952*</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>Gross regional domestic product per capita</td>
<td>0.735*</td>
<td>0.664*</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.212)</td>
</tr>
<tr>
<td>Employment share in non-service sector</td>
<td>1.179*</td>
<td>1.145*</td>
</tr>
<tr>
<td></td>
<td>(0.339)</td>
<td>(0.325)</td>
</tr>
<tr>
<td>Temperature</td>
<td>-0.813</td>
<td>-0.655</td>
</tr>
<tr>
<td></td>
<td>(0.448)</td>
<td>(0.437)</td>
</tr>
</tbody>
</table>

* represents: $p < 0.05$
### Table 2.4. THE GHG EMISSIONS UNDER THE THREE HYPOTHETICAL SCENARIOS COMPARED WITH THE BASELINE (STATUS QUO) GHG EMISSIONS ACROSS THE FOUR DIFFERENT SPATIAL MODELS (TONS OF CO₂e)

<table>
<thead>
<tr>
<th>Models</th>
<th>Baseline</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total emission</td>
<td>Change in emission</td>
<td>Total emission</td>
<td>Change in emission</td>
</tr>
<tr>
<td>Model 2 First-order Queen contiguity</td>
<td>293,161,854</td>
<td>299,788,918</td>
<td>6,627,064</td>
<td>(2.26%)</td>
</tr>
<tr>
<td>Third-order Queen contiguity</td>
<td>263,677,029</td>
<td>269,436,962</td>
<td>5,759,932</td>
<td>(2.18%)</td>
</tr>
<tr>
<td>Model 3 First-order Queen contiguity</td>
<td>298,708,785</td>
<td>303,843,284</td>
<td>5,134,499</td>
<td>(1.72%)</td>
</tr>
<tr>
<td>First-order Queen contiguity Hybrid</td>
<td>295,286,783</td>
<td>300,611,705</td>
<td>5,324,921</td>
<td>(1.80%)</td>
</tr>
</tbody>
</table>
Figure 2.1. STUDY AREA
Figure 2.2. VISUALIZATION OF INTERPOLATION PROCEDURE
Figure 2.3. THE CLUSTER MAP OF THE LOCAL INDICES OF SPATIAL ASSOCIATION (LISA) OF THE CO$_2$e IN 2005
Chapter 3: Cost-Benefit Analysis of Highway Infrastructure Investment under the American Recovery and Reinvestment Act
Abstract

This study evaluated the impact of highway disbursements under the American Recovery and Reinvestment Act (ARRA) on highway demand in a cost-benefit framework. Vehicle miles traveled were used to estimate a highway demand equation employing a spatial Durbin model and panel data for the 48 contiguous US states during 1994-2008. The estimates from the equation were used to validate the hypothesis that different highway disbursements caused different upwards shifts in the highway demand curves of states. The different shifts in demand curves resulted in a wide range of consumer surplus increases across states. The consumer surplus estimates, along with explicit and implicit costs associated with additional highway usage, were used to estimate the total net benefit of ARRA highway disbursements and the net benefits per dollar spent for each state. Estimated total net benefits for the 48 states as a result of the $27.2 billion in ARRA highway disbursements were $4.6 billion in, which yield an average net benefit of $0.17 per dollar spent.
Introduction

As the United States entered an economic recession in December 2007, President Obama signed the American Recovery and Reinvestment Act (ARRA) into law in February 2009, typically referred to as the “stimulus package,” to rehabilitate the deeply depressed economy (Romer 2009). The ARRA has allowed the U.S. government to spend $787 billion under three types of funding programs (i.e., $228 billion for tax benefits, $275 billion for contracts, grants, and loans and $224 billion for entitlements), aiming to create employment opportunities and save existing jobs (Recovery 2012). As the stimulus package mainly focused on saving and creating jobs almost immediately, its priority was ready-to-go (referred to as “shovel-ready”) projects that could start straightaway (Berrens et al. 2002; Johnson 2009). Some of the most common shovel-ready projects funded under the ARRA were related to transportation (Rall 2009). Of the $48.1 billion ARRA funds designated for transportation contracts, grants and loans, $27.5 billion were allocated to highway infrastructure investment (Recovery 2012).

The ARRA highway disbursement is intended to satisfy increasing need for highway, to maintain aging facilities, to improve security and safety, and to release traffic congestion (US Department of Transportation 2012). The ARRA highway disbursement is expected to increase highway usage differently by state, based on its purpose (e.g., construction, maintenance and extension) and the scale of investment. The resulting state-level increases in highway demand are expected to increase the benefits and costs (e.g., negative externalities—air pollution and traffic congestion) of highway usage differently by state, emphasizing the need for a cost-benefit analysis of the ARRA highway disbursement at the state level.

The objective of this research is to explore the costs and benefits of the ARRA highway disbursement, focusing on the explicit cost (i.e., cost of ARRA highway disbursement) and
implicit cost (i.e., cost of negative externalities including air pollution and traffic congestion) of the additional highway usage for each of the 48 contiguous states, and the benefits of increased highway usage in each state measured by increased consumer welfare. The state-level cost-benefit analysis is based on the hypothesis that different levels and purposes of ARRA highway disbursements shift the state-level demand curves upward by different amounts under the *ceteris paribus* assumption.

The different upward shifts in the highway demand curves are hypothesized because differences in ARRA highway disbursements are expected to improve the quality and quantity of state-level highway systems differently (e.g., saved time due to a new and expanded facilities, reduced user costs, improved safety, greater comfort, security and convenience, and reliability to passengers or less damage to goods to freighters). The benefits from the improved quality and quantity of highway systems due to ARRA highway disbursements can be quantified by changes in consumer surplus as the state-level demand curves shift upward reflecting increases in consumer welfare (Lee 2000).

The hypothesis was tested by estimating a highway demand equation using panel data at the state level for the 1994-2008 period. In estimating the equation, the price of highway usage was proxied by the sum of the average cost of gasoline ($/mile) and the opportunity cost of travel time ($/mile), and highway demand was represented by vehicle miles traveled (i.e., total number of miles traveled by all the vehicles within a state and year) (US Environmental Protection Agency 2012). *Ex post* simulations of the highway demand equation with and without the ARRA highway disbursement using 2009 data generated predicted changes in highway usage for each state. The *ex-post* simulated changes in highway usage for each state were used to estimate changes in (1) consumer surplus and (2) costs of negative externalities, such as air pollution and
traffic congestion, based on changes in simulated vehicle usage and estimates taken directly from previous research.

This research contributes to the literature by estimating state-level highway demand curves for use in evaluating nationwide investments, such as the ARRA highway disbursement. Several highway computer simulation models have been developed to perform cost-benefit analysis of highway development, starting with COst-Benefit Analysis (COBA) developed by UK government (Department of Transport, UK, 2012) and followed by other computer simulation models, such as the Highway Investment Analysis Program (HIAP), Highway Economic Requirements Model (HERS), Micro-computer Benefit Cost Analysis Model (MicroBENCOST), and the Strategic Benefit Cost Analysis Model (StratBENCOST) (McElroy and Huheey 1992; Lee 2000; Snarr and Axelsen 2007). However, because those computer simulation models focus on utilizing micro-level data for a specific highway-project (e.g., I-70 Hyper Fix Project in Indianapolis), they cannot be used for the macro-scale analysis needed to evaluate the benefits and costs of the ARRA highway disbursement at the state level.

**Empirical Model**

*Highway demand equation*

Highway demand in a given area is specified based on the relationships found in previous literature (e.g., Noland 2001; Choo et al. 2004; Small and Van Dender 2005; Washington State Department of Transportation 2010). The equation is specified with highway demand $Q$, measured by vehicle miles traveled, being a function of the price of highway usage $P$, proxied by the sum of the average cost of gasoline per mile and the cost of travel time per mile, and other factors $V$, including the number of licensed drivers to represent population of highway consumer,
ARRA highway disbursement, per capita income to reflect other socio-economic characteristics, and total miles of highway in the state:

(1) \[ Q = f(P, V). \]

Using the panel data, the highway demand equation is:

(2) \[ Q_{it} = \alpha + X_{it} \beta + \mu_i + \lambda_t + \epsilon_{it}, \]

where \( i \) represents the \( i \)th state (\( i = 1, 2, \ldots, N; N=48 \)), \( t \) denotes the year in the 1994-2008 period (\( t = 1, 2, \ldots, T; T=15 \)), \( X \) is 1×5 row vector of explanatory variables including \( P \) and \( V \), \( \beta \) is a 5 × 1 parameter vector, and \( \epsilon \) is an error term. The terms \( \mu \) or \( \lambda \) respectively denote unobserved spatial specific effects and time specific effects, depending on the spatial and temporal characteristics of the data. Data for all variables were converted to natural logs before estimating the equation.

A highway system is intrinsically a spatial network system that may produce spatial dependence among the observations (e.g., LeSage and Pace (2009); Parent and LeSage (2010)) in the equation (2). A spatial regression model, such as spatial autocorrelation, may be needed to address the spatial dependence of the regression residuals. While no clear-cut consensus has yet emerged on criteria for determining the need for a spatial regression model, two approaches (i.e., specific-to-general approach and general-to-specific approach) have been commonly used to choose between aspatial and spatial models and the structure of the spatial model if chosen (Florax et al. 2003; Mur and Angulo 2009; Elhorst 2010).

Following Elhorst (2010) both approaches were employed. The aspatial highway demand equation was tested against the corresponding spatial model under the specific-to-general approach. Under the general-to-specific approach, the generalized spatial model was tested.
against two spatial models—the spatial error model and spatial lag model—and the corresponding aspatial model.

**Tests under specific-to-general and general-to-specific approaches**

Spatial lagrange multiplier (LM) tests (Anselin 1988; Debarsy and Ertur 2010) and robust LM tests (Anselin et al. 2008) were performed in the context of the specific-to-general approach for the choices between aspatial and spatial models and between the spatial lag and spatial error models.\(^{10}\) The tests were performed assuming two hybrid spatial weight matrices that captured both distance decay and spatial contiguity effects: a queen first-order contiguity matrix multiplied by an inverse-distance matrix (hereafter referred to as “\(HW1\)” and a queen second-order contiguity matrix multiplied by an inverse-distance matrix (hereafter referred to as “\(HW2\)”\(^{11}\). The hybrid weight matrices were row-standarized to avoid a singular matrix in estimating the reduced form of the spatial model (Kelejian and Prucha 2010).

Robust and non-robust LM statistics (hereafter referred to as “LM statistics”) of 3.74-156.78 for spatial lag model indicated that, except for the time-specific-effects model with \(HW1\) (LM = 3.74), all aspatial models were rejected at the 5% level (critical value = 3.84) in favor of the spatial lag model (hereafter referred to as “significant” if rejected at the 5% level). On the other hand, LM statistics of 0.003-99.49 for the spatial error model generated conflicting results (i.e., 9 of 16 for the 4 model specifications with \(HW1, HW2\), and robust and non-robust tests rejected the aspatial model).

\(^{10}\) The LM tests have a chi-square distribution with one degree of freedom.

\(^{11}\) Third- and higher-order hybrid spatial weight matrices were not considered because, in many cases, neighbors defined by these weight matrices cover more than half of the continental United States, diminishing the variation among neighborhoods and mitigating the role of the spatial weight matrix (i.e., determining the set of neighbors).
Wald and likelihood ratio (LR) tests were performed for the general-to-specific approach based on the spatial Durbin model for panel data (SDMP) that includes both spatial lag and spatial error structures (LeSage and Pace 2009):

\[
Q_{it} = \rho \sum_{j=1}^{N} w_{ij} Q_{jt} + \alpha + X_{it} \beta + \sum_{j=1}^{N} w_{ij} X_{jt} \phi + \mu_i + \lambda_t + \epsilon_{it},
\]

where subscripts \(i\) and \(j\) represent \(i\)th and \(j\)th states, \(w_{ij}\) is element \((i, j)\) of the \(N \times N\) spatial weight matrix \(W\) (i.e., \(HW1\) or \(HW2\)) whose diagonal elements are zero, \(\sum_{j=1}^{N} w_{ij} Q_{jt}\) is annual vehicle miles traveled within the neighbors defined by the spatial weight matrix \(W\), \(\rho\) is a parameter of spatially lagged annual vehicle miles, and \(\phi\) is a \(5 \times 1\) parameter vector of spatially lagged independent variables. \(\mu_i\) and \(\lambda_t\) represent the spatial-specific time-invariant effect and time-specific spatial-invariant effect, respectively.

The hypotheses \(H_0: \phi = 0\) and \(H_0: \phi + \rho \beta = 0\) were tested to determine if the SDMP can be simplified to the spatial lag model or spatial error model, respectively (Burridge 1981). The Wald and LR statistics for \(H_0: \phi = 0\) ranged from 88.57 to 251.35 and 117.67 to 476.43, respectively, rejecting the null hypothesis. Likewise, the Wald and LR statistics for \(H_0: \phi + \rho \beta = 0\) ranged from 88.97 to 287.97 and from 53.86 to 341.67, respectively, rejecting the null hypothesis. These results indicate that the SDMP cannot be simplified to either the spatial lag model or spatial error model.

While the specific-to-general approach is inconclusive on the choice between the spatial lag and spatial error models, the general-to-specific approach unequivocally supports the SDMP. Thus, I specified the highway demand equation as the SDMP in equation (3).
**Panel data model specification**

In the panel data model, unobserved effects can be estimated through the demeaning and recovering procedure (Baltagi 2005). As with the aspatial model with the four specific effects mentioned in the previous section, the SDMP can be specified with those effects. The LR statistics of 1,640.47 rejected the null hypothesis that the spatial specific effects are jointly insignificant. This result suggested that the highway demand equation include spatial specific effects (Elhorst 2010). For the purpose of ex-post simulation of highway usage in 2009, the time specific spatial-invariant effects were excluded from our model consideration. The justification for this exclusion is that the time-specific effects are unknown because they differs across time, while the spatial-specific effects are time invariant.

Another panel data issue is to determine if unobserved effects should be treated as random effects—assumed to be uncorrelated with other explanatory variables, i.e.,

\[ E(\mu_i | x_i) = 0 \] —or fixed effects—not assumed to be uncorrelated. The fixed effect model is more appropriate when a specific set of \(N\) observations is focused as in this study, while the random fixed effect model is a better choice when the observations are a sample drawn from a large population (Baltagi 2005). Hausman’s specification test was used to test the null hypothesis that the unobserved effects can be treated as random effects (Hausman 1978; Lee and Yu 2010). Hausman test statistics of 94.00 and 359.73 with \(HW1\) and \(HW2\), suggested rejection of the null hypothesis, which supports the estimation of the highway demand equation with a fixed effect model.

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12 Baltagi (2005) labeled the model with either \(\mu_i\) or \(\lambda_i\) as a one-way error component model and the model with both \(\mu_i\) and \(\lambda_i\) as a two-way error component model.
Estimation method

Based on the test results and panel data model specification discussed above, the highway demand equation was specified using SDMP with spatial fixed effects and $HW1$ and estimated by maximum likelihood. The log-likelihood function of the equation (3) is expressed as:

$$\ln L = -\frac{NT}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[ Q_{it} - \rho \sum_{j=1}^{N} w_{ij} Q_{jt} - X_{it}\beta - \sum_{j=1}^{N} w_{ij} X_{jt}\phi - \mu_t \right]^2 + T \ln |I_N - \rho W|,$$

where the last term on the right hand side of the equation is the Jacobian term that addresses the endogeneity of the spatially lagged dependent variable $\sum_{j=1}^{N} w_{ij} Q_{jt}$ (Anselin 1988). After taking the derivative of equation (4) with respect to $\mu_t$, $\mu_t$ is solved as:

$$\mu_t = \frac{1}{T} \sum_{i=1}^{T} \left[ Q_{it} - \rho \sum_{j=1}^{N} w_{ij} Q_{jt} - X_{it}\beta - \sum_{j=1}^{N} w_{ij} X_{jt}\phi \right].$$

The log-likelihood function (4) is reexpressed by replacing $\mu_t$ with the right hand side of the equation (5):

$$\ln L = -\frac{NT}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[ Q_{it}^* - \rho \left( \sum_{j=1}^{N} w_{ij} Q_{jt}^* \right) - X_{it}^*\beta - \left( \sum_{j=1}^{N} w_{ij} X_{jt}^* \right)\phi \right]^2 + T \ln |I_N - \rho W|,$$

where $$Q_{it}^* = Q_{it} - \frac{1}{T} \sum_{t=1}^{T} Q_{it},$$ $$\left( \sum_{j=1}^{N} w_{ij} Q_{jt} \right)^* = \sum_{j=1}^{N} w_{ij} Q_{jt}^* - \frac{1}{T} \sum_{t=1}^{T} \left( \sum_{j=1}^{N} w_{ij} Q_{jt} \right),$$ $$X_{it}^* = X_{it} - \frac{1}{T} \sum_{t=1}^{T} X_{it},$$ $$\left( \sum_{j=1}^{N} w_{ij} X_{jt} \right)^* = \sum_{j=1}^{N} w_{ij} X_{jt}^* - \frac{1}{T} \sum_{t=1}^{T} \left( \sum_{j=1}^{N} w_{ij} X_{jt} \right).$$
The estimates of $\beta$, $\phi$, $\rho$, and $\sigma^2$ that maximize the full log-likelihood function (6) were obtained by following Elhorst (2003)'s two-step procedure to attain the concentrated maximum likelihood function with respect to $\rho$. The first step is to stack the demeaned variables to construct an $NT \times 1$ vector of $Q^*$ and $(I_T \otimes W)Q^*$, and an $NT \times 5$ matrix of $X^*$ and $(I_T \otimes W)X^*$. The second step is to regress $Q^*$ on $X^*$ and $(I_T \otimes W)X^*$, and to regress $(I_T \otimes W)Q^*$ on $X^*$ and $(I_T \otimes W)X^*$ to respectively obtain OLS estimators of $\gamma_{\rho}^*$ and $\gamma_{\iota}^*$, and corresponding residuals, $\epsilon_{0}^*$ and $\epsilon_{1}^*$. The two-step procedure yields the concentrated log-likelihood function in equation (6):

\[
\ln L = C - \frac{NT}{2} \ln \left[ (\epsilon_{0}^* - \rho \epsilon_{\rho}^*)^T (\epsilon_{0}^* - \rho \epsilon_{\rho}^*) \right] + T \ln |I_N - \rho W|, 
\]

where $C$ denotes a constant term not related to $\rho$. Equation (7) was solved with a numerical optimization algorithm. Once $\rho$ was obtained, the other parameters (i.e., $\beta$, $\phi$, and $\sigma^2$) were estimated based on $\rho$. Let $Z = [X^* (I_T \otimes W)X^*]$, and $\theta = [\beta \phi]$. Then,

$\theta = (Z^T Z)^{-1} Z^T \left[ Q^* - \rho (I_T \otimes W)Q^* \right]$, and $\sigma^2 = \frac{1}{NT} \left[ (\epsilon_{0}^* - \rho \epsilon_{\rho}^*)^T (\epsilon_{0}^* - \rho \epsilon_{\rho}^*) \right]$. 

**Decomposition of total marginal effect into direct and indirect effect**

In the spatial regression model, interpretation of parameter estimates, i.e., $\beta$ and $\phi$, is not straightforward because spatial spillover effects play significant roles in determining the marginal effects of the variables (LeSage and Pace 2009). Applying the approach by LeSage and Pace (2009), the total marginal effect of a change in an explanatory variable in state $i$ on vehicle miles traveled as a whole, for example, was decomposed into the effect on vehicle miles traveled in
state $i$ as a direct effect and the effect on vehicle miles traveled outside state $i$ as an indirect effect.

As an illustration, the marginal effects $P$ (price) are derived to show the differences in demand curves among states. For simplicity, equation (3) is reexpressed in vector form after supressing the $t$ and $i$ subscripts:

$$(8) \quad Q = \rho W Q + \alpha j_N + X \beta + WX \phi + \mu + \varepsilon,$$

where $j_N$ is an $N \times 1$ vector of ones, which can be again reexpressed as:

$$(9) \quad Q = \rho W Q + P \beta_p + WP \phi_p + A,$$

where $P$ is an $N \times 1$ price vector, $\beta_p$ and $\phi_p$ are parameter scalars, and $A$ contains the other terms in (8) which are not involved in calculating the marginal effects of $P$. The total marginal effect of $P$ in a given state ($i = 1$) on $Q$ is:

$$(10) \quad \frac{\partial Q}{\partial P_{i=1}} = (I - \rho W)^{-1} (i, \beta_p + Wi \phi_p),$$

where $i' = [1, 0, \cdots, 0]_N$, which can be reexpressed as:

$$(11) \quad \frac{\partial Q}{\partial P_{i=1}} = (I - \rho W)^{-1} \begin{bmatrix} \beta_p + w_{i1}\phi_p \\ w_{i2}\phi_p \\ \vdots \\ w_{in}\phi_p \end{bmatrix}.$$

Let $v_{ij}$ be an $(i,j)$ element of $(I - \rho W)^{-1}$, then equation (11) can be solved as:
The first element of the vector in equation (12) denotes the direct effect of $P$ in a given state ($i = 1$) on $Q$, the other elements of the vector represent the indirect effects on $Q$ in the other states ($i \neq 1$), and the sum of all elements in (12) is the total marginal effect in the 48 states. The marginal effects of $P$ in (12) vary across states because the elements in $(I - \rho W)^{-1}$ and $W$ differ in value depending on the spatial unit where an initial shock occurs.

Estimating cost-benefit analysis with and without ARRA highway disbursement

To derive each state’s highway demand curve, vehicle miles traveled without ARRA highway disbursement ($\hat{Q}^{wo}$), vehicle miles traveled in state $i$ with ARRA highway disbursement ($\hat{Q}^{w_i}$), and in all 48 states collectively ($\hat{Q}^{w_{all}}$) were predicted:

(13) \[ \hat{Q}^{wo} = (I - \hat{\rho}W)^{-1}(\hat{\alpha}X^{wo} + X^{wo} \hat{\beta} + WX^{wo} \hat{\phi} + \hat{\mu}) \]

\[ \hat{Q}^{w_i} = (I - \hat{\rho}W)^{-1}(\hat{\alpha}X^{w_i} \hat{\beta} + WX^{w_i} \hat{\phi} + \hat{\mu}) \]

\[ \hat{Q}^{w_{all}} = (I - \hat{\rho}W)^{-1}(\hat{\alpha}X^{w_{all}} \hat{\beta} + WX^{w_{all}} \hat{\phi} + \hat{\mu}) \]

where superscript $wo$ denotes “without” and $w$ denotes “with”, $X^{wo}$ is a matrix of explanatory variables in 2009 without the ARRA highway disbursement, $X^{w_i}$ and $X^{w_{all}}$ are matrices of
explanatory variables in 2009 in state \( i \) and in all 48 states, respectively, with the ARRA highway disbursement.

Assuming a constant-elasticity demand curve, the equations for each state’s demand curves, \( P = \hat{w}_o Q^o, \ P = \hat{w}_i Q^i, \) and \( P = \hat{w}_{48} Q^{48} \) were obtained where \( k \) denotes all other factors that shift the demand curves through different levels of ARRA highway disbursement (referred to as “demand curve shifter”), and \( \eta \) is inverse of price elasticity of demand obtained from the direct effect of \( P \) in a given state.\(^{13} \)

Hypothetical highway demand curves corresponding to \( \hat{w}_o Q^o, \hat{w}_i Q^i, \) and \( \hat{w}_{48} Q^{48} \) are shown in Figure 3.1. The relationships, \( \hat{w}_o < \hat{w}_i, \hat{w}_i < \hat{w}_{48}, \) and \( \hat{w}_{48} < \hat{w}_{48} \), are hypothesized because I expect ARRA highway disbursement to shift the demand curve upward, and the vehicle miles traveled with ARRA highway disbursement in all 48 states are expected to increase more than in a given state.

Given the estimated highway demand curves, the benefits of increased vehicle miles traveled for each state due to the ARRA highway disbursement in a given state and in all 48 states were estimated by calculating the additional consumer surplus due to the upward shifts in the highway demand curves in a state and in all the 48 states (shown as \( \Delta CS_i \) and \( \Delta CS_{48} \) in Figure 3.1). The additional consumer surplus due to the ARRA highway disbursement in all 48 states was calculated by integrating the area \( \Delta CS_{48} \):

\(^{13} \) The price elasticities of demand based on the indirect and total effects were not considered because the indirect and total effects involved locationally mismatched Ps and Qs (i.e., \( P \) in a state \( i \) did not correspond to \( Q \) in other states).
\[
\Delta CS_{\text{All}} = \left[ \int_{Q}^{\bar{Q}} (k^{w}_{\text{All}} Q^{\eta}) dQ - P_{2009} (\hat{Q}^{\text{All}}_{\text{All}} - \bar{Q}) \right] - \left[ \int_{Q}^{\bar{Q}} (k^{w_{o}} Q^{\eta}) dQ - P_{2009} (\hat{Q}^{w_{o}}_{\text{All}} - \bar{Q}) \right]
\]

\[
= \frac{k^{w}_{\text{All}}}{\eta + 1} \left( (\hat{Q}_{\text{All}}^{w_{o}})^{\eta+1} - (\bar{Q})^{\eta+1} \right) - \frac{k^{w_{o}}}{\eta + 1} \left( (\hat{Q}_{\text{All}}^{w_{o}})^{\eta+1} - (\bar{Q})^{\eta+1} \right) - P_{2009} (\hat{Q}^{w_{o}} - \bar{Q})
\]

where \( k^{w}_{\text{All}} \) and \( k^{w_{o}} \) denote demand shifters with and without ARRA highway disbursement, respectively, and \( \bar{Q} \) is an arbitrarily chosen but reasonably low cutoff value (i.e., vehicle miles traveled, \( Q \), corresponding to the price ceiling of 1,000 times of \( P_{2009} \) in the demand curve of \( P = k^{w_{o}} Q^{\eta} \)). Likewise, \( \Delta CS_{i} \) was also calculated.

The decomposition of \( \Delta CS_{\text{All}} \) into \( \Delta CS_{i} \) and \( (\Delta CS_{\text{All}} - \Delta CS_{i}) \) is meaningful because \( \Delta CS_{i} \) measures the additional consumer surplus in a given state related to the ARRA highway disbursement in that state, while \( (\Delta CS_{\text{All}} - \Delta CS_{i}) \) measures the additional consumer surplus in the given state related to the ARRA highway disbursements in the other states (referred to as “spillover consumer welfare”).

The difference between the predicted vehicle miles traveled without and with ARRA highway disbursement in all 48 states \((\hat{Q}_{\text{All}}^{\text{w_{o}}} - \hat{Q}^{w_{o}})\) was multiplied by $0.09 per mile (taken directly from Litman and Doherty (2009), see details in the Study Area and Data section) to calculate the additional implicit cost of negative externalities. Subsequently, the total net benefit from the ARRA highway disbursement for each state was calculated by subtracting the sum of explicit and implicit costs from total additional consumer surplus. The net benefits from the ARRA highway disbursement for each state were aggregated across states to arrive at the total net benefit from the ARRA highway disbursement for the 48 contiguous states.
Study Area and Data

The data used in the study pertain to the 48 contiguous U.S. states for 15 years (1994-2008). The same cross-section data for 2009 were used to simulate the impact of the ARRA highway disbursement on highway demand. The annual retail price of gasoline was obtained from the US Energy Information Administration (US EIA 2012); per capita income was collected from the US Department of Commerce, Bureau of Economic Analysis (USDC BEA 2012); and vehicle miles traveled, highway disbursement, length of highway, number of licensed drivers, and fuel tax per gallon were obtained from the Highway Statistics series published by the US Department of Transportation, Federal Highway Administration (USDT FWHA 2012). Highway disbursements by state for 2009 were not available and were predicted by each state’s time trend using the data from 1994 to 2008.

The average opportunity cost of travel time per mile for the United States (i.e., $0.11 per mile) was obtained from Litman and Doherty (2009), as was the cost of congestion per mile, which was estimated as a weighted average of congestion levels for urban peak, off-peak and rural areas, multiplied by weighted hourly wages. The ARRA highway disbursement for 2009 was obtained from www.recovery.gov, the US government’s official website (Recovery 2012).

The cost of negative externalities of air pollution and traffic congestion (i.e., $0.09 per mile) from Litman and Doherty (2009) was estimated by summing $0.04 for the non-greenhouse gas air pollution cost, $0.02 for the greenhouse gas cost, and $0.03 for the congestion cost, all per average vehicle mile traveled. All data, except travel time cost and the costs of negative externalities, were obtained at the state level and all dollar values (i.e., gasoline price, travel time cost, disbursement, and per capita income) were adjusted to 2007 dollars using the consumer
price index (US Department of Labor, Bureau of Labor Statistics 2012). Definitions of the variables used in the regressions and descriptive statistics are reported in Table 3.1.

Annual vehicle miles traveled for each state were used to represent the highway demand. The vehicle miles traveled in the United States steadily increased by 26% from 2,342 billion miles in 1994 to 2,955 billion miles in 2008, with the exception of a slight drop in 2008 during the recession. As shown in Figure 3.2a, California and Texas stand out as the states with the most vehicle miles traveled during 1994-2008, 307 and 215 billion miles, respectively while Delaware, North Dakota, Rhode Island, South Dakota, Vermont and Wyoming hold the shortest vehicle miles traveled with less than 10 billion miles traveled (Figure 3.2a).

The per-mile retail price of gasoline, state-level fuel tax, and opportunity cost of travel time were summed to represent the price of a vehicle mile traveled. The retail price of gasoline has varied across states with a range of around 10% between the highest and the lowest prices. The West Coast and New England are in the higher price range while the Midwest is in the lower price range (Figure 3.2b). Over the 15-year study period, average real gasoline prices for individual states have increased by 131% to 179%. Fuel taxes that add to the price of gasoline differed in 2008 from $0.36 per gallon in West Virginia to $0.08 per gallon in Georgia.

In the estimation, highway disbursement is total investment in highways by federal, state and local governments (e.g., capital outlay, maintenance and services, administration, and research and planning). Between 1994 and 2008, highway disbursement in 2007 dollars increased by 50% from $88 billion to $132 billion. Highway disbursements were highest in California, Texas and New York (over $6 billion per year) on average over the 15 years, while Vermont, Rhode Island and North Dakota (less than $0.4 billion per year) had the lowest

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14 The raw data of gasoline price denoted as $/gallon were converted to $/mile using the average mileage rate 25 miles/gallon.
hingway disbursments. The allocation among states of the ARRA highway disbursement of $27 billion amounted to between 12.6% and 47.5% of each state’s highway disbursement in 2008. Correlation between state highway disbursements in 2008 and state ARRA highway disbursements was 0.96, indicating that the share of the total ARRA disbursement was distributed according to each state’s existing share of highway disbursement (see Figures 3.3a and 3.3b for the distribution of highway disbursement in 2008 and ARRA highway disbursement, respectively).

**Empirical Results**

*Regression results*

The parameter estimates and direct, indirect and total effects of the SDMP are shown in Table 3.2. The positive and significant spatial lag parameter ($\rho$) suggests spatial spillover effect of vehicle miles traveled, which is consistent with the results of the spatial LM, Wald, and LR tests discussed in the Empirical Model section. Specifically, a 1% increase in vehicle miles traveled in the neighbors yielded 0.18% increase in the own state’s vehicle miles traveled.

All non-lagged explanatory variables except the length of highway were significant. The signs of all the significant variables were in agreement with expectations. The states with higher highway disbursement, per capita income and number of licensed drivers had higher vehicle miles traveled. The spatially lagged variables (price, length of highway and number of licensed drivers) were positive and significant, reflecting positive spatial spillover effects on vehicle miles traveled.

An increase in highway disbursement in a state by 1% increased vehicle miles traveled inside of the state by 0.02% and in overall states by 0.05%, respectively. These results suggest
that government investments in highways enhance the quality and quantity of the highway stock and thus increased highway usage. The higher total effect of the highway disbursement than direct effect in the state implies that a regional shock at the highway disbursement is absorbed bigger in large-scale highway network than at the regional level. The results suggest that predicted vehicle miles traveled will be greater with than without the ARRA highway disbursement.

The price per mile had direct, indirect and total effects on vehicle miles of -1.02, 0.81, -0.21, respectively. These effects suggest that the elastic demand for highway usage based on the direct effect is moderated by the positive indirect effect to yield inelastic demand based on the total effect. The positive indirect effect suggests that an increase in the price of highway usage in a state increases vehicle miles traveled in other states. This finding implies that highway usage in one state is a substitute for highway usage in neighboring states.

The direct and total effects of per capita income on vehicle miles traveled suggest that a 1% increase in the per capita income in a state increased vehicle miles traveled by 0.27% and 0.40% in the state and in other states, respectively. These findings suggest that highway usage is a necessity, implying that highway usage is not highly reduced by economically tough times.

The indirect and total effects of highway length were both positive and significant. These results suggest that a 1% increase in highway length in a state increased vehicle miles traveled outside of the state and in the overall states by 0.34% and 0.35%, respectively. These results imply that an increase in highway length in a state increased the accessibility of its neighboring states’ highways, inducing greater highway usages in the neighboring states, resulting in an overall increase in highway demand.
The direct, indirect and total effects of the number of licensed drivers are all positive and significant. This variable plays a crucial role in the regression to control the effects of population on vehicle miles traveled, accounting for the large variation in population size across states populations are largely different. The estimates suggest that a 1% increase in the number of licensed drivers in a state increased highway usages in the state, outside the state and in all states by 0.34%, 0.52% and 0.86%, respectively. The higher indirect effect than the direct effect implies a greater effect on vehicle miles traveled in other states than within the state.

*Simulation results*

Additional vehicle miles traveled by ARRA highway disbursement in a given state and in all 48 states were predicted based on the estimates of the SDMP with spatial fixed effects model with neighbors defined by $HW1$. The predicted values of addition vehicle miles traveled resulting from the ARRA highway disbursement and their corresponding effects on consumer surplus, costs and net benefits are presented in Table 3.3. Results suggest that the ARRA highway disbursement increased national vehicle miles traveled by 28 billion miles in the 48 states (or 0.9% from 3.11 trillion miles to 3.14 trillion miles). Predicted vehicle miles traveled with the ARRA highway disbursement summed over the 48 states is greater than for a given state, and both of the former have greater predicted vehicle miles traveled without the ARRA highway disbursement, i.e., $\hat{Q}^\omega < \hat{Q}^w < \hat{Q}^{' all}$. The findings support the hypotheses that the ARRA highway disbursement shifted the demand curve for highway usage upward and the ARRA highway disbursement increased vehicle miles traveled in all 48 states more than in any given state.

Increases in vehicle miles traveled in a given state resulting from that state’s ARRA highway disbursement ranged from 31 million miles for Delaware to 1.57 billion miles for
California, whereas increases in vehicle miles traveled in a given state with the ARRA highway disbursement distributed throughout all states ranged from 61 million for Delaware to 2.93 billion miles for California. These increases in vehicle miles traveled generated additional consumer surplus between $40 million for Delaware and $2.01 billion for California ($\Delta CS_y$) when the ARRA disbursement was for a given state, and between $79 million and $3.76 billion ($\Delta CS_{all}$) when the ARRA disbursements were distributed throughout all states. Given the implicit costs of negative externalities by state of between $5 million and $258 million and explicit costs of between $122 million and $2.78 billion, total net benefits ranged from –$188 million for New Jersey to $721 million for California, which summed to $4.65 billion over the 48 states. As a result, the net benefit per dollar spent was in the range of –$0.39 for Delaware to $0.71 for Georgia, and weighted averaged $0.17 per dollar spent across the 48 states.

Of the total increase in vehicle mile traveled for the 48 states ($\hat{Q}_{all} - \hat{Q}^{\text{no}}$) of 28.15 billion miles, which generated $34.38 billion in additional consumer surplus ($\Delta CS_{all}$), about a half (or 14.16 billion miles generated $17.28 billion in additional consumer surplus ($\Delta CS_{all} - \Delta CS_y$)) was attributed to benefits received by states other than the one receiving the ARRA disbursement. The considerable differences between the increases in predicted vehicle miles traveled in a given state from the ARRA disbursement in that state and the predicted vehicle mile traveled when the ARRA disbursement was made to all 48 states imply the ARRA highway disbursement had sizable spatial spillover impacts of on highway demand.
Conclusions

This study evaluated the impact of the ARRA highway disbursement on vehicle miles traveled, reflecting a shift in highway demand, in the framework of cost and benefit analysis. I estimated a highway demand equation that employed SDMP based on panel data pertaining to the 48 U.S. contiguous states for the 1994-2008 period. The estimates from the equation supported the hypothesis that different state-level ARRA highway disbursements resulted in different upward shifts in the highway demand curve by state. The different effects on the state-level demand curves resulted in increases in vehicle miles traveled that were different for each state, generating a wide range of predicted increases in consumer surplus. The estimated figures and explicit and implicit costs associated with additional highway usage were used to estimate total net benefit and net benefit per dollar spent for each state. Our estimates found $4.6 billion in total net benefits summed across the 48 states as a result of $27.2 billion of ARRA highway disbursement, which yielded an average of $0.17 in net benefit per dollar spent.

Besides the core finding of the net benefits of ARRA highway disbursement on vehicle miles traveled across and over the 48 states, another key finding of the study is that about a half of the increased vehicle miles traveled resulting from the ARRA highway disbursement was due to the spatial spillover impacts on vehicle miles traveled in neighboring states of the ARRA highway disbursement in a given state. This result implies that improvements in the highway system of a given state are disseminated outside the state to the users of larger-scale regional-level highway networks.

The estimated net benefits of the ARRA highway disbursement on vehicle miles traveled across and over the 48 states in this study does not offer an obvious answer to the question about whether the ARRA has been beneficial to rehabilitate the deeply depressed economy. However,
given the assumptions imposed in the SDMP, ex post simulated welfare calculations, our estimates suggest positive total net benefits for the 48 contiguous states, implying a positive impact of the ARRA, at least with regards to increasing highway demand.

Another implication of this study is that while the ARRA highway disbursement is the shock that is simulated in the SDMP, dollar value of the ARRA highway disbursement is not the only element that dictates net benefit per dollar. For example, Georgia was the state with the highest estimated net benefit per dollar spent, $0.71, whereas the state ranked as 9th in the dollar value of ARRA highway disbursement. In addition to the amount of ARRA highway disbursement of each state, neighbor structure of ARRA highway disbursement also affects in determining \( \hat{W}_{\text{all}} \). This finding suggests an implication that neighbor structure of ARRA highway disbursement could be considered for improving states’ return per dollar spent when future highway funds are disbursed.

One caveat of the study should be noted. The reasonably low cutoff value \( \bar{Q} \) when integrating the area shown as \( \Delta CS_{\text{all}} \) in Figure 3.1 is an arbitrary value. Sensitivity analyses were performed to test sensitivity of \( \Delta CS_{\text{all}} \) by varying the price ceiling of 1,000 times of \( P_{2000} \) by ±50%, i.e., \( \bar{Q} \) corresponding to 1,500 times of \( P_{2000} \) and 500 times of \( P_{2000} \) which are respectively denoted \( \bar{Q}_{+50\%} \) and \( \bar{Q}_{-50\%} \). The net total benefits result in $6.6 billion and $1.3 billion corresponding to \( \bar{Q}_{+50\%} \) and \( \bar{Q}_{-50\%} \), respectively, which yield an average of $0.24 and $0.05 in net benefit per dollar spent, respectively. Despite of these changes, the order of states in rank of net benefit per dollar spent was not substantially changed by the varying cutoffs. For example, for the two different cutoffs, \( \bar{Q}_{+50\%} \) and \( \bar{Q}_{-50\%} \), 41 and 34 states out of the 48 states, respectively, held the same rank with the original cutoff and no state had change more than three ranks. The sensitivity
analyses imply that although some confidence is allowed to answer the question which state received more benefits from the ARRA highway disbursement, because of the arbitrary nature of the low cut-off value used in our study and its sensitivity, the additional consumer surplus calculated in equation (14) must be interpreted with caution.
References


Recovery. 2012. The US government’s official website of ARRA [http://www.recovery.gov/Pages/default.aspx](http://www.recovery.gov/Pages/default.aspx)


Appendix
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<th>Variable</th>
<th>Description</th>
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<th>Std Dev</th>
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<td>Licensed drivers</td>
<td>Total number of licensed drivers (million)</td>
<td>3.960</td>
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Table 3.2. Regression Results of the SDMP with Spatial Fixed Effects Model and Neighbors Defined by \( HW1 \)

<table>
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<tr>
<th>Variables</th>
<th>Parameter</th>
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<th>Indirect effects</th>
<th>Total effects</th>
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<td>0.023</td>
<td>0.023</td>
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<td></td>
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<td></td>
<td>(0.008)</td>
<td>(0.021)</td>
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Adjusted \( r \)-squared 0.8554

* denotes \( p < 0.05 \).
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<th>Spillover consumer welfare</th>
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<th>Explicit Cost ($ million)</th>
<th>Total net benefit ($ million)</th>
<th>Net benefit per dollar spent ($)</th>
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<td></td>
<td>$\hat{Q}^* - \hat{Q}^{**}$ (million mile)</td>
<td>$\hat{Q}<em>{\text{spillover}}^* - \hat{Q}</em>{\text{spillover}}^{**}$ (million mile)</td>
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<td>Total $Q^{all} - Q^{wo}$ (million mile)</td>
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Figure 3.1. Estimated demand curves without and with ARRA highway disbursement in a given state and in all 48 states.
Figure 3.2a. AVERAGE VEHICLE MILES TRAVELED DURING 1994-2008 (million miles)

Figure 3.2b. GASOLINE PRICE PER GALLON IN 2008 ($ per gallon)
Figure 3.3a. HIGHWAY DISBURSEMENT IN 2008 ($ million)

Figure 3.3b. ARRA HIGHWAY DISBURSEMENT ($ million)
Chapter 4: Summary
Summary
The two essays in this thesis evaluated impacts of national policies in South Korea and the United States on their greenhouse gas (GHG) emissions and highway demand, respectively. The first essay focused on how population dynamics affect GHG emissions. The effects of the South Korean government’s decentralization efforts on GHG emissions were assessed. The second essay was to explore the costs and benefits of the American Recovery and Reinvestment Act (ARRA) highway disbursement, focusing on the explicit cost and implicit cost associated with additional highway usage, and the benefits measured by consumer welfare from more highway usage with additional funds used to improve, extend, and maintain highways for each state.

Simulation results in the first essay suggest that the direction of change in total GHG emissions depends on the share of the population redistributed from higher to lower population density regions. If the entire redistributed population of 877,000 persons expected from the government’s decentralization project were from the Seoul Area, annual CO₂e would increase by 1.72%-2.26% compared to benchmark levels. Alternatively, more balanced migration between higher and lower population density regions, i.e., 65% of the 877,000 persons from higher-density locations to lower-density destinations and 35% from lower-density to higher-density regions, decreases CO₂e by 1.49%-2.42%.

The decentralization efforts in South Korea make sense considering the high cost of the overly-concentrated population in Seoul (e.g., traffic congestion and overheating of the real estate market); however, the results of the first essay highlight a potential major cost that has not yet been considered, the effects on GHG emissions. The contrast in the simulated effects of population redistribution suggests that the decentralization plan can be implemented to not only achieve the goal of decentralization but also the goal of mitigating national GHG emissions.
The second essay used panel data for the 48 contiguous US states during 1994-2008 to estimate highway demand curve. The estimated figures and explicit and implicit costs associated with additional highway usage were used to estimate total net benefit and net benefit per dollar spent for each state. The estimated net benefits of the ARRA highway disbursement on vehicle miles traveled across and over the 48 states does not offer an obvious answer to the question about whether the ARRA has been beneficial to rehabilitate the deeply depressed economy. However, given the assumptions imposed in the spatial panel model, ex post simulated, welfare calculations, the estimates suggest positive total net benefits for the 48 contiguous states, implying a positive impact of the ARRA, at least with regards to increasing highway demand.

Another implication of this study is that while the ARRA highway disbursement is the shock that is simulated in the SDMP, dollar value of the ARRA highway disbursement is not the only element that dictates net benefit per dollar. For example, Georgia was the state with the highest estimated net benefit per dollar spent, $0.71, whereas the state ranked as 9th in the dollar value of ARRA highway disbursement. In addition to the amount of ARRA highway disbursement of each state, neighbor structure of ARRA highway disbursement also affects in determining $Q_{n\ell}^w$. This finding suggests an implication that neighbor structure of ARRA highway disbursement could be considered for improving states’ return per dollar spent when future highway funds are disbursed.
Vita

Daegoon Lee was born October 5, 1981 in South Korea. He received his bachelor’s degree in economics from Yonsei University in Seoul, South Korea in 2005. After completion of his undergraduate degree, he as an officer served in R.O.K Navy for three years from 2005 to 2008. After he was discharged, he attended the University of Tennessee where he completed a Master’s of Science degree in Agricultural & Resource Economics. From fall 2012, he begins to pursue his Doctorate of Philosophy in Agricultural Economics from Washington State University.