TWO ESSAYS

IN

APPLIED ECONOMICS

By

JEROME SEGURA III

Bachelor of Arts in General Business
Southeastern Louisiana University
Hammond, Louisiana
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Master of Arts in Economics
University of Missouri
Columbia, Missouri
2007

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Dissertation Approved:

Dr. Dan S. Rickman

Dissertation Adviser

Dr. Abdul B. A. Munasib

Dr. Karen Maguire

Dr. Dave Shideler

Dedicated to

my family.

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Name: JEROME SEGURA III

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Abstract: I provide two exercises which attempt to arrive at consistent estimates through the utilization of various instrumental variable (IV) and general method of moments (GMM) estimation approaches. My first study asks: is social network formation pro-cyclical or counter-cyclical? While viewing social network formation as an investment concept at the individual level is well-established, how this mechanism is affected by aggregate fluctuations has not yet been studied. I use the General Social Survey (1972-2010) to empirically test the net effect of aggregate fluctuations on individual-level social network investment. In my estimation, I attempt to address the reflection problem through the application of the Lee (2007) linear-in-means model which is most recently applied in Bramoullé et al. (2009) and Boucher et al. (2012). I also attempt to address possible bias resulting from unobserved heterogeneity. My findings indicate that social network investment is counter-cyclical. I use alternative measures of business cycle fluctuations and ad-hoc reference group formations; the results remain robust to these alternative measures and specifications. My second study asks: what are the growth effects of state and local fiscal policy. In deriving my estimable equation I combine a partial adjustment process with a factor market approach for modeling regional output. I utilize dynamic panel data estimation procedures in an attempt to arrive at a more refined set of estimates for the growth effects associated with state and local fiscal policy. I use annual observations for 48 contiguous U.S. jurisdictions ranging from 1977-2008 to empirically test the net effect of government fiscal policy on the growth rate of gross state product (GSP). To my knowledge, this is the first study which attempts to address the potential endogeneity of state and local fiscal policy. My findings indicate a large degree of heterogeneity between regions in response to effective tax rate hikes by state and local government. Although these results are robust to an alternative sample and following a reduction in the number of instruments, I am unable to verify the robustness of the estimated coefficients after a number of other alternative specifications. I interpret the results as an indication that policymakers should err on the side of caution in extrapolating the results of empirical studies to their own states and time periods.

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CHAPTER I

INTRODUCTION

The following two studies are samples of research I conducted as a doctoral student with the Department of Economics in the Spears School of Business at Oklahoma State University in Stillwater, Oklahoma. These studies are intended to exhibit my expertise as an applied microeconomist in the urban and regional economics field. My particular areas of interest are networking and public policy. I provide two exercises: I attempt to address the reflection problem, and I attempt to estimate a regional production function.

The second chapter of my dissertation is titled “Friendships through Thick and Thin? Effect of Business Cycle Fluctuations on Social Network Formation”. This study further investigates the determinants of individual investment in social networking. More specifically, I study the connection between the national unemployment rate and the frequency of individual socialization with friends and neighbors. Often times social behaviors are subject to the reflection problem because real peer effects are present (Manski, 1993, 2000). Specifically, peer effects are the portion of individual behavior attributable to reference group membership. If average group behavior is a determinant of individual behavior, then the dependent variable is on both sides of the estimable equation. I employ the most up to date approach of linear-in-means modeling in an attempt to achieve identification with regards to parameter estimates.

The third chapter of my dissertation is titled “The Effect of State and Local Taxes on Economic Growth: A Dynamic Panel Approach”. In this study I investigate the effects of state and local fiscal policy on the growth rate of gross state product (GSP). It is thought that state and local tax revenue and government expenditures as a share of GSP propagate into differences in regional household utility. Just as with local amenities, state and local fiscal policy may generate compensating wage differentials within a spatial equilibrium framework, (Gyourko and Tracy, 1989, 1991). I combine a partial adjustment process with the factor market approach for modeling regional output. Arriving at an autoregressive distributed lag (ARDL) model, I utilize dynamic panel data estimation strategies in an attempt to obtain at a more refined set of estimates for the growth effects associated with state and local fiscal policy.

These two studies combine to form my dissertation. In the remainder of this dissertation, chapter 2 explores the connection between the real business cycle and individual investment in social networking, chapter 3 explores the dynamic growth effects of state and local fiscal policy and chapter 4 concludes.

CHAPTER II

FRIENDSHIPS THROUGH THICK AND THIN? EFFECT OF BUSINESS CYCLE FLUCTUATIONS ON SOCIAL NETWORK FORMATION

The primary estimation issue addressed in spatial econometrics is the implicit endogeneity arising from the assumed spatial dependence between observations. This implicit endogeneity is particularly problematic within a locational choice framework wherein distances may be endogenous, e.g., through geographic sorting. A spatial autoregressive model (SAR) attempts to account for the spatial dependence between observations through the inclusion of spatial lags of the dependent variable on the right hand side of the estimable equation. Furthermore, the endogeneity concerns can be addressed through SAR estimation by taking either an instrumental variable (IV) approach or, when no valid external instruments are known, a general method of moments (GMM) approach.

The reflection problem arises when average characteristics and behavior of the reference group influences the behavior of the individual group member (Manski, 1993 and 2000). Therefore, if peer effects are present, then the weighted sum of the dependent variable may be on the right hand side of the estimable equation. In other words, the reflection problem can best be described as the identification problem which arises in SAR estimation. Additionally, the perfect collinearity between expected group behavior and observed group characteristics makes identification particularly difficult. Pinkse and Slade (2010) identify a number of other limitations of a first-order spatial autoregressive model.

Moreover, relative to time series econometrics, spatial econometric theory lags conspicuously behind the wide array of applications (Pinkse and Slade, 2010). Although partial identification has caught considerable attention in recent spatial studies, identification is not always a primary issue addressed in the estimation of econometric models with spatially dependent observations. For example, networking studies are often plagued by an estimable equation wherein the dependent variable appears on the right hand side once again. In application, this study attempts to achieve identification by isolating the portion of one's socializing behavior attributable to geographic sorting.

In the remainder of the chapter, section 2.1 introduces and motivates the exercise. Section 2.2 explains why social network stock is a determinant of social network flow. Section 2.3 discusses the reflection problem and how I try to account for it. Section 2.4 discusses the empirical model. Section 2.5 discusses the data. Section 2.6 discusses the ad-hoc reference group formation. Section 2.7 discusses the main set of results. Section 2.8 discusses some robustness checks and section 2.9 concludes.

2.1 INTRODUCTION

In a large number of instances, mutually beneficial trades take place not through the market but rather through interpersonal relationships. Diverse areas of research emphasize the beneficial aspects of social networks. For example, networks serve to channel information about new technology, employment, and market opportunities.[1] Social networks also reduce search costs; this is particularly important within labor markets where interpersonal relationships have a significant influence (Granovetter, 1985; Montgomery, 1991). Furthermore, social networks deliver several non-market benefits such as insurance during bad times when people fall back on personal contacts for support, e.g., financial support.[2] Social ties and contacts also have other non-economic returns such as prestige, respect, and social recognition of wealth and other desirable attributes (Lin, Cook, and Burt, 2001). An important motivation for individuals to engage in socializing is the satisfaction from interaction with others (Durlauf and Fafchamps, 2005).[3] In terms of aggregate level outcomes, Knack and Keefer (1997) find growth implications of societal trust and organizational membership. Rauch (2001) shows the importance of ethnic ties in international trade.

Social networks are shown to have a wide range of influences on the individual's economic and non-economic lives as well as the aggregate outcomes of the economy. As a result, the determinants of social networks have gained significant attention in the recent literature (Durlauf and Fafchamps, 2005; Calvo-Armengol, Patacchini and Zenou, 2009; Knack and Keefer, 1997; Rauch, 2001). A well-developed theoretical foundation of social networks has evolved over the last decade (Jackson, 2005; Calvo-Armengol and Ilkilic, 2009; Ballester, Calvo-Armengol and Zenou, 2010; Calvo-Armengol and Jackson, 2010). However, with a handful of exceptions such as Glaeser et al. (2002) and a few others discussed later, the empirical research on the determinants of social networks is conspicuously lagging behind. As a result, while the ubiquity

[1] In the literature on knowledge spillover, social ties and contacts play a crucial role not only in dissemination of ideas but also in the cross breeding of ideas through social interaction [Jacobs, 1969; Krugman, 1991].

[2] Carter and Maluccio [2003] in a study of South African households showed that households with more social capital seemed better able to weather shocks.

[3] Dasgupta [2005] describes socializing as a 'pleasurable activity'.

of social networks is well-established, little effort could be made to utilize social networks as a policy tool.

In this paper I focus on the determination of social network formation at the individual level. In Granovetter's celebrated *embeddedness hypothesis*, social and economic outcomes are achieved through the interaction between social, economic, physical and environmental conditions (Granovetter, 1985). The particular contextual feature that I focus on is aggregate business cycle fluctuations. In other words, I am the first to investigate the question: Is social network formation pro-cyclical or counter-cyclical?

Business cycles have been shown to influence individual decisions with regards to investment in human capital, housing and the consumption of durable goods (Gregorio, Guidotti, and Vegh, 1998; Dellas and Sakellaris, 2003; Christian, 2007).[4] Investment in health is also found to be counter-cyclical. For example, physical activity is found to be reduced during economic booms while individual eating habits are found to improve during economic downturns (Dave and Kelly 2010; Ruhm, 2005). During economic downturns the consumption of alcohol and tobacco increase while fruit and vegetable consumption decrease (Dee, 2001; Dave and Kelly, 2010).

Business cycle fluctuations may induce an adjustment in the individual's decision as expectations and the feasible set change. Just as this reasoning applies to investment in human capital or health, it applies to investment in social networks. If the intrinsic benefits associated with social networks improve during periods of deteriorating macroeconomic conditions, then the individual may have the incentive to invest more in social capital. Individuals may engage in more social network investment (especially maintenance investment) during economic downturn to extract greater social support. Individuals at high risk of experiencing an unemployment spell, in particular, may increase social network investment in order to seek information about economic

[4] Dellas and Sakellaris (2003) find that individual propensity to enroll in college is countercyclical. Li (2005) discuss U.S. business cycles and homeownership rates.

opportunities and receive other assistance from social networks. Diminished opportunity costs could also lead the individual to the same behavior, e.g., reduced opportunity costs due to lower incomes during recessions. On the other hand, recessions may impose additional constraints on individual's time and other resources leading to a lowering of social network investment. The impact of business cycle fluctuations on investment in social networking, therefore, must be tested empirically.

I use the General Social Survey (GSS) (1972-2010) to empirically test the net effect of aggregate fluctuations on individual-level social network investment. The contributions of the paper are the following. First, I show the equation to estimate social network investment should include social network stock on the right hand side. Note that social network stock refers to a measure of the total number of links in the individual's social network at a point in time. On the other hand, social network investment flow refers to the rate of activities employed by the individual to acquire and/or maintain these network links. For example, the number of friends an individual has at a point in time is a measure of her stock while the time she spends with her friends in weekly card games is a measure of her investment activities. From a theoretical point of view, investment, a policy variable in a dynamic program, is a function of the state variable, the stock. Intuitively, an individual with a large stock of friends need to spend more time – compared to someone with a smaller stock of friends – in maintenance of this large circle of friends. While stock is reported for a very small subset of my sample, stock measures are only reported in three years. Following Manksi (1993) I omit the stock variable from the empirical analysis, because measurements of individual stock are not widely available.[5]

Second, as with most social behaviors, social network investment is also subject to the identification problem known as the *reflection problem* (Manski 1993, 2000). In section 2.4, I

[5] I have devised a strategy which allows for the inclusion of stock wherein state unemployment rates are instrumented with the change in industry mix by state.

show that if the endogenous effect is left untreated the effect of business cycles on social network investment may not be identified. I apply the Lee (2007) linear-in-means model to the ad-hoc group approach in addressing the reflection problem and arrive at more refined estimates for the determinants of social network investment. To my knowledge Bramoullé et al. (2009) and Boucher et al. (2012) are the only two papers which empirically apply the Lee (2007) model.

Finally, unobserved heterogeneity may play a role in a regression of individual social network investment on business cycles. There can be cultural trends or other intangible attitudinal factors influencing both the individual's behavior as well as macroeconomic performance. In that case, the coefficient of the business cycle variable may be subject to bias. I instrument the business cycle variable with money supply growth to address this issue. While money supply is strongly correlated with economic performance, there is no *a priori* reason to believe individual social networking behavior would follow money supply fluctuations.

My findings suggest that business cycle fluctuations do affect social network investment of the individual and it is counter-cyclical. My results are robust to a number of alternative measures of the flow of social networks. I also use alternative measures of business cycle fluctuations that I obtain from different sources, all of which show a similar pattern.

2.2 METHODOLOGY

I follow the investment approach of Glaeser et al. (2002) in modeling individual investment in social networking. I model an individual embedded within a social 'reference group', G_i. The individual maximizes lifetime returns by choosing the optimal investment in social networking, I. Let s be a continuous stock of social networking such that $s_i' = g\left(I_i, s_i; \theta_i, P_{G_i}\right)$, where, a prime indicated next period's value, θ_i denotes individual characteristics, P_{G_i} denotes the characteristics of the reference group, G_i. The individual maximizes the return to social networking,

$r\left(I_i, s_i; \psi, \theta_i, \rho_{G_i}\right)$, where , ψ are the current macroeconomic conditions. The return to social networking is the difference between utility, $u\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right)$, and costs, $c\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right)$.

Therefore, $\forall\, I \in \boldsymbol{\mathcal{R}}^{+}$ and $\delta \in (0,1)$, the infinite horizon Bellman equation is

(E2.1) $V(s_i) = \max_{\{I_i\}} r\left(I_i, s_i; , \psi, \theta_i, P_{G_i}\right) + \delta V\left(g\left(I_i, s_i; \theta_i, P_{G_i}\right)\right)$.

The individual chooses I_i which maximizes the lifetime return to social networking by satisfying both the individual's intertempoal optimality condition and Envelope condition. The Euler equation is

(E2.2) $0 = r_I\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right) + \ \delta\lambda\left(g\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right)\right) g_I\left(I_i, s_i; \theta_i, P_{G_i}\right)$,

and the Envelope condition is

(E2.3) $\lambda(s_i) = \ r_s\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right) + \delta\lambda\left(g\left(I_i, s_i; \theta_i, P_{G_i}\right)\right) g_s\left(I_i, s_i; \theta_i, P_{G_i}\right)$,

where, $\lambda(s_i) = \frac{\partial V(s_i)}{\partial s_i}$. Equation (E2.3) indicates the shadow price of social capital is equal to the marginal rewards from the additional capital stock, both present and future. Equation (E2.3) implies

(E2.4) $\delta\lambda\left(g\left(I_i, s_i; \theta_i, P_{G_i}\right)\right) = \frac{\lambda(s_i) - \ r_s\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right)}{g_s\left(I_i, s_i; \theta_i, P_{G_i}\right)}$.

Combining equations (E2.2) and (E2.4) yield,

(E2.5) $0 = r_I\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right) + \left[\lambda(s_i) - \ r_s\left(I_i, s_i; \psi, \theta_i, P_{G_i}\right)\right] \frac{g_I\left(I_i, s_i; \theta_i, P_{G_i}\right)}{g_s\left(I_i, s_i; \theta_i, P_{G_i}\right)}$.

Equation (E2.5) implies the implicit function for the individual investment decision, (E2.6) $I_i = I(s_i; \psi, \theta_i, P_{G_i})$.

Equation (E2.6) indicates that individual's current investment in social networking may be written as a function of her current stock of social networking and current macroeconomic conditions, parameterized by her own characteristics and her group's characteristics.

2.3 REFLECTION PROBLEM

To illustrate the reflection problem associated with estimating equation (E2.6) I follow Manski (1993). Figure 2.1 shows the different sources of influence on social network investment activity of the individual. I assume that influences of the group on individual's social network investment decision come from the following sources: average investment in group G_i $E[I_i|G_i]$, group characteristics measured as average of the individual characteristics of group G_i, $E[\theta_i|G_i]$, and unobserved characteristics of the individuals belonging to group, ρ_{G_i}. I specify the log linear regression equation version of (E2.6) as,

(E2.7) $I_i = \beta_0 + \theta_i'\beta_1 + \beta_2 E[I_i|G_i] + E[\theta_i|G_i]'\beta_3 + \rho_{G_i}'\beta_4 + \beta_5\psi + \mu$,

where I_i is the logarithm of I, ρ_{G_i} are reference group dummies, ψ are indicators of current macroeconomic conditions, and μ is the error term.[6] Note the unobserved influences of the group are captured by the group dummies. My primary coefficient of interest is β_5 that estimates the direct effects of business cycle fluctuations on investment in social networking. If $\beta_2 \neq 0$ then there exists *endogenous* social effects, and $\{\beta_3, \beta_4 \neq 0\}$ represent existence of *exogenous* social effects and *correlated* effects, respectively. Note that equation (E2.7) is similar to equation (E2.1) in Manski (1993).

6 For notational simplicity, in this exposition s_i is treated as a part of θ_i. Also, the influences of ρ_k are split into the observed characteristics $E[I_i|k,c]$ and $E[\theta_i|k,c]$, and unobserved characteristics.

Integrating both sides of (E2.7) with respect to G_i shows that $E[I_i|G_i]$ solves the "social equilibrium" equation,

(E2.8) $E[I_i|G_i] = \beta_0 + E[\theta_i|G_i]'(\beta_1 + \beta_3) + \beta_2 E[I_i|G_i] + \rho'_{G_i}\beta_4 + \beta_5\psi + \mu.$

Provided that $\beta_2 \neq 1$, equation (E2.1) has the unique solution,

(E2.9) $E[I_i|G_i] = \frac{\beta_0}{1-\beta_2} + E[\theta_i|G_i]'\left(\frac{\beta_1+\beta_3}{1-\beta_2}\right) + \rho'_{G_i}\frac{\beta_4}{1-\beta_2} + + \frac{\beta_5}{1-\beta_2}\psi\frac{\mu}{1-\beta_2}.$

This implies that unless β_2 is identified $(\beta_0, \beta_1, \beta_3, \beta_4, \beta_5)$ are not identified.

2.4 EMPIRICAL MODEL

To estimate equation (E2.6) I follow Lee (2007) whereas individual investment in social networking is represented by a linear-in-means model

(E2.10) $$I_i = \beta_1\theta_i + \beta_2\frac{\sum_{j\in G_i} I_j}{n_i - 1} + \beta_3\frac{\sum_{j\in G_i}\theta_j}{n_i - 1} + \rho'_{G_i}\beta_4 + \beta_5\psi + \epsilon_i,$$

where the individual i is embedded within some reference group G_i where $i \notin G_i$. Notice this is similar to equation (9) in Bramoullé et al. (2009) and equation (1) in Boucher et al. (2012). Recall that my primary coefficient of interest is β_5 which estimates the direct effects of business cycle fluctuations on investment in social networking.

Exogenous variation to group size, n_i, is a necessary condition with regards to the identification strategy discussed in Lee (2007) and Bramoullé et al. (2009). The within reference group effect attributed to any particular individual is inversely related to the size of that group. An increase in group size leads to a reduction in the influence of each individual on the group itself. Therefore, variation in group size is what allows for the disentaglement of β_2, β_3 and ρ_{G_i} capturing the endogenous effect, the exogenous effect and the correlated effects, respectively i.e., possible weak identification of the reflection problem. Again, exogenous variation in reference group size, n_i, is a source of weak identification in this model .

Boucher et al. (2012) goes on to show that the Lee (2007) linear-in-means model may be fully identified. Also, Boucher et al. (2012) clarifies the intuition by focusing on an individual characteristic. For example, take educational attainment. Identification in the Lee (2007) model arises through the omission of the individual in calculating group means of the exogenous variables, e.g., group mean educational attainment. Given any arbitrary reference group I could sort individual members by educational attainment in order to obtain the most educated member. Being above average, the most educated member of the reference group unavoidably has a group of peers with a mean educational attainment which is below average.

This negative correlation reduces the dispersion in individual investment in social networking provided a positive affect associated with both individual and group mean educational attainment, i.e., $\beta_1, \beta_3 > 0$. Within the Lee (2007) framework smaller groups would inherently experience greater variance in group mean educational attainment, and as a result the reduction in outcome dispersion is greater in smaller groups. This is indicative of the negative relationship between group size and the within reference group effect attributed to the educational attainment of any particular individual. If $\beta_2 > 0$, then the endogenous effect reduces the dispersion in individual investment as well. In addition, the assumed simultaneity between average group behavior and mean group characteristics result in different shapes of dispersion reduction. Therefore, following the within group transformation, identification of the endogenous, exogenous, and correlated effects is made possible by distinguishing between shapes of outcome dispersion, i.e., β_2, β_3 and β_4, respectively.

Bramoullé et al. (2009) write the structural model of equation (E2.10) in matrix notation such that

(E2.11) $$\boldsymbol{I} = \beta_1\boldsymbol{\theta} + \beta_2\widehat{\boldsymbol{GI}} + \beta_3\boldsymbol{G\theta} + \beta_4\boldsymbol{\rho}_{\boldsymbol{G}_i} + \beta_5\boldsymbol{\psi} + \boldsymbol{\epsilon},\ \widehat{\boldsymbol{GI}} = \boldsymbol{GI}\left(\boldsymbol{\theta}, \boldsymbol{G\theta}, \boldsymbol{G}^2\boldsymbol{\theta}, \boldsymbol{\rho}_{\boldsymbol{G}_i}\right),$$

where $\boldsymbol{G}$ is a weighting matrix.[7] Suppose I have two groups, $G_i = 1{,}2$. Then the weighting matrix $\boldsymbol{G} = \begin{bmatrix} \mathbf{T_1} & 0 \\ 0 & \mathbf{T_2} \end{bmatrix}$, where $\mathbf{T_i}$ is a block diagonal matrix with off-diagonals taking the value of $\frac{1}{n_i - 1}$.

The matrix operation $\boldsymbol{GI}$ yields the average investment in social networking by group, G_i, i.e., the weighted average of individual level flow for group G_i. Notice that individual i is excluded from their own group average. Therefore, each individual within the group may have a unique set of observed group level characteristics. The matrix operation $\boldsymbol{G^2}$ yields a block diagonal matrix $\boldsymbol{G^2} = \begin{bmatrix} \mathbf{T_1^2} & 0 \\ 0 & \mathbf{T_2^2} \end{bmatrix}$, where $\mathbf{T_i^2}$ is a block diagonal matrix with diagonals equal to $\frac{1}{n_i - 1}$ and the off diagonals taking the value of $\frac{(n_i - 2)}{(n_i - 1)^2}$ when group size is larger than two. $\boldsymbol{G}$ and $\boldsymbol{G^2}$ are linearly independent.

I explicitly estimate equation (E2.11) using a two-step process including reference group indicator variables, i.e., a 2SLS fixed effects estimator. First, following Bramoullé et al. (2009) and Boucher et al. (2012) I instrument $\boldsymbol{GI}$, average group flow, with $\boldsymbol{\theta}, \boldsymbol{G\theta}, \boldsymbol{G^2\theta}$ and $\boldsymbol{\rho_{G_i}}$ in order to obtain the predicted group average flow $\widehat{\boldsymbol{GI}}$. Next, I estimate the determinants of individual investment in social networking excluding $\boldsymbol{G^2\theta}$ from the second-step estimation.

Identification also relies on the linear indepenence of $\boldsymbol{G}$ and $\boldsymbol{G}^2$. This property is ensured under the Lee (2007) linear-in-means model. Appendix A2.1 revisits the reflection problem under the Lee (2007) linear-in-means model and follows equations (E2.5) through (E2.7) of Bramoullé et al. (2009) in order to show that higher order moments of the weighting matrix $\boldsymbol{G}$ are valid instruments for average reference group behavior.

[7] Notice that equation (E2.11) is similar to equation (1) in Bramoullé et al. (2009).

2.5 DATA

I use the *General Social Survey* (GSS[8]) *1972-2012 Cross-Sectional Cumulative Data* which is a repeated annual cross-section of 1,200 to 2,500 individuals. The primary measure for the flow of social networking, *lnsocflow*, is the number of social evenings spent "with someone who lives in your neighborhood" and the number of social evenings spent "with friends who live outside the neighborhood" per year. My primary sample consists of 15,746 employed respondents with year of survey ranging from 1988 through 2010. The data set includes the following individual demographic characteristics: age, sex, race, marital status, educational attainment and homeownership status. A full list of variables with data source and variable description is included in Appendix A2.2.

In particular, I am concerned about the investment in social networking arising from business cycle fluctuations within the labor market. Here, my primary variable of interest is the two-period moving average of the unemployment rate, i.e., the two-period average of the number of unemployed to labor force ratio, as well as two other measures: two-period moving averages of unemployed to employed ratio and unemployed to population ratio. To account for the potential unobserved heterogeneity which may arise from, say, social attitudes with regards to the future economic climate, e.g., feelings of optimism or pessimism, I instrument each of the macroeconomic indicators using lagged M1 and M2 growth. Table 2.1 contains the summary statistics for all macroeconomic indicators: *natunemppopma, natunemppopma, natunempempma, m1gthl1, m2gthl*.

[8] Smith, Tom W, Peter Marsden, Michael Hout, and Jibum Kim. General Social Surveys, 1972-2012 [machine-readable data file] /Principal Investigator, Tom W. Smith; Co-Principal Investigator, Peter V. Marsden; Co-Principal Investigator, Michael Hout; Sponsored by National Science Foundation. --NORC ed.-- Chicago: National Opinion Research Center [producer]; Storrs, CT: The Roper Center for Public Opinion Research, University of Connecticut [distributor], 2013.

2.6 GROUPINGS

My identification strategy involves assuming an exogenous classification of reference group, G_i. I attempt to address the reflection problem discussed in Section 2.4 by forming reference groups based on three criteria: First, the decade in which the individual responded to the survey. Second, the population of the city in which the survey was conducted. And lastly, the respondent's geographic state of residence. Unlike in Manksi (2000) wherein 1970 occupational code defines reference group, I define groups by decade, city population, and U.S. geographic state. The decade component of group formation is intended to further account for inter-temporal group heterogeneity in the absence of year fixed effects. This reference group structure isolates 107 individuals. I drop these randomly isolated individuals. Summary statistics for this sample is included in Table 2.1.[9] The group count variable summarizes the distribution of group size, n_i. Figure 2.2 is a kernel density plot of group size. Notice that group size is relatively small. As a robustness check, I redefine reference groups by a categorical variable of city population by state for each decade.

2.7 RESULTS

Again, the business cycle variables are yearly measures, therefore, including year dummies create multicollinearity problems. Recall that group formation is ad-hoc and based on the decade over time. Furthermore, I use an instrumental variable approach to account for unobserved heterogeneity, cultural trends, and/or unobserved attitudinal factors that may be correlated with both individual social network investment and the business cycle.

Table 2.5 includes my main set of results. All regressions, excluding the macroeconomic instrumentation, include recoverable, reference group fixed effects. Again, following Bramoullé et al. (2009) I now instrument group flow, $\boldsymbol{GI}$, with my full set of explanatory variables, $\boldsymbol{\theta}, \boldsymbol{G\theta}$,

[9] Summary statistics for the isolated sample is included in Table 8.

$\boldsymbol{G^2\theta}$ and $\boldsymbol{\rho_{G_i}}$. Column 1 of Table 2.5 is the first stage results, i.e., determinants of group investment. Summary statistics of the predicted group social flows are presented in Table 2.2. The general significance of $\boldsymbol{\theta}, \boldsymbol{G\theta}$ and $\boldsymbol{G^2\theta}$ indicate my technical instruments do have some explanatory power. Although, the first stage regression is overidentified, I do not correct the standard errors because these are merely technical instruments.[10]

Column 2 of Table 2.5 is the individual investment regression, i.e., the second stage regression, which includes the two-period moving average of the national unemployment rate, *natunemplfma*, as an explanatory variable. In column 3, I instrument *natunemplfma* using lagged M1 and M2 growth. Table 2.4 summarizes the predicted labor market indicators. Column 4 of Table 2.5 is the regression of primary interest and includes both the average, predicted group flow and the predicted 2-period moving average of the nation unemployment rate, *natunemplfma*. The coefficient on *natunemplfma* is positive and significant in columns 2 and 4 with a reduction in magnitude following instrumentation of the macroeconomic indicator. F-stats for the overall fit of the models are significant throughout all of Table 2.5. I find evidence that white respondents invest more frequently in social networking. Perhaps whites invest more in networking due to increased returns to social networking. I find evidence of a nonlinear response to age. This is consistent with the life cycle view of social networking wherein the young foresee relatively large returns to social networking and with respect to aging make subsequently smaller investments in social networking. Consistent with Manski (2000) the estimated coefficients suggest homeowners along with college graduates invest more in social networking. Consistent with the literature, married individuals invest less, perhaps, as they fall back on their spouse's network for support as well.

[10] Recall that identification of the business cycle coefficient is only possible after I have identified the peer effects, i.e. the endogenous effect, $\boldsymbol{GI}$, the exogenous effect, $\boldsymbol{G\theta}$, and the correlated effects, $\boldsymbol{\rho_{G_i}}$.

Table 2.6 exhausts the remaining macroeconomic indicators. Column 5-7 substitutes the two-period moving average of national unemployment to population for *natunemplfma* from columns 2-4 of Table 2.5. Similarly, columns 8-10 substitute two-period moving average of national unemployment to employment for the previous. My results are robust to the changes. The positive coefficient on the two-period moving average of the national unemployment rate indicates in Table 2.5 and again in Table 2.6 that the flow of social networking is up when unemployment rates are up. Again, people invest more in social networking during times of high unemployment.

2.8 ROBUSTNESS

As a robustness check, reference groups are redefined using a categorical city size measure, geographical state of residence and the decade dummy variables. This reference group specification reduces the 107 isolated individuals to only 9. However, the average group count increases from 19 to 80. Bramoullé et al. (2009) points out identification may depend explicitly on the distribution of group size in complex ways. Conceptually, smaller group sizes are preferred to larger group size. Table 2.8 includes these robustness checks. Columns 11 through 13 are the same as regressions 2 of Table 2.5 and regressions 5 and 8 from Table 2.6. Columns 14 through 16 substitute in the predicted macroeconomic indicators as with regressions 4 of Table 2.5 and regressions 7 and 10 of Table 2.6. Again, I find evidence that investment in social networking is counter-cyclical. However, the relatively large group size may restrict the models ability to identify the peer effects individually.

2.9 CONCLUSIONS

Social networks have profound impacts on our economic and non-economic lives. To my knowledge, this paper is the first to analyze the impact of business cycles on individual level social network formation. Business cycles can affect social network investment in different ways.

I try to address the reflection problem and account for unobserved heterogeneity. I believe this analysis expands our understanding of individual's social network formation.

Although measurements of individual stock are not widely available, a small subset of individuals report stock during non-downturn years only. Inter-state variation in unemployment rates may be exploited in a way which allows for the inclusion of a measurement for individual stock as well as annual fixed effects.

CHAPTER III

THE EFFECT OF STATE AND LOCAL TAXES ON ECONOMIC GROWTH: A DYNAMIC PANEL APPROACH

In the previous chapter, I attempted to address the estimation issues which arise when observations are assumed to be spatially dependent, i.e., SAR estimation issues. In this chapter I extend the static work of Brown et al. (2003) by deriving a dynamic factor market approach to model regional output. I arrive at a first order autoregressive distributed lag, ARDL, estimable regional production function. Whereas the SAR model incorporates spatial lags in an attempt to account for the spatial dependence between observations, the ARDL model incorporates time series lags in an attempt to account for the inter-temporal dependence between observations. Therefore, this chapter attempts to address the estimation issues which arise when inter-temporal dependencies between observations are assumed, e.g., when estimating either an Euler equation or a production function.

In this chapter, I attempt to address the issues associated with estimating an ARDL regional production function. However, physical capital stock measures are not widely available at the state level. Alternatively, I estimate a reduced-form regional production function which does not require the quantities of private capital and labor.

Within this framework, the reduced-form output equation relates state and local fiscal policy and other variables to statewide output. This is in stark contrast to the dynamic framework of Blundell and Bond (2000) and Bond (2002) which fit a Cobb-Douglas production function to firm level data. I use two estimation approaches in an attempt to arrive at consistent estimates for the effect of state and local fiscal policy and other variables on state output growth. Additionally, this chapter attempts to address an extensive list of other estimation issues common to microeconomic studies.

In the remainder of the chapter section 3.1 introduces and motivates the exercise. Section 3.2 builds the theoretical framework by substituting the partial adjustment migration process from Partridge and Rickman (2003) into the Brown et al. (2003) factor market approach for modeling regional economic growth. Section 3.3 presents the ARDL empirical model. Section 3.4 discusses the data. Section 3.5 presents the main set of results. Section 3.6 evaluates an extensive set of robustness checks and section 3.7 concludes.

3.1 INTRODUCTION

An extensive literature examines the connection between state and local fiscal policy and the local economic environment, e.g., Helms, (1985), Mofidi and Stone (1990), Bartik, (1991) and Wasylenko (1997). Brown et al. (2003) divide the literature into three distinct sets. First, studies such as Carlino and Mills (1985), Bartik (1985 and 1988), Carlton (1983), Papke (1991), and Gray (1997) examine the effect of state and local fiscal policy and natural amenities on regional economic growth, e.g., personal income, GSP, or firm location. A second set of literature examines how differences in state and local fiscal policy and natural amenities propagate into regional differentials in wage rates, e.g., Roback (1982), Beeson and Eberts (1989), Gyourko and Tracy (1989), and Haughwout (2002). Lastly, the third set of studies such as Aschauer (1989), Munnell (1990), Holz-Eakin (1994), Bartik (1996), Garcia-Milà, McGuire and Porter (1996), Morrison and Schwartz (1996), Kelejian and Robinson (1997), Boarnet (1998), Button (1998), Fernald (1999), and Puig-Junoy (2001) examine the connection between regional variation in factor inputs and regional output.

Within the literature it is thought state and local fiscal policy may alter the relative attractiveness between jurisdictions, thereby, affecting local area conditions. For example, as with natural amenities within the Rosen-Roback spatial equilibrium framework, Gyourko and Tracy (1989) show publicly produced services create compensating wage differentials. Therefore, tax rates and infrastructure investments by the state and local government are thought to be a source of regional competition for economic activity (Haughwout, 2002). The literature generally finds evidence in support of the claim that local conditions are affected by state and local fiscal policy. However, the growth effect estimates of any particular government policy decision are wildly inconsistent from study to study. This paper proposes that, perhaps, regional response heterogeneities to state and local fiscal policy play a critical role in the inconsistent results of previous tax studies. For example, suppose that households and/or firms find southern states to be highly substitutable. Then, policymakers in the South would face relatively high levels of competition from neighboring states in attracting firms and households. Therefore, the growth effects of a tax hike in the South may be particularly different from the national average.

Reed (2008) outlines a number of issues common to the study of growth effects associated with state and local fiscal policy. Under the consideration that theoretical derivations yield the estimable equation, Reed (2008) stresses the importance of theoretical modeling[12]. The lack of theoretical modeling has led to an extensive list of non-fiscal controls having been used from time to time, e.g., percent unionization, population density, population, percentage of the population

[12] Reed (2008) identifies three unique estimation issues, i.e. the use of economic theory to derive an estimable equation, the role of time, and selection of control variables. In contrast to the previously mentioned study, I group these estimation issues into the importance of appropriate theoretical modeling.

that is working age, the unemployment rate, and crime rate. A survey of the literature indicates the growth effect estimates are highly dependent upon the particular set of control variables. On the other hand, studies such as Merriman (1990), Garcia–Milá and McGuire (1992), Evans and Karras (1994), Holz–Eakin (1994), Garcia–Milá, McGuire and Porter (1996), Aschauer (2000), Yamarik (2000), Shioji (2001), and Reed (2008) model local output within a Barro (1990) endogenous growth framework wherein local factors such as land, labor, and capital, are growth determinants.

Although state capital stock measures are not widely available, a number of studies do obtain estimates for highways, sewers, and water supply systems and total state and local government capital, e.g., Morrison and Schwartz (1996) and Kelejian and Robinson (1997). The data are typically estimated following the Munnell (1990) approach wherein U.S. estimates of private capital are decomposed into state-level industry estimates based on information from industry censuses. Missing observations are filled by imposing an industry specific, national rate of growth during non-census years. Under this approach, as Brown et al. (2003) point out, the growth rate of private capital stock estimates differ from the national rate only during census years. Therefore, Brown et al. (2003) fill the missing observations with an interpolation strategy which accounts for capital stock growth rate differentials during non-census years as well. In contrast to the studies which rely on state capital, I estimate a reduced form regional production function wherein only local characteristics matter.

Reed (2008) points out that time plays two key roles from a modeling standpoint. First, the length of time period may play a significant role in determining the measured effects associated with state and local fiscal policy, e.g., annual studies, quinquennial studies, or decennial studies. Second, the effects of a state and local fiscal policy may be dynamic in nature tax. ”Much of the previous literature has restricted taxes to have only contemporaneous effects on economic activity” (Reed, 2008). In contrast, this paper takes a dynamic approach in modeling local, private GSP. The first contribution of this study is the refinement to the Brown et al. (2003) factor market approach for modeling private GSP. I adopt a partial adjustment process for modeling local output growth which is similar to the process governing migration in Partridge and Rickman (2003). Through the incorporation of a dynamic adjustment process I arrive at an autoregressive distributed lag model for local private output.

Reed (2008) identifies that a second issue arises in structuring of the dataset. Studies which focus on cross sectional data ignore potentially time-varying behavior in the control variables. In the absence of location fixed effect cross sectional studies also suffer from the common omitted variable bias. On the other hand, studies which focus on annual panel data are particularly sensitive to measurement error bias. Furthermore, this bias is worsened with the inclusion of jurisdiction fixed effects. Lastly, serial correlation is a particularly relevant threat to studies focused on panel data. In contrast, multi-year interval data are less sensitive to measurement error and serial correlation. Previous research on state and local taxes and growth have relied primarily on either cross sectional data, e.g., Romans and Subrahmanyam (1979), Mullen and Williams (1994), and Yamarik (2000), or annual panel data, e.g., Helms (1985) and Crain and Lee (1999). I follow the latter and examine the growth effects of state and local fiscal policy using annual observations for 51 jurisdictions within the U.S. including the District of Columbia ranging from 1977 through 2008.

Reed (2008) identifies that a third issue arises in choosing the appropriate estimator. Most of the previous studies apply ordinary least squares (OLS) estimation, e.g., Garcia–Milá and McGuire (1992), Chernick (1997), and Crain and Lee (1999). A subset of studies attempt to address error structures typical to panel data estimation. For example, Aschauer (2000) and Tomljanovich (2004) account for heteroskedastic errors, whereas, Evans and Karras (1994) attempt to address serial correlation in the errors. On the other hand, some of the studies attempt to apply feasible generalized least squares (FGLS) to account for random effects. However, the FGLS estimates are often rejected for the alternative OLS with fixed effects, e.g., Brown et al. (2003), and Reed (2008). With respect to a dynamic approach, Nickell (1981) derives the inconsistencies in the least squares dummy variable (LSDV) estimates of an ARDL model. Dynamic panel estimation on the other hand, e.g., Holz–Eakin (1994), Shioji (2001), and Bania et al. (2007), provides consistent estimates when the estimable equation includes both a lagged dependent variable and fixed effects. Bania et al. (2007), in particular, pursue the Arellano and Bond difference GMM approach (Arellano and Bond, 1991) in estimating the growth effects of state and local fiscal policy in an endogenous growth framework wherein government expenditures are categorized as either productive or health and welfare. In contrast to the previously mentioned study, I include a more extensive list of government expenditure categories. Additionally, I pursue two identification strategies in an attempt to obtain consistent estimates for the dynamic growth effects of state and local fiscal policy. First, I estimate the ARDL production function following an OLS approach which excludes jurisdictional fixed effects. Second, I apply a GMM, dynamic panel estimation approach to the ARDL estimable equation.

The fourth issue which Reed (2008) identifies is the role of influential observations. "Point estimates may mask the fact that results can be driven by just a few time periods, or just a few states" (Reed, 2008). Therefore, I take deliberate steps in order to maximize the number of years contained within the data. I use a substantially larger dataset relative to Brown et al. (2003). My dynamic panel data set consists of annual observations for 48 contiguous jurisdictions within the U.S. ranging from 1977 through 2008. I evaluate the growth implications of state and local tax rates linearly and nonlinearly. Additionally, I search for evidence of changing tax sensitivities over time. A number of studies I have come across end their studies in 1997. Therefore, I search for evidence of a break in tax sensitivities occurring after 1997. Lastly, the empirical analysis continues under the assumption of heterogeneous responses to fiscal policy by region.

I follow the existing literature and lag all explanatory variables by one period such that they are all at least nominally predetermined, e.g., Garcia-Milà, McGuire and Porter (1996) and Brown et al. (2003). However, predetermined variables certainly may not be strictly exogenous. Therefore, in addition to the four previously discussed empirical challenges, I also assume the set of control variables is endogenous. This study adds a fifth issue in estimating the growth effects associated with state and local fiscal policy, control set endogenity. Weak exogeneity is my primary empirical challenge in the absence of suitable instruments. To my knowledge, this is the first paper to address the potential endogeneity concerns of state and local fiscal policy.

In this study, I must also address issues common in ARDL estimation, i.e., the combined presence of autocorrelation, predetermined variables and time invariant jurisdiction characteristics which may be correlated with the explanatory variables. GMM estimation attempts to address the potential endogeneity of the control variables. In an attempt to avoid introducing a spurious correlation between these variables and the error term GMM estimation uses appropriate lags to instrument all predetermined and endogenous variables. Furthermore, GMM estimates are derived through the comparison of two observably similar U.S. states, using the portion of fiscal policy attributable to their fiscal histories. Therefore, GMM estimation addresses the concerns over the role of time in determining the effects of fiscal policy, In addition, GMM estimation procedures are robust to both measurement error and omitted variable bias.

My preliminary results indicate that GSP is nearly a random walk process. Therefore, I apply the system GMM estimator to the dynamic panel dataset. I employ a two-step GMM estimation approach which is "efficient and robust to all patterns of heteroskedasticity and cross correlation" (Roodman, 2009). Also the finite sample tends to severely bias standard errors toward zero (Arellano and Bond, 1991; Blundell and Bond, 1998). In other words, the asymptotic properties of the system GMM estimator in estimating the ARDL model do not hold with cross-sectional dominant data, i.e., small time dimension relative to the number of jurisdictions. Therefore, significance tests of the GMM estimates are based on the appropriately corrected standard errors. I find no evidence to support a linear, nonlinear response to fiscal policy, or changing sensitivities with respect to time period in a nationwide/pooled context. On the other hand, both the OLS estimates with no jurisdiction dummies and the system GMM estimates indicate a large degree of heterogeneity at the regional level in response to a tax rate hike by state and local government, i.e., U.S. Census region. Although these results are robust to an alternative sample and a reduction in the number of instruments, I am unable to verify the robustness of the estimated coefficients following a number of other alternative specifications.

3.2 METHODOLOGY

I follow the factor market approach of Brown et al. (2003) in modeling regional economic growth. This is a spatial equilibrium framework which incorporates state and local fiscal controls in the determination of regional output levels. Under this framework firms use primarily three inputs: land, labor and capital, L, N and K respectively. Local households sell one unit of labor to local firms in order to produce output. Output in jurisdiction j, Q_j, is governed by a well behaved production function $Q(L_j, N_j, K_j)$. The interaction between workers and perfectly competitive firms drives economic activity within local input markets. Local profits dictate the entry and exit of firms.

Land, L, is assumed to be perfectly immobile. Therefore, the price of the land,

(E3.1) $$\ell_j = \ell(X_j),$$

reflects all aspects of the local jurisdiction j, where $X_j = \{\tau_j, G_j, Y_j, A_j\}$, τ_j is the vector of revenue sources for the U.S. state and local government. G_j represents the vector of public goods and services funded by the state and local government. Y_j is the unemployment rate in jurisdiction j

and A_j is a vector of jurisdictional natural amenity levels. Meanwhile, the household, i.e., labor, is assumed to be highly mobile. Households migrate to capture all jurisdiction specific benefits. Compensating differentials in wages,

(E3.2) $$w_j = w(X_j),$$

reflect all jurisdictional differences excluding taxes on land, such that the expected utility in jurisdiction j is the same in all J jurisdictions, $U_j = \bar{V}$. Lastly, capital, is perfectly mobile across all J jurisdictions which ensures a national rate of return to capital, $r_j = r, \forall\, j \in J$.

Given the three factor price equations for ℓ, w, and r, I obtain reduced form private input requirements for labor and capital in jurisdiction j.

(E3.3) $$N_{\mathrm{j}} = N(X_j)$$

(E3.4) $$K_j = K(X_j)$$

Substituting equations (E3.3) and (E3.4) into jurisdiction j's well behaved production function yields the static equilibrium of private output level in jurisdiction j, Q_j^* where

(E3.5) $$Q_j^* = Q(X_j).$$

Equation (E3.5) suggests the desired private output level in jurisdiction j, Q_j^*, reflects all aspects of the local jurisdiction: the vector of revenue sources by the U.S. state and local government, the vector of state and local government services, the unemployment rate in jurisdiction j and the vector of natural amenity levels. This is identical to the estimable equation in Brown et al. (2003), equation (15). Log output can be expressed linearly as,

(E3.6) $$Q_{jt}^* = \alpha_0 + \alpha_1 X_{jt} + \mu_{jt}.$$

If for example labor immobility is measurable, then the private output level in jurisdiction j may be regulated by a linear partial adjustment process such that

(E3.7) $$Q_{jt} - Q_{jt-1} = \lambda(Q^*_{jt} - Q_{jt-1}),$$

where λ is the speed of adjustment. Equation (E3.7) is similar to equation 3 from Partridge and Rickman (2003).[13] Substituting equation (E3.6) into equation (E3.7) yields the following autoregressive distributed lag (ARDL) model for private output level in jurisdiction j

(E3.8) $$Q_{jt} = \varphi_0 + \varphi_1 Q_{jt-1} + \varphi_2 X_{jt} + \varphi_3 X_{jt-1} + \varepsilon_{jt},$$

where $\varphi_3 = 0$ if $\lambda \in (0,1)$. It is important to note the estimates for the parameters in equation (E3.6) and equation (E3.7) are recoverable, i.e., $\varphi_0 = \alpha_0\lambda$, $\varphi_1 = 1 - \lambda$ and $\varphi_2 = \alpha_1\lambda$.

3.3 EMPIRICAL MODEL

State output, equation (E3.8), is once again rewritten to reflect individual aspects of the local jurisdiction,

(E3.9) $$Q_{jt} = \beta_0 + \beta_1 Q_{jt-1} + \beta_2 \tau_{jt} + \beta_3 G_{jt} + \beta_4 Y_{jt} + \beta_5 A_{jt} + s_j + v_t + e_{jt},$$

where s_j are fixed effects which capture time invariant differences in output by jurisdiction, v_t capture time fixed effects, and e_{jt} represent random disturbances in jurisdictional output. Whereas, most of the literature estimates some variation of equation (E3.6), this study focuses on the consistent estimation of equation (E3.8). The parameters β_2 and β_3 give the percent change in private GSP due to a one percent increase in some government fiscal category, e.g., tax revenue or highway infrastructure expenditures as shares of GSP. In this model deficit spending and

[13] Partridge and Rickman (2003) propose a partial adjustment process for migration with regards to the exploitation of regional differentials in utility levels.

miscellaneous revenue are the omitted government fiscal categories. Therefore, β_2 and β_3 are interpreted as the growth effects resulting from incremental changes in revenue or expenditure variables against a change in the omitted fiscal category. For example, β_2 measures the sensitivity of jurisdictional output given a change in tax revenue hikes against an increase in deficit spending. Meanwhile, $\beta_2 + \beta_3$ measures the net effect of an incremental increase in any particular expenditure category fully financed through raised revenue. Equation (E3.9) is referred to as the levels equation. The differenced equation,

$$\text{(E3.10)} \qquad \Delta Q_{jt} = \beta_1 \Delta Q_{jt-1} + \beta_2 \Delta \tau_{jt} + \beta_3 \Delta G_{jt} + \beta_4 \Delta Y_{jt} + \beta_5 \Delta A_{jt} + \Delta v_t + \Delta e_{jt},$$

removes all time invariant influences.

With respect to the levels equation Mishra and Newhouse (2009) point out three empirical issues common to ARDL model estimation. The first issue arises from the combined presence of the lagged dependent variable, predetermined variables, and time-invariant jurisdictional characteristics, which may be correlated with the explanatory variables[14] in the set of explanatory variables. The LSDV estimates of equation (E3.9) are inconsistent when jurisdictional dummies, s_j, are included (Nickell, 1981). In order to avoid the potentially inconsistent estimates of the within estimation, my OLS estimates drop the state fixed effects from equation (E3.9), i.e., $s_j = 0$. β_0, β_1, β_2, β_3, β_4 and β_5 are identified in the OLS version of equation (E3.9) where s_j are omitted by using both across-jurisdiction and within-jurisdiction variation. Significance of my OLS estimates are based upon standard errors clustered by U.S. geographic state.

Second, Mishra and Newhouse (2009) point out the ARDL empirical model is potentially subject to an omitted variable bias. If these omitted, time varying, country specific factors are correlated with state and local fiscal policy, then the estimated coefficients, β_2 and β_3, would be biased. For

[14] For example, natural amenity levels, geography, etc.

example, if state and local governments tend to increase highway infrastructure spending as the quality of their highway system declines, then β_3 is underestimating the benefits of highway infrastructure expenditures as a share of GSP. The last empirical issue Mishra and Newhouse (2009) point out is the potential for measurement error. Measurement error in the state and local data, would also bias OLS estimates to zero. A 1984 agreement established the Governmental Accounting Standards Board (GASB) which establishes and improves standards of accounting and financial reporting for U.S. state and local governments.[15]

Mishra and Newhouse (2009) address the previous three issues common to ARDL estimation through GMM dynamic panel data estimation strategy. A concern that state and local fiscal policy control variables are not strictly exogenous, $E\left[\varepsilon_{jt} \middle| X_{js}\right] \neq 0 \; \forall \; t, s$, coupled with the absence of valid external instruments increases the overall attractiveness of GMM estimation. The GMM estimates are derived through the comparison of two observably similar U.S. states, using the portion of fiscal policy attributable to their fiscal histories, where all predetermined and endogenous variables are instrumented by their appropriate lags. The inclusion of the lagged dependent variable and country fixed effects in the control set implies β_0, β_1, β_2, β_3, β_4 and β_5 are identified by the difference between the average observed fiscal policy across all jurisdictions and within-jurisdiction change in fiscal policy over time.

If $\beta_1 \cong 1$ in equation (E3.9), then GSP is close to a random walk. Blundell and Bond (2000) show that lagged levels of a random walk process are weak instruments in the first differences equation. In terms of estimating equation (E3.10), the difference GMM estimator (Arellano and Bond, 1991) is a weak estimator because lagged levels of X_{jt} and Q_{jt} are poor instruments for ΔQ_{jt-1} and ΔX_{jt}. Meanwhile, when the data are persistent the system GMM estimator increases estimator efficiency through the use of additional moment conditions. Specifically, the system

[15] The GASB is regarded as the official source of generally accepted accounting principles (GAAP) for state and local governments.

GMM estimator also uses lagged differences of the endogenous variables as instruments in the levels equation (E3.9) (Arellano and Bover, 1995). This is in addition to using lagged levels of the endogenous variables as instruments in the differenced equation (E3.10). Therefore, by utilizing moment conditions from both the levels equation (E3.9) and the differences equation (E3.10), the system GMM estimator fits the data to a system of estimable equations.

Although the system GMM estimator is preferred when data are persistent, the estimator does have a number of drawbacks. First, the underlying assumptions of the system GMM estimator are strong. The identification restrictions are first derived in Arellano and Bover (1995) and later refined in Blundell and Bond (2000). Formally stated, the model assumptions are

$$\text{(E3.11)} \qquad \begin{gathered} E[s_j]E=[e_{jt}]=E[s_j e_{jt}]=0 \\ E[e_{js}e_{jt}]=0, s\neq t \\ E[X_{j1}e_{jt}]=0, t=2,\dots,T \\ E[Q_{j1}e_{jt}]=0, t=2,\dots,T \\ E[\Delta X_{j2}s_j]=0 \\ E[\Delta Q_{j2}s_j]=0 \end{gathered} .$$

The Blundell and Bond (2000) refinements to the identification assumptions are represented by the bottom four equations in (E3.11). These initial moment conditions assume the initial levels of state and local fiscal policy and jurisdictional output are uncorrelated with all future disturbances in output. Furthermore, these moment conditions also assume the initial changes in fiscal policy and output are uncorrelated with the time-invariant, unobserved jurisdiction specific characteristics.

Another drawback to this class of GMM estimator is the tradeoff between estimator performance and the number of instruments. Too many instruments weaken this type of GMM estimator. Specifically, a large number of instruments tend to weaken the power of Hansen's J test for over identifying restrictions, leading to cases where the test falsely fails to reject the null hypothesis that the instruments are valid. Roodman (2009) goes on to suggest the number of instruments should not exceed the number of jurisdictions. In my first attempt to reduce the number of instruments, I calculate the within year and within state transformations in place of including annual and state dummy variables. This reduces the number of instruments in the system GMM model by 77, $T + J - 2$. Also, the general treatment of this class of GMM estimator is to create a unique instrument for each variable at each time interval. Therefore, the number of instruments increases exponentially as the time dimension grows. I collapse the instruments with respect to time and use two lags as instruments. The collapsed instrument set reduces the number of moment conditions to one per variable. Given the large number of instruments in my estimations one should be conservative in choosing the appropriate significance levels for all specification tests.

In any event, the system GMM estimator is likely to provide the most accurate estimates relative to all other estimators that simultaneously control for autocorrelation and unobserved fixed effects. GMM estimation is also an attractive estimator in the absence of valid external instruments for the potentially endogenous set of state and local fiscal policy control variables. In addition, I test estimate robustness to a reduction in the number of instruments and a number of other changes in model specification.

3.4 DATA

I rely on a substantially larger dataset than most studies on the growth effects of state and local fiscal policy, covering 48 jurisdictions from 1977 to 2008. I take deliberate steps in order to maximize the number of observations. I extend the size of the dynamic panel in two dimensions: J and T. Alaska and Hawaii are included for robustness checks. The state and local fiscal data are subject to missing observations in 2001 and 2003. These data gaps explode after taking first differences. The missing data issue is exacerbated by the GMM estimator's dependence on lagged moment conditions, both levels and differences. Therefore, I replace the missing observations with lagged values. I follow the existing literature, e.g., Garcia-Milà, McGuire and Porter (1996), and Brown et al. (2003), and lag all explanatory variables by one period such that they are all at least nominally predetermined. The final sample includes 1,488 observations for 48 U.S. jurisdictions over 31 years ranging in from 1978 through 2008.

The dependent variable in my analysis is the common log of nominal, private GSP. I do not impose additional measurement error by adopting national gross domestic product (GDP) deflators in an attempt to derive real GSP. Private industry GSP data are collected from Regional Economic Accounts, U.S. Bureau of Economic Analysis. Unemployment rate data are collected from Local Area Unemployment Statistics, U.S. Bureau of Labor Statistics. Amenity data are widely available from the USDA Economic Research Services. Although the data are constructed at the county level, a statewide amenity scale can be calculated by taking the weighted average by county population estimates. I drop A_{jt} in practice from the estimable equation in order to preserve degrees of freedom because natural amenity measures are time invariant. Furthermore, jurisdiction fixed effects should capture all time invariant jurisdictional characteristics.

The remaining explanatory variables are broken into two main categories: government revenue variables and government expenditure variables. State and local government financial data are collected from Government Finance Statistics, U.S. Census Bureau. Revenue sources include net federal intergovernmental revenue, total charges, and total taxes. Total taxes are defined as the sum of property tax, total sales tax, individual income tax, and corporate income tax. Government expenditures are categorized into the following locally provided government services: public welfare, highway transportation, environment and housing, public safety, education as well as health and hospital, and other government services.

Environment services include natural resource, and park and recreation expenditures, whereas, housing services include community reinvestment and sanitation. Lastly, public safety includes expenditures on police and fire protection. All government financial variables are scaled by the private GSP then multiplied by 100, e.g., the tax variable measures the total tax revenue as a percentage of GSP in jurisdiction j. Therefore, estimated coefficients measure the effect of a one percent change in any government fiscal policy as a share of GSP when financed by the omitted fiscal categories, a one percent increase in miscellaneous revenues and deficit spending as a share of GSP. A full list of variables with data source and variable description is included in Appendix A3.1.

3.4.1 OVERVIEW OF THE DATA

For the full sample of contiguous U.S. states, excluding D.C.,[16] and during the period 1977 through 2008, the national average of state and local tax revenue as a share of GSP by year ranges from as low as 9% to as nearly high as 11%. Figure 3.1 contains the plotted data points and is a graphical representation of the national average state and local effective tax rate. The figure indicates that state and local effective tax rates declined on average during the last half of the 1970's and much of the mid to late 1990's through the early 2000's. In contrast, average state and local effective tax rates were increasing throughout the 1980's and into the early 1990's as well as the mid through late 2000's.

Figure 3.2 takes a more spatial view of state and local fiscal policy by plotting the average tax revenue as a percentage of GSP by U.S. Census region, i.e., Midwest, Northeast, South, and West. The regional average effective tax rate of state and local government plots of Figure 3.2 tend to reflect the trends in Figure 3.1. However, there appears to be a large degree of heterogeneity in fiscal policy by region. For example, while the average state and local tax rates tend to be increasing during the 1980's throughout the Midwest, South, and West, the average

[16] Congress abolished D.C.'s local government in 1874. Although the Home Rule Act of 1973 provides D.C. with an elected mayor and city council, the approval of the local budget requires an act of Congress.

effective tax rate in the Northeast appears to trend downward. Furthermore, the average effective tax rate varies by as much as two and a half percentage points between Census regions in 1977 and in 2008 by almost two percentage points. Figure 3.2 also suggests Census regions can generally be ranked from high to low in terms of the effective tax rates as follows: Northeast, West, Midwest, and South. The average effective tax rate in the Northeast ranges from 10-12% while in the South average rates range from 8.5-10%.

Table 3.1 ranks the contiguous U.S. states from high to low based on state and local tax revenue as a share of GSP starting in 1977 and continuing on a quinquennial basis through 2007. Based solely on the effective tax rate of state and local government there appears to be a large degree of variability annually when ranking the states from high to low. For example, Oklahoma ranges in rank from as low as 9th to as high as 37th. Meanwhile, Louisiana ranks from lowest in the nation to as high as 29th. In contrast, New York ranges between ranks of 46th and 48th. The last column of Table 3.2 contains the average annual rank for each state from 1977 through 2008, excluding 2001 and 2003 when the data are missing. Tennessee and Texas come in at for the lowest and second lowest average rank over the 31 year period. Oklahoma comes in mid pack at 26nd, and Louisiana is 4th lowest overall by average rank. New York holds the highest average annual ranking for state and local taxes at 48th.

Although potentially misleading, Figure 3.3 is a simple scatter plot of log GSP and state and local tax share of GSP following within Federal Information Processing Standard (FIPS) code and within year transformations. Simple correlations between current log GSP and the lagged state and local tax share of GSP indicate a negative relationship for levels and differences, -0.037 and -0.166, respectively. Table 3.2 contains the summary statistics for all variables.

3.5 RESULTS

Some studies have found evidence that the random effects estimator is preferred to the fixed effects estimator. Therefore, my empirical analysis begins with Hausman (1978) specification tests. Under the null hypothesis the FGLS random effects (RE) estimator is the efficient and consistent estimator. Meanwhile, rejection of the null implies the presence of state fixed effects. The FE and RE estimates of equation (E3.9) are presented in columns (1) and (2) of Table 3.3. In Table 3.3, the first row includes the number assigned to each specific set of regression results while the first column contains the variable names. The second row of Table 3.3 indicates the estimator employed to derive estimates. Lastly, the third row contains the name of the dependent variable.

Significance of the coefficients in columns (1) and (2) are based on conventional standard errors. The null hypothesis under the Hausman test is rejected at a significance level of 1% with a p-value equal to zero indicating the presence of state fixed effects. Although, I get the first indication that GSP may be close to a random walk, i.e., $\beta_1 \cong 1$, I ignore these results. Nickell (1981) shows the estimates in column (1) are inconsistent. Therefore, these results are dismissed.

3.5.1 ORDINARY LEAST SQUARES

I begin my growth analysis in Table 3.4 with the OLS estimates of equation (E3.9). The first row of Table 3.4 indicates the number assigned to that specific set of regression results while the first column contains variable names. The second row of Table 3.4 indicates the estimator. Lastly, the third row contains the name of the dependent variable. I examine the pooled average effect of an increase in state and local government revenue sources and expenditure categories as a share of GSP on GSP growth in the following year. Recall that my estimated coefficients measure the growth effects attributable to a particular government fiscal category relative to the omitted variable. The omitted fiscal category in my analysis is miscellaneous revenue and deficit spending. Additionally, $\beta_{tax} + \beta_{expenditure}$ measures the net effect of an incremental increase in any particular expenditure category as a share of GSP fully financed through tax rate hike.

All OLS estimates discussed in this section are obtained from the within year transformed data over the full sample (Nickell, 1981). Furthermore, standard errors in the OLS regressions follow Brown et al. (2003) with clustering at the state identifier level. OLS estimates of equation (E3.9), excluding jurisdiction fixed effects, are presented in column (3) of Table 3.4. With respect to the national average, the coefficient associated with state and local tax revenue as a share of GSP is not significantly different from zero. On the other hand, government charges and intergovernmental revenue to finance deficit spending are positively correlated with GSP growth rates.

Still in column (3) of Table 3.4, the estimated coefficients on the set of controls for state and local government expenditure categories indicate that expenditures as a share on GSP on welfare, transportation, environment and housing, and education, health and hospital, all serve as GSP growth deterrents when financed by deficit spending. Safety expenditure is the only expenditure to exhibit a positive relationship with GSP growth when financed by deficit spending, i.e., expenditures on safety and fire protection. The estimated effect of higher safety expenditures as a share of GSP suggests a greater than one to one increase in GSP growth rate following the hike in safety expenditures. The estimated coefficient on the unemployment rate variable indicates that higher unemployment rates tend to slow GSP growth rates in the following period.

Columns (5) and (7) in Table 3.4 continue the OLS growth analysis. Column (5) adds a squared version of the tax variable and is intended to capture the nonlinear effects associated with the effective rate of state and local tax revenues. I find no statistical evidence of nonlinear response in growth effects. Column (7) incorporates an interaction term between the tax variable and a time period dummy for years prior to 1998 and is intended to capture the shift in sensitivities for a change in the effective rate associated with state and local tax revenues. Similarly, given a change in the effective tax rate, I find no evidence of a sectional break in growth effects occurring in 1998.

Column (9) of Table 3.4 incorporates a set of interaction terms between the tax variable and U.S. Census region dummies in an attempt to capture regional heterogeneities in sensitivities to the effective rate of state and local tax revenues. The omitted region is the Midwest. Therefore, the response in any region measured relative to the Midwest is the sum of the estimated tax coefficient and the estimated coefficient on the interaction term between the regional dummy and the tax variable. I find evidence which suggests that the response of GSP growth to taxes is positive in the Midwest region. While GSP growth rates are less sensitive in the Northeast and South regions, there remains a positive net effect associated with tax rate hikes to finance state and local deficit spending. Meanwhile, the West region experiences a negative shock to the GSP growth rate following a tax rate hike. OLS parameter estimates are stable with the inclusion of the additional control variables.

3.5.2 SYSTEM GENERAL METHOD OF MOMENTS

Although the primary coefficient of interest in this study measures the effect of state tax rate on GSP growth, the primary coefficient of interest at the moment is on the 1 period lag of log GSP in column (3) of Table 3.4, i.e., Lag log10GSP. Again, $\beta_1 \cong 1$ implying GSP follows close to a random walk. Recall, when the data are highly persistent Blundell and Bond (2000) indicates the system GMM estimator is the preferred estimator because lagged levels of a random walk process make for weak instruments in the first differences. The system GMM estimates the effect of state and local fiscal policy on future output growth by solving the appropriately weighted set of moment conditions for the system of equations (E3.9) and (E3.10). The difference between the average observed fiscal policy across all jurisdictions and within-jurisdiction change in fiscal policy over time identify β_0, β_1, β_2, β_3, β_4 and β_5.

Following Mishra and Newhouse (2009), two and three period lagged levels of GSP and the other predetermined variables are used as instruments in the equation (E3.10) whereas one and two-period lagged differences are used as instruments in equation (E3.9). Therefore, my estimates are obtained by comparing two observably similar U.S. states through the use of the portion of fiscal policy which is attributable to their fiscal histories (Mishra and Newhouse, 2009). I employ a two-step GMM estimation approach which is "efficient and robust to all patterns of heteroskedasticity and cross correlation" (Roodman, 2009). Also, the finite sample tends to bias standard errors severely downwards (Arellano and Bond 1991; Blundell and Bond 1998). Therefore, reported standard errors undergo the Windmeijer (2005) small sample correction.

The system GMM estimates are presented in columns (4), (6), (8), and (10) of Table 3.4. The version of the model estimated in the preceding columns, i.e., (3), (5), (7), and (9), is reestimated in columns (4), (6), (8), and (10), respectively. Recall that given the large number of instruments, one should be conservative in choosing the appropriate significance levels for all specification tests. Column 4 reports the system GMM estimates for the most basic system of equations (E3.9) and (E3.10). Three reported statistics are of particular relevance. First, I fail to reject the over identification restrictions based on the Hansen J test. Therefore, under the null, my instrument set is valid. Second, the AR1 test of the model's estimated errors indicate evidence of first order autocorrelation just as my theoretical model predicts. Third, the AR2 test of the model's estimated errors indicate evidence of no second order autocorrelation.

In column (4), the rate of output adjustment in a dynamic framework is given by the estimate for β_1, i.e., the estimated coefficient for the one-period lag of the dependent variable. The estimate implies that the rate of output adjustment in my dynamic model is about 1/5th of what the static models predict, i.e., $\lambda = .177$. Also, the system GMM estimates indicate no evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. However, in column (4) net intergovernmental revenue as a share of GSP promotes GSP growth rates when used to finance deficit spending. Increased expenditures on environment, housing, and sanitation as a share of GSP financed by deficit spending serve as GSP growth rate deterrents. Similarly, education, health, and hospital expenditures as a share of GSP and a higher state unemployment rate today is associated with slower growth rates of GSP in the future.

Similar to the OLS analysis, column (6) adds a squared version of the tax variable and column (8) incorporates an interaction term between the tax variable and a time period dummy for years prior to 1998. Column (6) of Table 3.4 provides no statistical evidence of a nonlinear response in growth effects, while in similar fashion column (8) provides no evidence of a break in tax sensitivities occurring in 1998. It is important to note that in addition to within jurisdiction and within year transformations, the data in column (8) also undergo a within period transformation.

Column (10) of Table 3.4 incorporates a set of interaction terms between the tax variable and U.S. Census region. The omitted region is still the Midwest. Again, the estimated interaction term measures the additional response given a change in the effective tax rate in that particular region. In addition, the data in column (10) undergo the within region transformation. Estimates are stable to the GMM dynamic panel estimation of the growth effects associated with a tax rate hike in the Midwest and Northeast regions. In contrast to the OLS estimates in column (9), the South and West now experience negative growth effects associated with tax rate hikes. Other system GMM parameter estimates are stable to the inclusion of the additional control variables.

3.5.3 COMPARISON OF THE OLS ESTIMATES AND SYSTEM GMM ESTIMATES

In this section I will be comparing α_1 from the static framework of equation (E3.6) when estimated in the dynamic framework equation, (E3.8). Recall, I estimate φ and λ such that α is recoverable, i.e., $\varphi_0 = \alpha_0\lambda$, $\varphi_1 = 1 - \lambda$, and $\varphi_2 = \alpha_1\lambda$. The estimated tax coefficient in column (9) of Table 3.4 indicates that given a 1% hike in the effective tax rate used to finance state and local deficit spending, GSP growth rates increase by 0.3% in the Midwest, the omitted U.S. Census region. In the case wherein state and local government increase charges as a share of GSP by 1% to finance state and local deficit spending the GSP growth rate increases by 0.17%. On the other hand, when financed by government deficit spending, increasing state and local expenditures on education as a share of GSP by 1% reduces the growth rate of GSP by 0.24%. However, a 1% hike in the effective tax rate to finance the same 1% increase in education expenditures as a share of GSP results in only a 0.06% increase in the GSP growth rate. Lastly, if the state and local government increases charges in a similar fashion to finance the increase in education expenditures then the GSP growth rate decreases by 0.07%.

The magnitude of the estimated coefficient for the state unemployment rate in the system GMM estimator, column (10), is over three times as great as the OLS estimates, column (9), -0.20 and -0.62 respectively. Therefore, the two coefficients suggest that a 1 percentage point increase in the state unemployment rate this period translates to between a 0.20% and 4.5% reduction in the future growth rate of GSP. Similarly, the GMM estimates in column (10) suggests that given a one percentage point increase in general education expenditures as a share of GSP relates to the GSP growth rate slowing down by nearly 5.1 %. Meanwhile, for the same increase in education expenditures as a share of GSP, OLS estimates in column (9) suggest a more modest slowdown of approximately 0.24%. The statistically significant GMM estimates for the growth effects of state and local fiscal policy as a determinant for output growth are generally greater in magnitude relative to the OLS estimates. This is consistent with noise in the fiscal policy variables biasing the OLS estimates towards zero. On the other hand, this is also consistent with positive correlations between the unobserved components of GSP and state and local fiscal policy. This may also suggest the effective size of state and local government grows in response to worsening statewide economic conditions.

Now, I will revisit column (10) of Table 3.4. Recall, column (10) estimates test for growth effect heterogeneities by U.S. Census region. Figures 3.4-3.7 are impulse response functions in the growth rate of GSP given a 1% hike in the effective tax rate by state and local government. Each figure includes two panels. Panel (a) models the response to a one-time tax hike. Meanwhile, panel (b) models the response to a permanent tax hike. Lastly, each panel includes two plots. The black plot measures the static response in the GSP growth rate, i.e., the log difference of equation (E3.6). The grey plot measures the dynamic response in the GSP growth rate, i.e., the log difference of equation (E3.8). Figures 3.4-3.7 contain the various impulse response functions for the Midwest, the Northeast, the South, and the West regions, respectively.

Beginning in Figure 3.4, it is easy to see that the static model is significantly more responsive to the tax hike. For example, panel (a) indicates the 1% tax hike this period will grow GSP by 5.0% in the static framework, Q_t^*, whereas GSP grows by less than one-fifth of that in the dynamic model, Q_t. Also notice the shock of the one-time tax hike occurring in the first period is fully exhausted in the second period of the static model. In contrast the dynamic framework predicts that, in the Midwest, the positive growth effects persist for several periods following a tax rate hike before dying off to zero. Jumping to Figure 3.5, one will notice a similar but significantly less sensitive response to a tax hike in the Northeast region.

The impulse response functions presented in Figures 3.6 and 3.7 are quite different from Figures 3.4 and 3.5. Figure 3.6 indicates that GSP growth rates in the South respond negatively to tax hikes. Panel (b) of Figure 3.6 in particular estimates a permanent reduction of -4.8% in the growth rate of GSP following a permanent tax hike. In contrast to the immediate response predicted by the static model, the dynamic model anticipates a -0.66% reduction in GSP growth rates the first year after the policy. The long run effect converges to the permanent -4.8% slowdown in the growth rate of GSP. This is consistent with the notion that southern states face fierce competition in attracting migrants. Therefore, the negative tax coefficient in the South indicates that southern states with higher effective tax rates experience slower growth rates in GSP. Figure 3.7 indicates that states in the West are even more sensitive to a tax rate hike. This suggests that tax rate hikes to finance deficit spending promote economic growth rates in the Midwest and Northeast, whereas, similar tax hikes serve as growth deterrents in the South and West.

3.6 ROBUSTNESS

In addition to the previous sets of results, I test the robustness of my estimates to a large number of alternatives. First, I obtain estimates over an alternate sample. Then, I evaluate the models performance to a reduction in the number of instruments. Later, I also evaluate a number of other lag structure specifications in the empirical model. Afterwards, I estimate a secondary system of equations following an alternative transformation of equation (E3.9).

3.6.1 OLS AND SYSTEM GMM WITH AN ALTERNATE SAMPLE

First, I attempt to investigate the role of influential observations with an alternate sample. Within the literature, it is common to consider Alaska and Hawaii to be outliers and subsequently omit them from the sample. Table 3.5 recreates Table 3.4 with the alternate sample consisting of all 50 U.S. states. Table 3.5 contains both OLS and system GMM estimates. The model now rejects the null under the Hansen J-test in columns (12) and (14). Estimates in columns (16) and (18) are generally robust to the alternate sample in sign, magnitude, but not in significance. This is particularly true with the regional-tax interaction terms for the Northeast and West. Tax rate hikes in the South, on the other hand, continue to serve as growth deterrents.

3.6.2 SYSTEM GMM WITH ALTERNATE INSTRUMENT STRUCTURE

Next, I attempt to address a previously ignored drawback often associated with GMM estimation. In GMM estimation the researcher must pick the number of lags which are to be used as instruments for the endogenous and predetermined variables. As an alternative to the previous instrument structure, Table 3.6 includes the estimates using two-period lagged levels of the explanatory variables are used as instruments in the equation (E3.10) and one-period lagged differences of the covariates are used as instruments in equation (E3.9). Table 3.6 shows the Hansen's J test for over identifying restrictions rejects the null hypothesis in columns (19). It is possible the linear model does not fit the data as well as the nonlinear, sectional break, and regional models in columns (20), (21) and (22). On the other hand, the power of the J-test is diminishing as the number of instruments grows. In addition, the Hansen critical values in column (20) and (22) are not particularly large, therefore, this alternative instrument structure is assumed invalid.

3.6.3 SYSTEM GMM WITH ALTERNATIVE CONTROL VARIABLE LAG STRUCTURES

Now, I also examine two alternative lag structures of the control variables. First, log GSP is regressed on contemporaneous control variables. The control set is no longer predetermined but rather the model suffers from simultaneity. Here, one and two-period lagged levels of GSP and the other endogenous variables, are used as instruments in the equation (E3.10) whereas contemporaneous and one-period lagged differences are used as instruments in equation (E3.9). Table 3.7 shows statistically significant AR(1) and insignificant AR(2) test statistics in all columns. In addition, the Hansen's J test for over identifying restrictions rejects the null hypothesis indicating the instrument set is invalid.

Next, log GSP is regressed on the two-period lags of control variables. Now, three and four period lagged levels of GSP and the other predetermined variables, are used as instruments in the equation (E3.10) whereas two period lagged differences are used as instruments in equation (E3.9). Table 3.8 shows the Hansen's J test for over identifying restrictions rejects the null hypothesis indicating the instrument set is invalid. The AR(1) test indicates that the errors are serially correlated of order one. Meanwhile, the AR(2) test fails to reject the null hypothesis, suggesting that the errors are not serially correlated beyond order one. Once again, I conclude the model is invalid because model does not fit the data well.

3.6.4 SYSTEM GMM WITH BACKWARD ORTHOGONAL DEVIATIONS

Replacing the missing data with lagged values biases the estimates to zero. Hayakawa (2009) recommends implementing backward orthogonal transformation in an attempt to reduce bias arising from the missing observations. Also, the orthogonal transformations prevent the data gaps from exploding. The backward orthogonally transformed version of equation (E3.10) is obtained by replacing the first differences with the change since the initial set of observations. Here, two and three period lagged levels of GSP and the other predetermined variables, are used as instruments in the backward orthogonally transformed version of equation (E3.10) whereas one period lagged backward orthogonal deviations are used as instruments in equation (E3.9).

Table 3.9 shows the Hansen's J test for over identifying restrictions rejects the null hypothesis indicating the instrument set is invalid. Again, the AR(1) test indicates that the errors are serially correlated of order one while the AR(2) indicates that the errors are not serially correlated beyond order one. Once again, I conclude the model is invalid because data do not fit the model well.

3.7 CONCLUSIONS

This analysis explored the connection between regional economic growth and the effective state and local tax rate. I have attempted to account for the growth effects resulting from the vast array of public goods and services funded by state and local governments omitting deficit spending and miscellaneous revenues. A review of the state and local government finance literature indicates that competent tax studies attempt to address the following key issues: theoretical modeling, structuring of the data, appropriate estimation, and influential observations. This is the first study that I believe attempts to address the potential endogeneity of the state and local fiscal policy.

Through appropriate theoretical modeling and the implementation of dynamic panel estimation strategies, I have attempted to address estimation issues common to the tax literature. Furthermore, I have attempted to address estimation issues typically associated with an ARDL estimable equation, e.g., inconsistent estimates arising from autocorrelation, predetermined variables, and time invariant jurisdiction characteristics which may be correlated with the explanatory variables, as well as, estimation bias arising from an omitted variable and/or the measurement error of state and local data. I follow the estimation approach of Mishra and Newhouse (2009) and obtain two sets of consistent estimates for the growth effects associated with state and local fiscal policy.

A summary of my empirical analysis is organized into Tables 3.10 – 3.13 based on the following four categories: linear regressions, non-linear regressions, sectional break regressions, and regional regressions, respectively. The first column indicates the row number. The next two columns of these tables indicate the location of the regression estimates by table and column number. The fourth column indicates estimator while the fifth column indicates the lag structure of the right hand side (RHS) variables, i.e., contemporaneous, one-period lag, two-period lag. The sixth column indicates the sample, i.e., 48 contiguous U.S. states or the 50 U.S. states. These tables also include a column which describes the set of instrumental variables utilized in the GMM estimation, all relevant statistical tests and the results, as well as, a discussion of the findings in general. When statistical tests fail to support the model general findings are dismissed. Note, the summary of OLS and GMM estimates for the main sample and alternate sample are presented in rows (1) through (4), respectively. Row (5) summarizes the model following a reduction in the number of instruments. Row (6) and (7) include contemporaneous and 2 period lagged explanatory variables, respectively. Row (8) concludes with a summary of the orthogonally transformed model.

First, my pooled OLS estimates with only annual fixed effects indicate that a hike in the effective tax rate of state and local government is not a statistical determined of GSP growth in the following period. This is in contrast to simple correlations which predict a crowding out effect of taxation. System GMM estimates are consistent in indicating that hikes in the effective tax rate are not a significant determinant of state economic growth in the pooled, nation-wide analysis. The results are not robust to an alternative sample wherein the Alaska and Hawaii are included, a reduction in the number of instruments, i.e., the rows (3) and (4) of Table 3.10., or a number of other alternative specifications, i.e., rows (4) through (8).

Second, I find no evidence in support of nonlinearities in the growth elasticities to the effective tax rate of state and local government in the pooled, nation-wide OLS analysis. The results of rows (1) and (2) of Table 3.11 are somewhat robust to an alternative sample wherein all 50 U.S. states are included, i.e., row (4) of Table 3.11. The results are again robust to a reduction in the number of instruments, i.e., row (5) of Table 3.11. However, I am unable to verify the robustness of the estimated coefficients following a number of other alternative specifications, i.e., rows (6) through (8) of Table 3.11

Third, I find no evidence in support of sectional breaks in the growth elasticities to the effective tax rate of state and local government in the pooled, nation-wide OLS analysis. The results of rows (1) and (2) of Table 3.12 are robust to an alternative sample wherein all 50 U.S. states are included, i.e., rows (3) and (4) of Tables 3.12. The results are again robust to a reduction in the number of instruments, i.e., row (5) of Table 3.12. However, I am unable to verify the robustness of the estimated coefficients following a number of other alternative specifications, i.e., rows (6) through (8) of Table 3.12.

Fourth, both the preliminary OLS and the system GMM estimators indicate a large degree of heterogeneity at the regional level in response to a hike in the effect tax rate of state and local government, i.e., U.S. Census region. These results are robust to an alternative sample wherein all 50 U.S. states are included, i.e., row (4) of Table 3.13. The results are again robust to a reduction in the number of instruments, i.e., row (5) of Table 3.13. I am unable to verify the robustness of the estimated coefficients following a number of other alternative specifications, i.e., rows (6) and (8) of Table 3.11.

Lastly, as one may expect federal transfers to the state and local government promote GSP growth rates. Expenditure categories to remain statistically significant throughout the exercise include the negative growth effects associated with higher expenditures on environment, housing, sanitation, education, health, and hospital as shares of GSP. The large variation between OLS and GMM estimates may well likely be an indication that governments increase expenditures as the quality of the public service deteriorates.

Additionally, these types of estimation strategies rely heavily on the assumption that expenditures by financial category as a share of GSP are good measures of the scope and/or quality of public goods and services. However, there is no *a priori* reason to believe that state and local government spending as a share of GSP reflects either the scope or the quality of the provided public good or service.

In conclusion, I interpret my results as an indication that state and local policymakers should not be so hasty in extrapolating the results of empirical studies to their own jurisdictions and time periods. What is good in one region at one moment in time may not necessarily result in similar effects outside that time or jurisdiction, i.e., it may be advisable for the local policy maker to respond to local fundamentals. These results are also consistent with the notion that some regions are subject to either over or under leveraging by the state and local government.

CHAPTER IV

CONCLUSION

My first study finds robust evidence of a countercyclical relationship between macroeconomic business cycle fluctuations and individual investment in social networking. I attempt to obtain a refined set of estimates for the determinants of individual investment in social networking. I apply the most recent linear-in-means modeling and estimation techniques to address the reflection problem. I also attempt to account for potential unobserved heterogeneity with a two-step estimation procedure wherein the first step instruments the observed macroeconomic indicators with lagged M1 and M2 growth. Initial ad hoc reference groups are based on state of residence, population of interview city, and decade of interview. Therefore, I attempt to achieve identification through the isolation of the portion of one's socializing behavior attributable to geographic sorting for each decade. Lastly, my estimates are robust to restructuring of the ad hoc groupings.

My second study finds evidence of regionally heterogeneous growth effects of state and local fiscal policy on GSP. I take a dynamic approach in modeling output by combining a partial adjustment process with a factor market approach for modeling regional output. I arrive at an ARDL model for regional economic growth and attempt to address an extensive list of modeling and estimation concerns, e.g., autocorrelation, predetermined variables, and time invariant jurisdiction characteristics which may be correlated with the explanatory variables. Additionally, to my knowledge, this is the first study which attempts to address the potential endogenity of the state and local fiscal policy variables. My refined set of estimates indicate a large degree of heterogeneity between U.S. Census region in response to a hike in the effect tax rate of state and local government. Although these results are robust to an alternative sample and to a reduction in the number of instruments, I am unable to verify the estimated coefficients to a number of other robustness checks.

I am an applied microeconomist in the urban and regional economics field. I provide two exercises: I attempt to address the reflection problem and I attempt to estimate a regional production function. These studies are intended to exhibit my expertise in particular areas of interest: networking and public policy. Additionally, these exercises demonstrate my proficiency in various modeling and estimation strategies. The previous studies are samples of my research conducted as an economics doctoral student with the Department of Economics in the Spears School of Business at Oklahoma State University in Stillwater, Oklahoma. These studies combine to form my dissertation.

APPENDICES

APPENDIX A2.1: REVISITING THE REFLECTION PROBLEM

Rewriting the Lee (2007) linear-in-means empirical model, equation (E2.10), in matrix notation yields:

(EA2.1.1) $\boldsymbol{Y} = \alpha\boldsymbol{\iota} + \beta\boldsymbol{GY} + \gamma\boldsymbol{X} + \delta\boldsymbol{GX} + \boldsymbol{\epsilon}$

Following equations (5) through (7) in Bramoullé et al. (2009) I first solve equation (EA2.1.1) for $\boldsymbol{Y}$ and obtain $\boldsymbol{Y} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{\iota} + \gamma(\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{X} + \delta(\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{GX} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{\epsilon}.$

Combining like terms yields:

(EA2.1.2) $\boldsymbol{Y} = \alpha(\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{\iota} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}(\gamma\boldsymbol{I} + \delta\boldsymbol{G})\boldsymbol{X} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-\mathbf{1}}\boldsymbol{\epsilon}$

From equation (EA2.1.2), $\boldsymbol{I} - \beta\boldsymbol{G}$ is invertible because $|\beta| < 1$. Additionally, in series notation, $\boldsymbol{I} - \beta\boldsymbol{G} = \sum_K \beta^k \boldsymbol{G}^k$. A subsequent series expansion of equation (EA2.1.2) yields:

(EA2.1.3) $\boldsymbol{Y} = \frac{\alpha}{1-\beta}\boldsymbol{\iota} + \gamma\boldsymbol{X} + (\gamma\beta + \delta)\sum_K \beta^k \boldsymbol{G}^{k+1}\,\boldsymbol{X} + \sum_K \beta^k \boldsymbol{G}^k\,\boldsymbol{\epsilon}$

The conditional mean of average reference group behavior is represented by:

(EA2.1.4) $E[\boldsymbol{GY}|\boldsymbol{X}] = \frac{\alpha}{1-\beta}\boldsymbol{\iota} + \gamma\boldsymbol{GX} + (\gamma\beta + \delta)\sum_K \beta^k \boldsymbol{G}^{k+2}\,\boldsymbol{x}$

Equation (EA2.1.4) is the theoretical basis for equation (E2.11). Therefore, $\mathrm{G}^{\mathrm{k+2}}$

are valid instruments for $\boldsymbol{GY}$ $\forall k \in \boldsymbol{\mathcal{R}}^{+}$. Asymptotically, so long as $\beta \neq 0$, $\gamma\beta + \delta \neq 0$ and matrices $\boldsymbol{I}$, $\boldsymbol{G}$, and $\boldsymbol{G}^2$ are linearly independent, social effects may be identified. $\gamma\beta + \delta \neq 0$ simply implies that reference group characteristics influence the embedded individual, directly, or indirectly.

APPENDIX A2.2: LIST OF VARIABLES AND DATA SOURCES

Name	Source	Description
natunemplfma	BLS	National Unemployment to Labor Force Ratio x 100
natunemppopma	BLS	National Unemployment to Population Ratio x 100
natunempempma	BLS	National Unemployment to Employment x 100
m1gthl1	USFRB	1 period lag of the log difference in M1
m2gthl1	USFRB	1 period lag of the log difference in M2
lnsocflow	GSS	Individual's flow of social capital (log investment)
male	GSS	Individual's sex (dummy variable, male = 1)
nonwhite	GSS	Individual's race (dummy variable, white = 0)
age	GSS	Individual's age
agesq	GSS	Individual's age squared
married	GSS	Individual's marital status (dummy variable, married = 1)
college	GSS	Individual's educational attainment status (dummy variable, college degree holder = 1)
homeowner	GSS	Individual's homeownership status (dummy variable, homeowner = 1)
gr_lnsocflow	GSS	Group's average flow of social capital (log investment)
gr_male	GSS	Group's average sex (dummy variable, male = 1)
gr_nonwhite	GSS	Group's average race (dummy variable, white = 0)
gr_age	GSS	Group's average age
gr_agesq	GSS	Group's average age squared
gr_married	GSS	Group's average marital status (dummy variable, married = 1)
gr_college	GSS	Group's average educational attainment status (dummy variable, college degree holder = 1)
gr_homeowner	GSS	Group's average homeownership status (dummy variable, homeowner = 1)

APPENDIX A2.3: IRB APPROVAL LETTER

Oklahoma State University Institutional Review Board

Date:	Thursday, August 25, 2011
IRB Application No	BU1122
Proposal Title:	Effects of the Surrounding Environment on Individual's Behavior
Reviewed and Processed as:	Expedited

Status Recommended by Reviewer(s): Approved Protocol Expires: 8/24/2012

Principal Investigator(s):

Abdul Munasib	Jerome Segura
326 Business	210 Hanner
Stillwater, OK 74078	Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

[x] The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval.
2. Submit a request for continuation if the study extends beyond the approval period of one calendar year. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of this research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact Beth McTernan in 219 Cordell North (phone: 405-744-5700, beth.mcternan@okstate.edu).

Sincerely,

Shelia M. Kennison

Shelia Kennison, Chair
Institutional Review Board

APPENDIX A3.1: LIST OF VARIABLES AND DATA SOURCES

Name	Source	Description
y	BEA	common log of GSP x 100
tax	Census	property and nonproperty taxes / GSP x 100
tax squared	Census	tax squared
tax x pre-1998 dummy	Census	if year < 1998 then Tax x pre-1998 dummy = tax, Tax x pre-1998 dummy =0 otherwise
tax x NE region dummy	Census	Northeast region dummy x tax
tax x S region dummy	Census	South region dummy x tax
tax x W region dummy	Census	West region dummy x tax
ignet	Census	net intergovernmental transfers / GSP x 100
charges	Census	total general charges and utility revenue / GSP x 100
welfare	Census	public welfare / GSP x 100
transportation	Census	hwy transportation / GSP x 100
environhousan	Census	natural resource and parks and rec & community and sanitation / GSP x 100
safety	Census	police and fire protection / GSP x 100
geneduchh	Census	primary, secondary and higher education & health and hospital / GSP x 100
other	Census	direct expenditure - transportation - environhousan - safety – geneduchh / GSP x 100
stateunemploymentrate	BLS	# unemployed / # labor force *100

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TABLES

2.1 SUMMARY STATISTICS

Variable	N	Mean	SD	Min	Max
natunemplfma	15639	0.06	0.01	0.04	0.09
natunemppopma	15639	0.04	0.01	0.03	0.06
natunempempma	15639	0.06	0.01	0.04	0.1
m1gthl1	15639	3.87	4.83	-3.42	12.45
m2gthl1	15639	4.57	2.1	1.04	8.03
lnsocflow	15639	3.45	2.46	-4.61	6.25
male	15639	0.46	0.5	0	1
nonwhite	15639	0.19	0.39	0	1
age	15639	45.42	16.6	18	89
agesq	15639	2338.11	1681.87	324	7921
married	15639	0.5	0.5	0	1
college	15639	0.33	0.47	0	1
homeowner	15639	0.63	0.48	0	1
gr_lnsocflow	15639	3.45	0.91	-4.61	6.25
gr_male	15639	0.46	0.19	0	1
gr_nonwhite	15639	0.19	0.24	0	1
gr_age	15639	45.42	7.59	18	89
gr_agesq	15639	2338.11	762.27	324	7921
gr_married	15639	0.5	0.23	0	1
gr_college	15639	0.33	0.22	0	1
gr_homeowner	15639	0.63	0.27	0	1
gr2_male	15639	0.46	0.17	0	1
gr2_nonwhite	15639	0.19	0.24	0	1
gr2_age	15639	45.42	7.33	18	89
gr2_agesq	15639	2338.11	735.31	324	7921
gr2_married	15639	0.5	0.22	0	1
gr2_college	15639	0.33	0.21	0	1
gr2_homeowner	15639	0.63	0.27	0	1
Group Count	15639	18.98	16.87	2	126

2.2 SIMPLE CORRELATIONS: INDIVIDUAL SOCIAL FLOWS AND MACROECONOMIC INDICATORS

variable	natunemplfma	natunemppopma	natunempempma
lnsocflow	0.0141	0.0145	0.0141

2.3 PREDICTED GROUP AVERAGE FLOWS

Variable	N	Mean	SD	Min	Max
gr_lnsocflowhat	15639	3.450522	0.8297051	-4.774074	7.034817

2.4 PREDICTED MACROECONOMIC INDICATORS

Variable	N	Mean	SD	Min	Max
natunemplfmahat	15639	0.0565928	0.0090588	0.0429855	0.0718197
natunemppopmahat	15639	0.0375349	0.0058166	0.0288285	0.0470744
natunempempmahat	15639	0.0601706	0.0103422	0.0446063	0.0778083

2.5 DETERMINANTS OF INDIVIDUAL INVESTMENT IN SOCIAL NETWORKING

VARIABLES	(1) Group Flow First Stage	(2) Flow 2sls	(3) natunemplf First Stage	(4) Flow 2sls
natunemplfma	-	5.400***	-	4.947**
m1gthl1	-	-	0.00186***	-
m2gthl1	-	-	-0.000253***	-
gr_lnsocflowhat	-	0.488	-	0.484
male	0.0272**	0.0481	-	0.0482
nonwhite	0.0165	-0.172**	-	-0.172**
age	0.00472**	-0.0568***	-	-0.0567***
agesq	-4.47e-05**	0.000252**	-	0.000251**
married	-0.0076	-0.667***	-	-0.669***
college	-0.0213	0.343***	-	0.344***
homeowner	0.0101	0.155**	-	0.155**
gr_male	0.465**	-0.777***	-	-0.775***
gr_nonwhite	0.211	1.133**	-	1.136**
gr_age	0.00528	0.126***	-	0.125***
gr_agesq	-0.0003	-0.00124***	-	-0.00124***
gr_married	-0.809***	0.0192	-	0.0142
gr_college	-0.0671	0.241	-	0.245
gr_homeowner	0.349	0.46	-	0.461
gr2_age	0.128***	-	-	-
gr2_agesq	-0.00135***	-	-	-
gr2_married	-0.468	-	-	-
gr2_college	-0.425	-	-	-
gr2_homeowner	0.782	-	-	-
Group FE	yes	yes	no	yes
Constant	-	-	0.0506***	-
Observations	15,639	15,639	15,639	15,639
R-squared	0.989	0.72	0.585	0.719
Aug R-sq	0.988	0.687	0.585	0.687
F-stat	15125	1372	14322	1829
Stock and Yogo critical value	31.50		19.93	
p-value of Sargan statistic	0.003		0.419	

Significance based on robust standard errors.
*** p<0.01, ** p<0.05, * p<0.1

2.6 ALTERNATIVE MACROECONOMIC MEASURES, DETERMINANTS OF INDIVIDUAL INVESTMENT IN SOCIAL NETWORKING

VARIABLES	(5) Flow 2sls	(6) natunemplfma First Stage	(7) Flow 2sls	(8) Flow 2sls	(9) natunemplfma First Stage	(10) Flow 2sls
natunemppopma	8.424***	-	7.636**	-	-	-
natunempempma	-	-	-	4.701***	-	4.344**
m1gthl1	-	0.00119***	-	-	0.00213***	-
m2gthl1	-	-0.000230***	-	-	-0.000216***	-
gr_lnsocflowhat	0.486	-	0.483	0.491	-	0.487
X	yes	no	yes	yes	no	yes
GX	yes	no	yes	yes	no	yes
G^2X	no	no	no	no	no	no
Group FE	yes	no	yes	yes	no	yes
Constant	-	0.0340***	-	-	0.0529***	-
Observations	15,639	15,639	15,639	15,639	15,639	15,639
R-squared	0.720	0.586	0.719	0.720	0.580	0.719
Aug R-sq	0.687	0.586	0.687	0.687	0.580	0.687
F-stat	1364	15093	1812	1390	13997	1958
Stock and Yogo 10% critical value	31.50	19.93		31.50	19.93	
p-value of Sargan overidentification statistic	0.003	0.397		0.003	0.431	

Significance based on robust standard errors.
*** p<0.01, ** p<0.05, * p<0.1

2.7 SUMMARY OF 107 ISOLATED INDIVIDUALS

Variable	N	Mean	SD	Min	Max
lnsocflow	107	3.19	2.65	-4.61	6.15
male	107	0.38	0.49	0	1
nonwhite	107	0.19	0.39	0	1
age	107	44.97	16.49	18	89
agesq	107	2291.83	1669.5	324	7921
married	107	0.54	0.5	0	1
college	107	0.35	0.48	0	1
homeowner	107	0.64	0.48	0	1

2.8 ALTERNATE AD-HOC GROUPINGS, DETERMINANTS OF INDIVIDUAL INVESTMENT IN SOCIAL NETWORKING

	(11)	(12)	(13)	(14)	(15)	(16)
	Observed Macro			Instrumented Macro		
	Flow	Flow	Flow	Flow	Flow	Flow
VARIABLES	2sls	2sls	2sls	2sls	2sls	2sls
natunemplfma	4.550***	-	-	3.918*	-	-
natunemppopma	-	7.107***	-	-	5.998*	-
natunempempma	-	-	3.969***	-	-	3.462*
X	yes	yes	yes	yes	yes	yes
GX	yes	yes	yes	yes	yes	yes
G^2X	no	no	no	no	no	no
Group FE	yes	yes	yes	yes	yes	yes
Observations	15,737	15,737	15,737	15,737	15,737	15,737
R-squared	0.697	0.697	0.697	0.697	0.697	0.697
Aug R-sq	0.689	0.689	0.689	0.689	0.689	0.689
F-stat	147.6	147.6	147.6	147.3	147.3	147.3
Stock and Yogo 10% critical value	31.50	31.50	31.50	19.93	19.93	19.93
p-value of Sargan overidentification statistic	0.080	0.081	0.079	0.200	0.187	0.208

Significance based on robust standard errors.
*** p<0.01, ** p<0.05, * p<0.1

3.1 STATE RANKINGS FROM LOWEST (1) TO HIGHEST (48) BASED ON ANNUAL STATE AND LOCAL TAX REVENUE AS A SHARE OF GSP.

USPS State Code	1977	1982	1987	1992	1997	2002	2007	Average Rank (1977-2008)
AL	11	14	11	6	12	15	17	12
AR	4	5	9	12	18	27	34	14
AZ	42	30	34	38	14	18	24	32
CA	44	27	23	26	22	24	31	23
CO	32	7	25	14	7	4	6	13
CT	35	21	18	32	38	26	28	31
DE	18	13	4	1	1	1	1	3
FL	25	17	15	31	31	20	32	19
GA	17	19	6	9	8	9	14	8.5
IA	15	31	37	29	21	21	10	22
ID	13	20	27	34	37	35	23	21
IL	20	24	13	10	13	17	16	15
IN	5	6	10	15	19	12	8	10
KS	22	12	22	25	33	30	35	33
KY	7	10	17	20	26	36	29	16
LA	1	1	2	7	10	29	13	4
MA	45	35	20	22	25	13	19	24
MD	46	47	41	44	42	45	42	46
ME	39	45	44	47	48	48	46	47
MI	29	44	36	33	28	23	30	38
MN	38	34	33	35	39	34	25	37
MO	6	3	5	3	9	11	11	6
MS	21	25	14	13	36	42	41	34
MT	37	41	45	46	46	39	38	43
NC	12	18	12	11	11	7	12	8.5
ND	31	11	28	21	41	31	27	35
NE	34	22	32	19	27	28	20	25
NH	23	9	1	28	4	5	9	7
NJ	43	38	31	40	29	33	43	40
NM	19	26	38	36	34	44	44	39
NV	14	8	7	4	5	8	5	5
NY	48	48	48	48	47	46	47	48
OH	3	16	16	17	20	32	36	17
OK	9	15	21	24	35	37	22	26
OR	28	40	40	39	15	10	4	27
PA	33	37	30	37	30	25	33	36
RI	41	46	35	43	43	38	40	42

SC	24	32	24	16	16	16	26	18
SD	30	29	19	5	6	3	2	11
TN	10	4	3	2	2	2	7	1
TX	2	2	8	8	3	6	3	2
UT	26	28	39	30	24	19	15	29
VA	36	33	26	23	23	14	21	20
VT	47	42	46	45	45	43	48	45
WA	27	23	29	27	32	22	18	28
WI	40	43	43	41	40	40	37	44
WV	16	36	42	42	44	47	45	41
WY	8	39	47	18	17	41	39	30

3.2 SUMMARY STATISTICS, 1978-2008.

Variable	N	Mean	SD	Min	Max
gdp	1488	130,000,000,000	182,000,000,000	3,460,000,000	1,680,000,000,000
y	1488	1082.97	50.72	953.91	1222.53
tax	1488	9.92	1.39	5.81	14.9
ignet	1488	3.76	1.28	1.58	12.78
charges	1488	3.63	1.33	1.27	9.84
welfare	1488	2.47	1	0.42	6.08
transportation	1488	1.57	0.57	0.61	3.98
environhousan	1488	1.37	0.3	0.73	3.25
safety	1488	0.83	0.19	0.41	1.39
geneduchh	1488	7.82	1.46	4.32	12.8
other	1488	6.34	1.45	2.86	13.51
stateunemploymentrate	1488	5.73	1.95	2.25	17.45

3.3 HAUSMAN SPECIFICATION TEST, 1978–2008.

VARIABLES	(1) FE log10GSP		(2) RE log10GSP
Lag log10GSP	0.915***		0.998***
tax	0.156**		0.115**
charges	0.620***		0.272***
ignet	0.386***		0.491***
welfare	-0.245**		-0.389***
transportation	-0.294*		-0.559***
environhousan	-0.675***		-0.237
safety	0.501		1.553***
geneduchh	-0.685***		-0.313***
other	-0.237***		-0.107**
stateunemploymentrate	-0.200***		-0.205***
Constant	-1.12e-06		-8.17e-07
Hausman chi-squared		147.1	
Hausman p-value		0.000	
Observations	1,488		1,488
Number of fips	48		48

Significance based on conventional standard errors.
*** p<0.01, ** p<0.05, * p<0.1

3.4 ESTIMATED EFFECT OF STATE AND LOCAL TAX RATE ON LOG DIFFERENCE IN GSP, 1978–2008.

VARIABLES	(3) OLS log10GSP	(4) sysGMM log10GSP	(5) OLS log10GSP	(6) sysGMM log10GSP	(7) OLS log10GSP	(8) sysGMM log10GSP	(9) OLS log10GSP	(10) sysGMM log10GSP
Lag log10GSP	0.998***	0.823***	0.998***	0.836***	0.998***	0.825***	0.999***	0.861***
tax	0.067	-0.232	0.0702	-0.283	0.0895	-0.25	0.303***	0.698***
tax squared			-0.00541	0.0588				
tax x pre-1998 dummy					-0.0346	0.259		
tax x NE region dummy							-0.263***	-0.537*
tax x S region dummy							-0.244**	-1.362***
tax x W region dummy							-0.366**	-1.610***
charges	0.195**	0.466	0.195**	0.541	0.193**	0.335	0.174**	0.693**
ignet	0.391***	0.318*	0.393***	0.320*	0.385***	0.294	0.442***	0.387**
welfare	-0.366***	0.0306	-0.365***	0.0225	-0.369***	0.183	-0.405***	-0.188
transportation	-0.493***	-0.342	-0.495***	-0.343	-0.493***	-0.435	-0.490***	-0.328
environhousan	-0.0914	-0.847*	-0.0902	-0.869*	-0.0835	-0.756*	-0.154	-1.105***
safety	1.418***	-0.597	1.410***	-0.918	1.413***	-1.36	1.397***	0.0719
geneduchh	-0.240***	-0.922***	-0.243***	-0.916***	-0.238***	-0.696***	-0.244***	-0.709***
other	-0.0695	-0.139	-0.0696	-0.126	-0.0676	-0.164	-0.0611	-0.107
stateunemploymentrate	-0.196***	-0.556***	-0.195***	-0.535***	-0.195***	-0.597***	-0.200***	-0.623***
Constant	-8.20E-07	-0.00424	0.00979	-0.0428	-8.21E-07	-0.0276	0.0119	0.00432
Hansen test: P-value		0.132		0.134		0.256		0.328
AR1 test: P-value		0.000		0.000		0.000		0.000
AR2 test: P-value		0.341		0.352		0.263		0.257
Observations	1,488	1,488	1,488	1,488	1,488	1,488	1,488	1,488
Number of fips		48		48		48		48
Number of instruments		34		37		37		43

Significance of the OLS estimates are based upon standard errors clustered at the state identifier. System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.
*** p<0.01, ** p<0.05, * p<0.1

3.5 ALTERNATE SAMPLE, 1978–2008.

VARIABLES	(11) OLS log10GSP	(12) sysGMM log10GSP	(13) OLS log10GSP	(14) sysGMM log10GSP	(15) OLS log10GSP	(16) sysGMM log10GSP	(17) OLS log10GSP	(18) sysGMM log10GSP
Lag log10GSP	0.998***	0.890***	0.999***	0.904***	0.998***	0.898***	0.999***	0.893***
tax	0.0818	0.196	0.0642	0.214	0.0639	0.0141	0.336***	0.806***
tax squared			0.0202	-0.0501				
tax x pre-1998 dummy					0.0263	0.298		
tax x NE region dummy							-0.311***	-0.613
tax x S region dummy							-0.282***	-1.250***
tax x W region dummy							-0.254	-0.628
charges	0.183**	0.135	0.184**	0.295	0.184**	0.0225	0.170**	0.287
ignet	0.421***	0.345*	0.412***	0.379**	0.424***	0.352*	0.462***	0.427**
welfare	-0.389***	0.0298	-0.385***	-0.0667	-0.386***	0.19	-0.407***	-0.072
transportation	-0.352**	-1.411	-0.345**	-1.417**	-0.353**	-1.293	-0.362**	-1.586
environhousan	-0.364	-0.756	-0.368	-0.751*	-0.368	-0.780*	-0.436	-0.902*
safety	1.626***	0.539	1.679***	0.503	1.628***	-0.298	1.629***	0.937
geneduchh	-0.259***	-0.819***	-0.244***	-0.839***	-0.260***	-0.606**	-0.281***	-0.741***
other	-0.0342	-0.107	-0.036	-0.15	-0.0349	-0.159	-0.0271	-0.0876
stateunemploymentrate	-0.168***	-0.555***	-0.172***	-0.528***	-0.169***	-0.558***	-0.172***	-0.567***
Constant	-3.49E-06	-0.0416	-0.0398	-0.0212	-3.49E-06	-0.0536	0.0147	-0.0264
Hansen test: P-value		0.0768		0.083		0.137		0.213
AR1 test: P-value		0.0314		0.0298		0.0285		0.0352
AR2 test: P-value		0.793		0.797		0.732		0.709
Observations	1,550	1,550	1,550	1,550	1,550	1,550	1,550	1,550
Number of fips		50		50		50		50
Number of instruments		34		37		37		43

Significance of the OLS estimates are based upon standard errors clustered at the state identifier. System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.
*** p<0.01, ** p<0.05, * p<0.1

3.6 ALTERNATE INSTRUMENTS, 1978–2008.

VARIABLES	(19) sysGMM log10GSP	(20) sysGMM log10GSP	(21) sysGMM log10GSP	(22) sysGMM log10GSP
Lag log10GSP	0.812***	0.812***	0.825***	0.834***
tax	-0.248	-0.346	-0.25	0.841**
tax squared		0.104		
tax x pre-1998 dummy			0.259	
tax x NE region dummy				-0.489
tax x S region dummy				-2.198***
tax x W region dummy				-1.969***
charges	0.639	0.643	0.335	0.623
ignet	0.0233	0.0269	0.294	0.336
welfare	0.313	0.304	0.183	-0.037
transportation	0.106	0.0932	-0.435	0.221
environhousan	-0.587*	-0.608*	-0.756*	-0.55
safety	-0.258	-0.111	-1.36	0.822
geneduchh	-1.439***	-1.403***	-0.696***	-0.936**
other	0.248	0.254	-0.164	0.0622
stateunemploymentrate	-0.763***	-0.760***	-0.597***	-0.767***
Constant	-0.0102	-0.0579	-0.0276	0.0183
Hansen test: P-value	0.0771	0.106	0.256	0.146
AR1 test: P-value	0.001	0.001	0.000	0.000
AR2 test: P-value	0.268	0.299	0.263	0.231
Observations	1,488	1,488	1,488	1,488
Number of fips	48	48	48	48
Number of instruments	23	25	37	29

System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.
*** p<0.01, ** p<0.05, * p<0.1

3.7 CONTEMPORANEOUS EXPLANATORY VARIABLES, 1978–2008.

VARIABLES	(23) sysGMM log10GSP	(24) sysGMM log10GSP	(25) sysGMM log10GSP	(26) sysGMM log10GSP
Lag log10GSP	0.687***	0.689***	0.677***	0.696***
tax	-1.041***	-1.036***	-0.747***	-1.058**
tax squared		0.111		
tax x pre-1998 dummy			-0.0823	
tax x NE region dummy				0.522
tax x S region dummy				-0.224
tax x W region dummy				-0.0972
charges	-0.335	-0.308	-0.44	-0.246
ignet	0.335	0.318	0.27	0.369
welfare	-0.219	-0.303	-0.155	-0.336
transportation	-0.277	-0.323	-0.304	-0.217
environhousan	-0.743	-0.766*	-0.835*	-0.696*
safety	-2.622	-2.291	-3.219*	-2.265
geneduchh	-1.259***	-1.246***	-1.072***	-1.230***
other	-0.272	-0.295	-0.306	-0.312
stateunemploymentrate	-0.0989	-0.109	-0.133	-0.136
Constant	-0.0262	-0.0668	-0.0297	-0.015
Hansen test: P-value	0.02	0.0311	0.0316	0.0635
AR1 test: P-value	0.000	0.000	0.000	0.000
AR2 test: P-value	0.152	0.116	0.18	0.195
Observations	1,488	1,488	1,488	1,488
Number of fips	48	48	48	48
Number of instruments	34	37	37	43

System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.8 TWO PERIOD LAGGED EXPLANATORY VARIABLES, 1978-2008.

VARIABLES	(27) sysGMM log10GSP	(28) sysGMM log10GSP	(29) sysGMM log10GSP	(30) sysGMM log10GSP
Lag log10GSP	1.081***	1.104***	1.085***	1.079***
tax	0.139	0.243	-0.138	0.478
tax squared		-0.155		
tax x pre-1998 dummy			0.325	
tax x NE region dummy				-0.147
tax x S region dummy				-0.356
tax x W region dummy				-0.637
charges	1.164*	1.188*	1.105*	1.099**
ignet	1.204***	1.229***	1.189***	1.291***
welfare	-0.00598	-0.0773	0.0419	-0.157
transportation	-1.203***	-1.187***	-1.212***	-1.054***
environhousan	-1.465**	-1.532**	-1.358**	-1.376**
safety	-0.6	-0.49	-0.732	-1.087
geneduchh	-0.0834	-0.103	-0.0194	-0.14
other	-0.272	-0.273	-0.243	-0.238
stateunemploymentrate	-0.399**	-0.355**	-0.431***	-0.376**
Constant	0.011	0.0647	0.00762	-0.0126
Hansen test: P-value	0.0205	0.0335	0.0462	0.102
AR1 test: P-value	0.002	0.001	0.001	0.001
AR2 test: P-value	0.829	0.93	0.799	0.775
Observations	1,440	1,440	1,440	1,440
Number of fips	48	48	48	48
Number of instruments	34	37	37	43

System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.9 BACKWARD ORTHOGONAL TRANSFORMATIONS, 1978-2008.

VARIABLES	(31) sysGMM log10GSP	(32) sysGMM log10GSP	(33) sysGMM log10GSP	(34) sysGMM log10GSP
Lag log10GSP	0.961***	0.957***	0.949***	0.956***
tax	-0.206	-0.133	0.057	0.374
tax squared		-0.0781		
tax x pre-1998 dummy			-0.342	
tax x NE region dummy				-0.146
tax x S region dummy				-0.978*
tax x W region dummy				-0.681*
charges	0.48	0.429	0.517	0.555
ignet	0.188	0.244**	0.110	0.216
welfare	0.183	0.117	0.100	0.125
transportation	-0.246	-0.0761	-0.099	-0.134
environhousan	-0.724	-0.683	-0.855	-0.978*
safety	0.564	-0.23	0.028	0.194
geneduchh	-1.048***	-1.002***	-1.110***	-1.089***
other	0.166	0.132	0.172	0.219*
stateunemploymentrate	-0.525***	-0.509***	-0.506***	-0.545***
Constant	-0.00589	0.0302	0.002	-0.00543
Hansen test: P-value	0.0356	0.0612	0.026	0.0869
AR1 test: P-value	0.000	0.000	0.000	0.000
AR2 test: P-value	0.365	0.368	0.359	0.239
Observations	1,488	1,488	1,488	1,488
Number of fips	48	48	48	48
Number of instruments	34	37	37	43

System GMM estimates undergo the two-step estimation approach which is efficient and robust to heteroskedasticity and cross correlation. System GMM reported standard errors are subject to Windmeijer (2005) small sample correction.
*** p<0.01, ** p<0.05, * p<0.1

3.10 SUMMARY OF EMPIRICAL ANALYSIS: LINEAR REGRESSIONS.

Row	Table	Column	Estimator	RHS Lag Structure	Sample	Set of Instrumental Variables	Statistical Test Results	General Findings
(1)	3.4	3	OLS	One Period Lag	48 contiguous US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. β_1≅1 implying that GSP follows close to a random walk.
(2)	3.4	4	Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. β_1≅0.82 implying that GSP does not follow a random walk.
(3)	3.5	11	OLS	One Period Lag	50 US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. β_1≅1 implying that GSP follows close to a random walk.
(4)	3.5	12	Two-step System GMM	One Period Lag	50 US States	Two and three period lagged levels and one period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(5)	3.6	19	Two-step System GMM	One Period Lag	48 contiguous US States	Two period lagged levels and one period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A

(6)	3.7	23	Two-step System GMM	Contemporaneous	48 contiguous US States	One and two period lagged levels and contemporaneous differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(7)	3.8	27	Two-step System GMM	Two Period Lag	48 contiguous US States	Three and four period lagged levels and two period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(8)	3.9	31	Orthogonal Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged orthogonal differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A

3.11 SUMMARY OF EMPIRICAL ANALYSIS: NONLINEAR REGRESSIONS.

Row	Table	Column	Estimator	RHS Lag Structure	Sample	Set of Instrumental Variables	Statistical Test Results	General Findings
(1)	3.4	5	OLS	One Period Lag	48 contiguous US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(2)	3.4	6	Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 0.84$ implying that GSP does not follow a random walk.
(3)	3.5	13	OLS	One Period Lag	50 US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(4)	3.5	14	Two-step System GMM	One Period Lag	50 US States	Two and three period lagged levels and one period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(5)	3.6	20	Two-step System GMM	One Period Lag	48 contiguous US States	Two period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 0.81$ implying that GSP does not follow a random walk.

(6)	3.7	24	Two-step System GMM	Contemporaneous	48 contiguous US States	One and two period lagged levels and contemporaneous differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(7)	3.8	28	Two-step System GMM	Two Period Lag	48 contiguous US States	Three and four period lagged levels and two period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(8)	3.9	32	Orthogonal Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged orthogonal differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A

3.12 SUMMARY OF EMPIRICAL ANALYSIS: SECTIONAL BREAK IN GROWTH EFFECTS OCCURRING IN 1998.

Row	Table	Column	Estimator	RHS Lag Structure	Sample	Set of Instrumental Variables	Statistical Test Results	General Findings
(1)	3.4	7	OLS	One Period Lag	48 contiguous US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(2)	3.4	8	Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 0.83$ implying that GSP does not follow a random walk.
(3)	3.5	15	OLS	One Period Lag	50 US States	N/A	N/A	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(4)	3.5	16	Two-step System GMM	One Period Lag	50 US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 0.90$ implying that GSP does not follow a random walk.
(5)	3.6	21	Two-step System GMM	One Period Lag	48 contiguous US States	Two period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. $\beta_1 \cong 0.83$ implying that GSP does not follow a random walk.

(6)	3.7	25	Two-step System GMM	Contemporaneous	48 contiguous US States	One and two period lagged levels and contemporaneous differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(7)	3.8	29	Two-step System GMM	Two Period Lag	48 contiguous US States	Three and four period lagged levels and two period lagged differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(8)	3.9	33	Orthogonal Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged orthogonal differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A

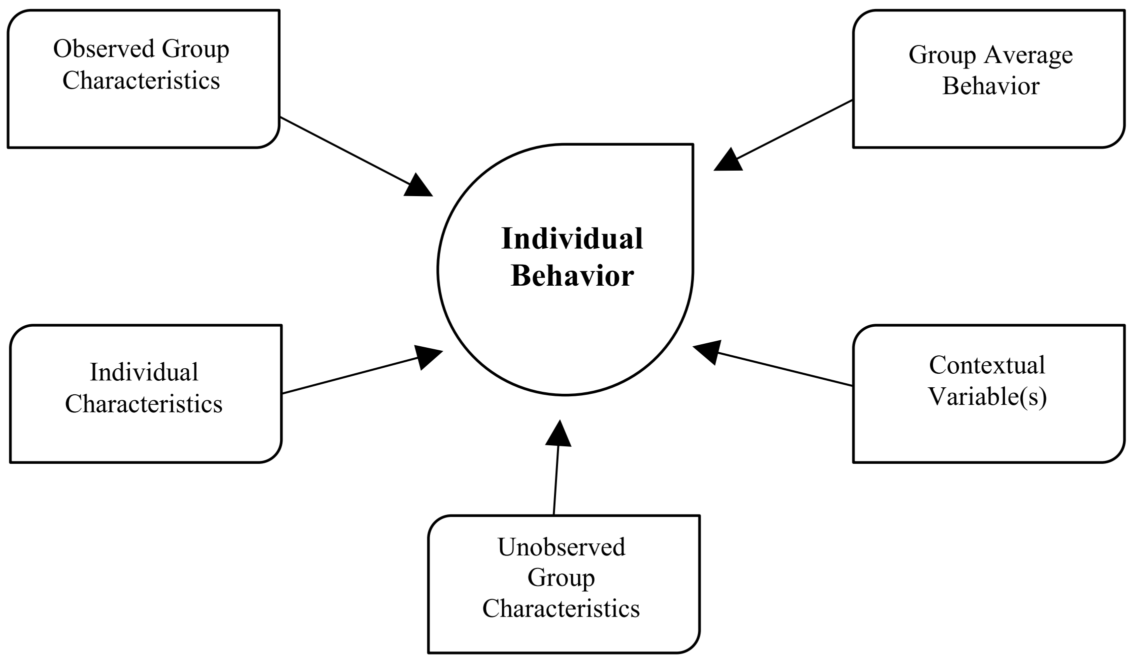
3.13 SUMMARY OF EMPIRICAL ANALYSIS: REGIONAL REGRESSIONS.

Row	Table	Column	Estimator	RHS Lag Structure	Sample	Set of Instrumental Variables	Statistical Test Results	General Findings
(1)	3.4	9	OLS	One Period Lag	48 contiguous US States	N/A	N/A	1% hike in the effective tax rate used to finance state and local deficit spending GSP growth rates increase by 0.3% in the W. Regional heterogeneities in tax sensitivities are present. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(2)	3.4	10	Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	1% hike in the effective tax rate used to finance state and local deficit spending GSP growth rates increase by 5.0% (West Region Omitted). Regional heterogeneities in tax sensitivities persist. $\beta_1 \cong 0.86$ implying that GSP does not follow a random walk.
(3)	3.5	17	OLS	One Period Lag	50 US States	N/A	N/A	1% hike in the effective tax rate used to finance state and local deficit spending GSP growth rates increase by 0.38% in the W. Regional heterogeneities in tax sensitivities are present. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(4)	3.5	18	Two-step System GMM	One Period Lag	50 US States	Two and three period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	1% hike in the effective tax rate used to finance state and local deficit spending GSP growth rates increase by 7.5% (West Region Omitted). Regional heterogeneities in tax sensitivities persist. $\beta_1 \cong 0.89$ implying that GSP does not follow a random walk.
(5)	3.6	22	Two-step System GMM	One Period Lag	48 contiguous US States	Two period lagged levels and one period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	1% hike in the effective tax rate used to finance state and local deficit spending GSP growth rates increase by 5.1% (West Region Omitted). Regional heterogeneities in tax sensitivities persist. $\beta_1 \cong 0.83$ implying that GSP does not follow a random walk.

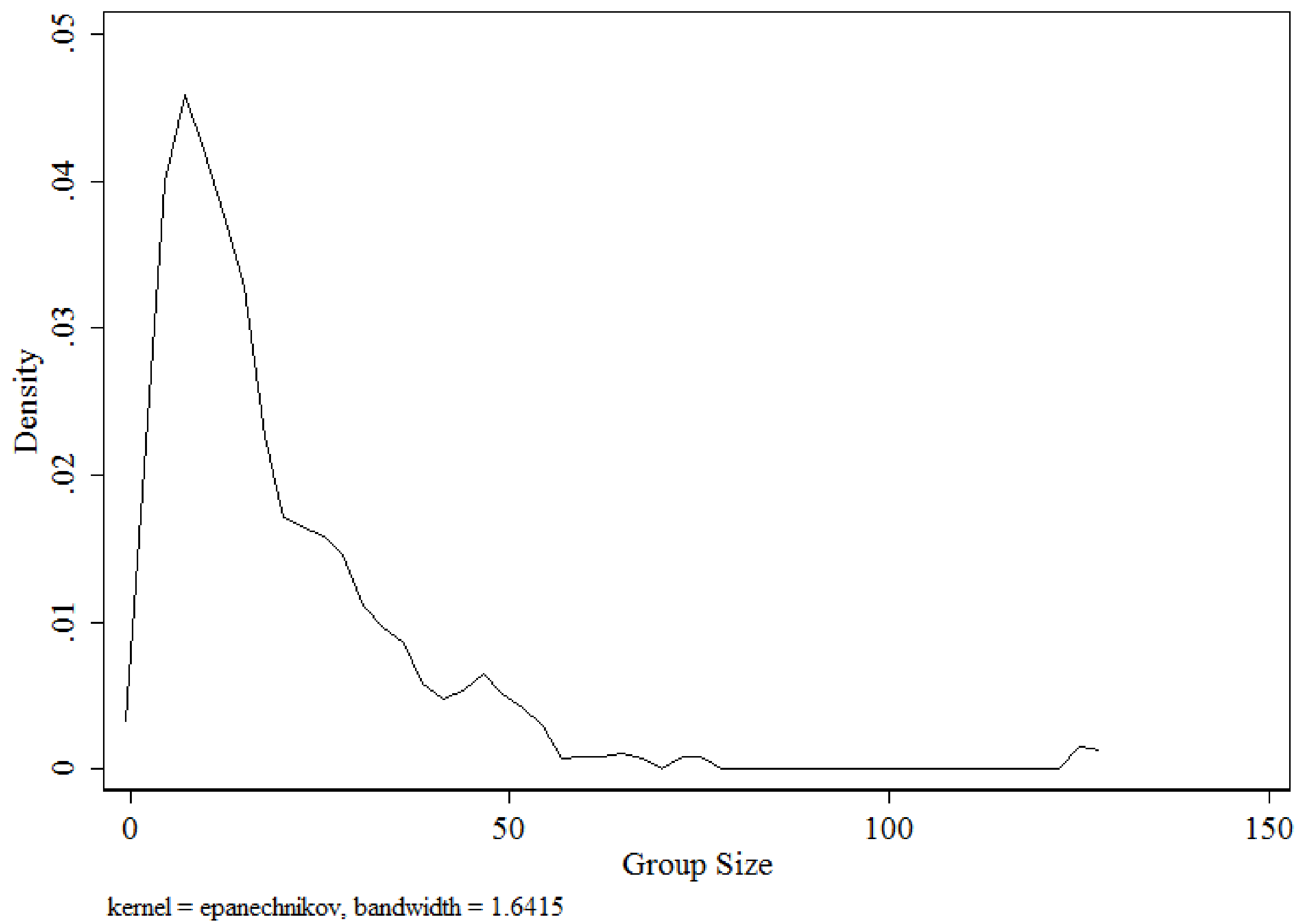
(6)	3.7	26	Two-step System GMM	Contemporaneous	48 contiguous US States	One and two period lagged levels and contemporaneous differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A
(7)	3.8	30	Two-step System GMM	Two Period Lag	48 contiguous US States	Three and four period lagged levels and two period lagged differences	The Hansen J test fails to reject the null hypothesis suggesting that model is statistically valid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one	No evidence of a statistical growth effect resulting from the effective tax rate when measured relative to deficit spending and miscellaneous revenue. No evidence of regional heterogeneities. $\beta_1 \cong 1$ implying that GSP follows close to a random walk.
(8)	3.9	34	Orthogonal Two-step System GMM	One Period Lag	48 contiguous US States	Two and three period lagged levels and one period lagged orthogonal differences	The Hansen J test rejects the null hypothesis suggesting that model is statistically invalid. Rejection of the null in the AR(1) test indicates that the errors are serially correlated of order one. The AR(2) test fails to reject the null suggesting that the errors are not serially correlated beyond order one.	N/A

FIGURES

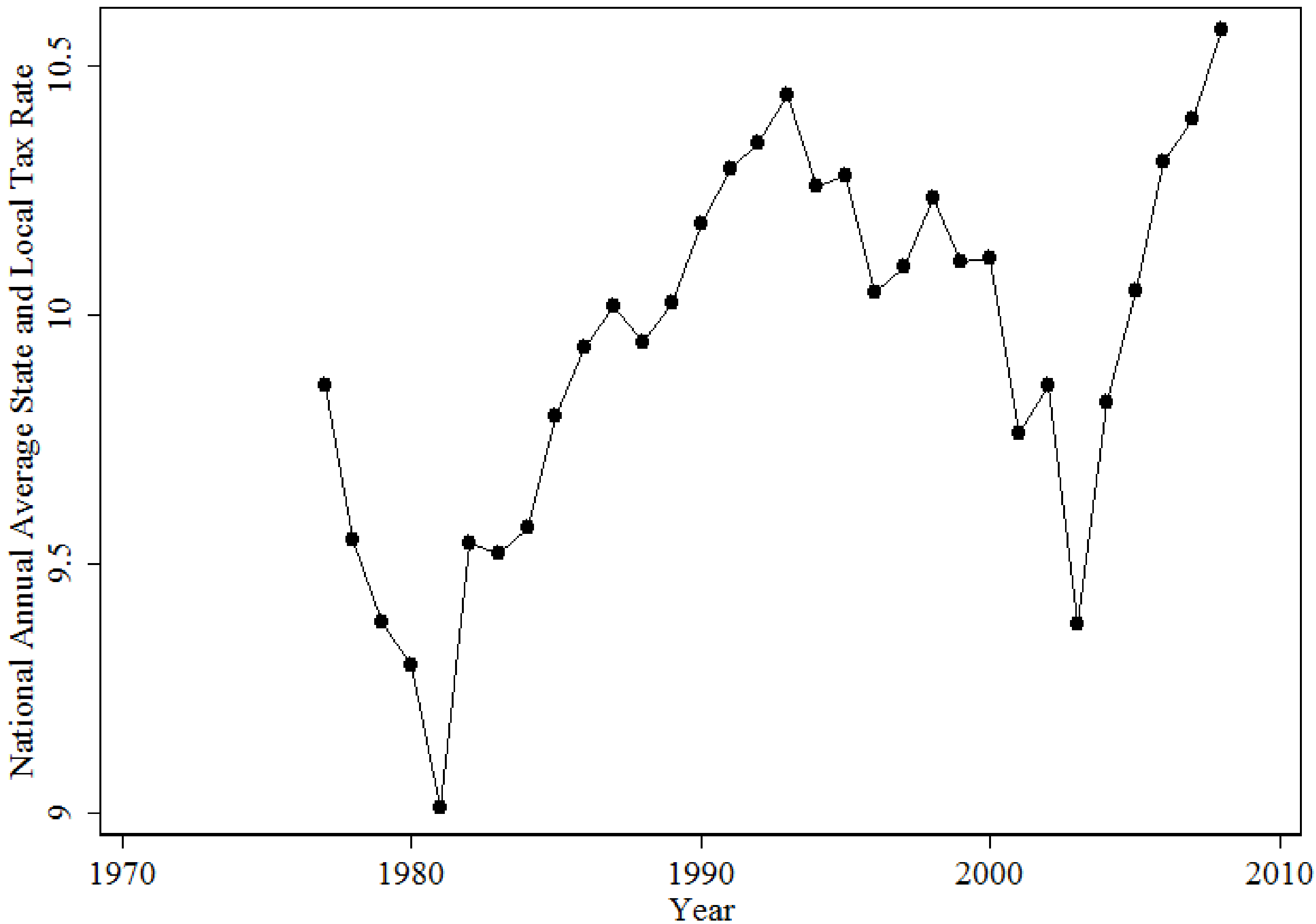
2.1 DIFFERENT SOURCES OF INFLUENCE ON INDIVIDUAL SOCIAL NETWORK INVESTMENT



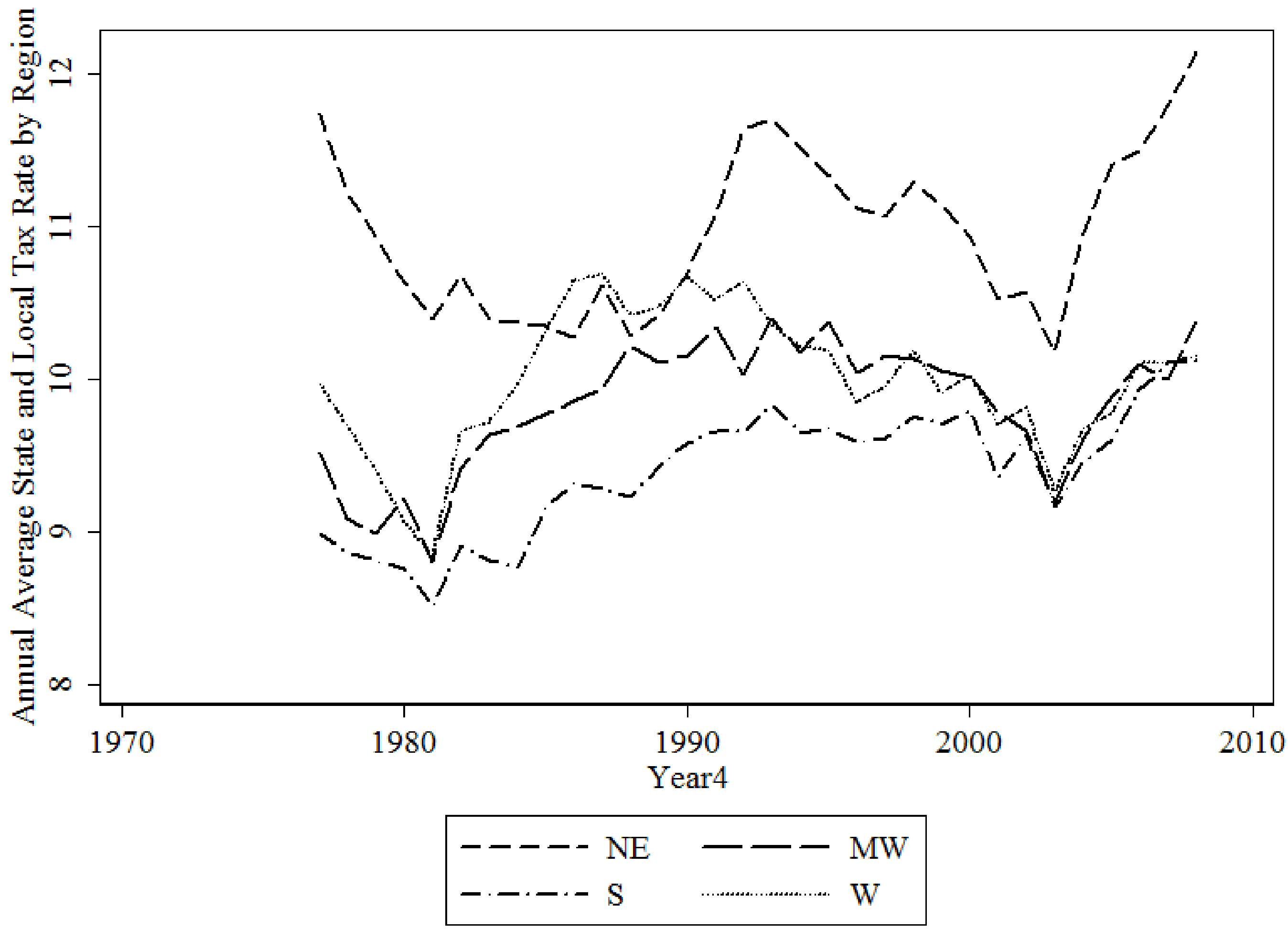
2.2 GROUP SIZE DENSITY PLOT



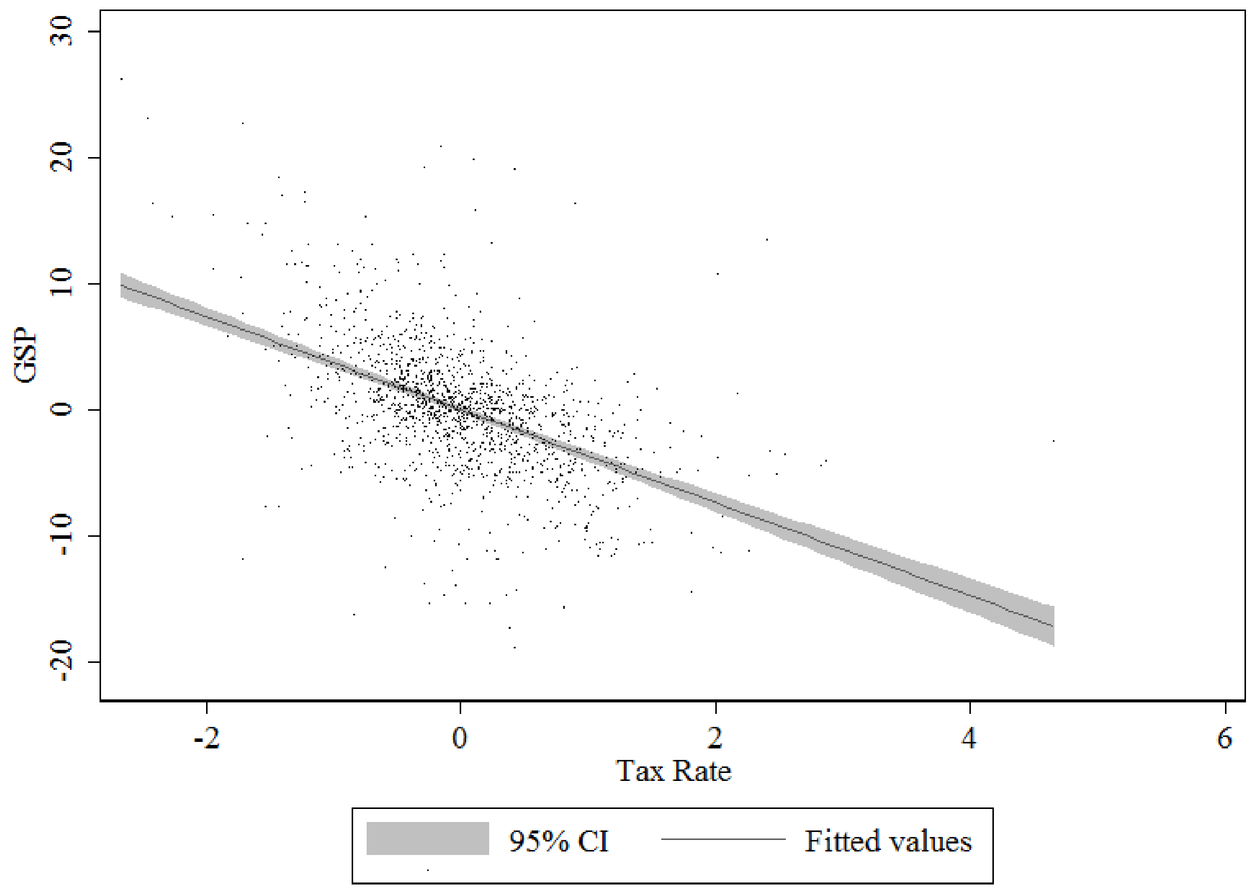
3.1 NATIONAL AVERAGE STATE AND LOCAL TAX RATE BY YEAR, 1977-2008.



3.2 ANNUAL AVERAGE STATE AND LOCAL TAX RATE BY U.S. CENSUS REGION, 1977-2008.

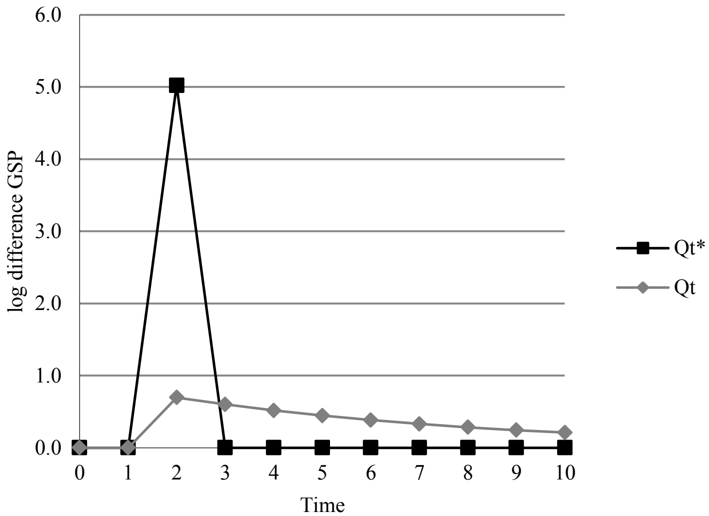


3.3 SCATTER PLOT OF LOG GSP AND STATE AND LOCAL TAX SHARE OF GSP FOLLOWING WITHIN FIPS AND WITHIN YEAR TRANSFORMATIONS (1977-2007)

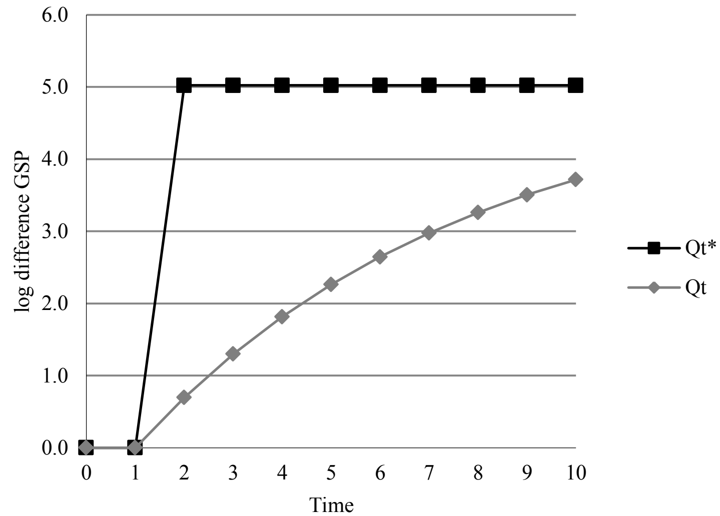


3.4 IMPULSE RESPONSE FOLLOWING A 1% INCREASE IN THE EFFECTIVE TAX RATE - MIDWEST REGION.

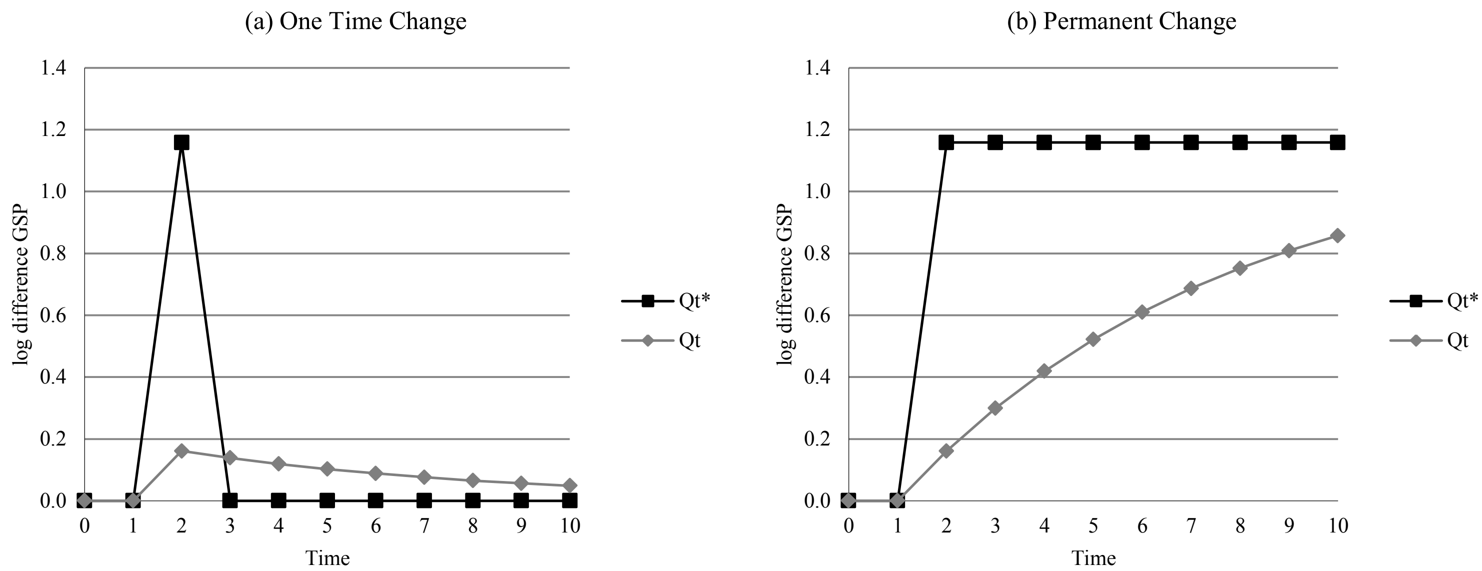
(a) One Time Change



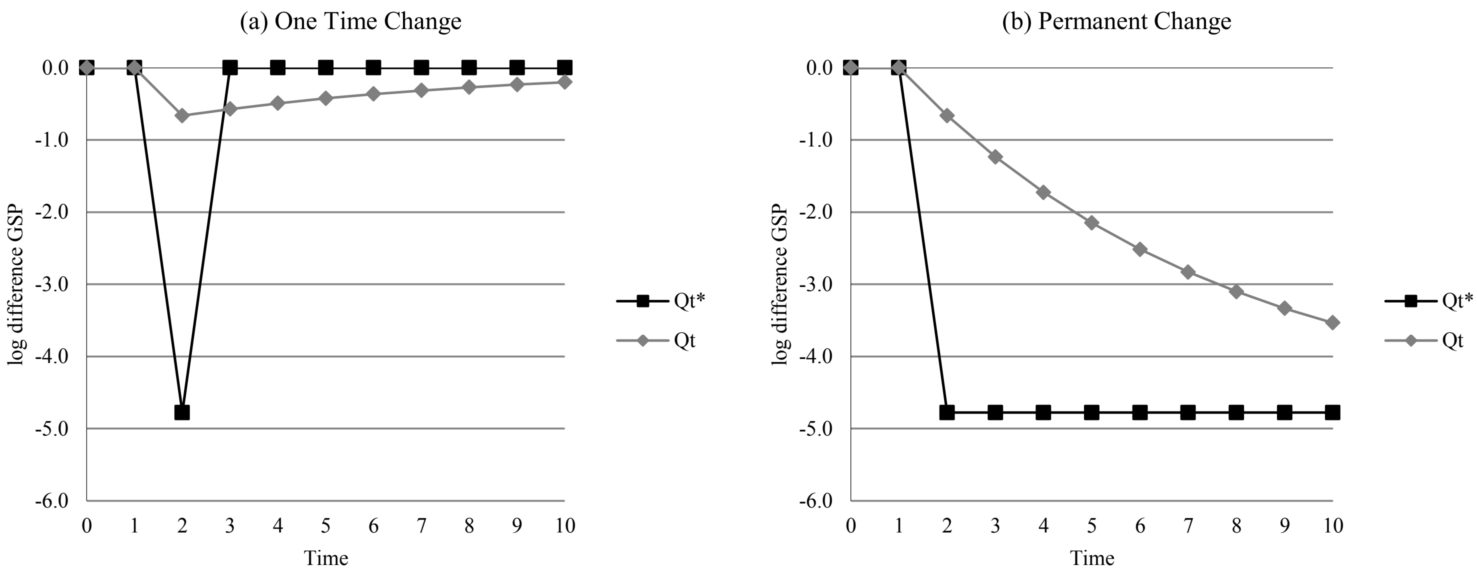
(b) Permanent Change



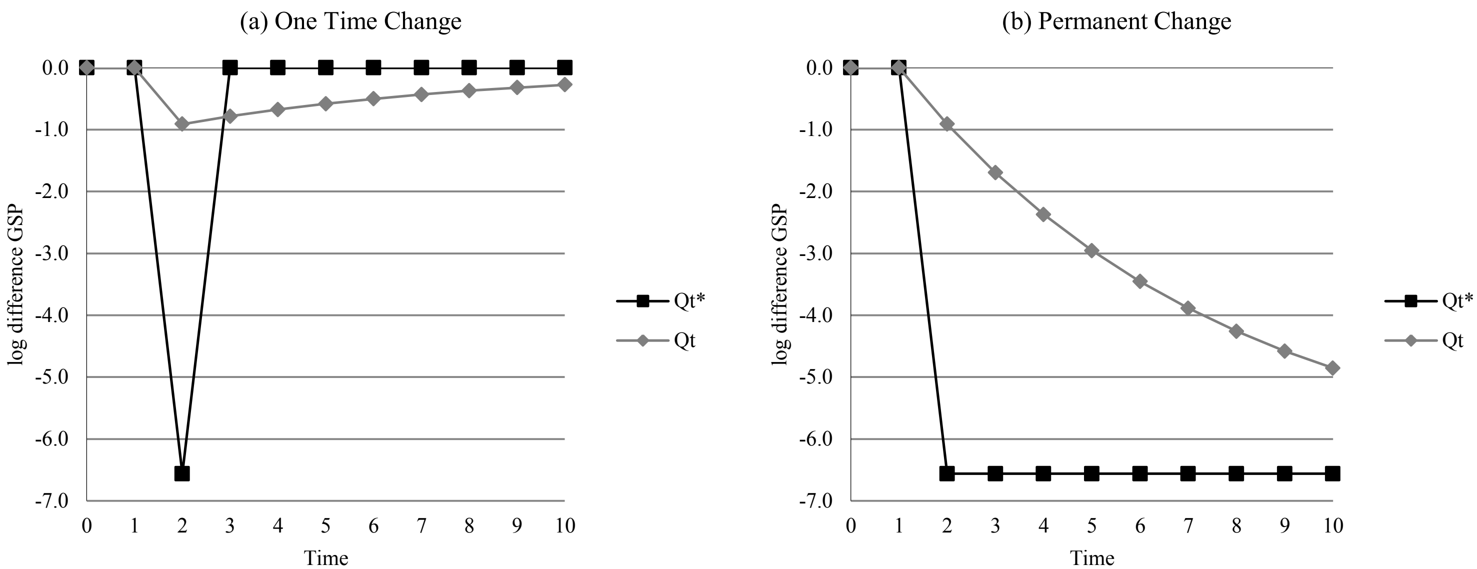
3.5 IMPULSE RESPONSE FOLLOWING A 1% INCREASE IN THE EFFECTIVE TAX RATE - NORTHEAST REGION.



3.6 IMPULSE RESPONSE FOLLOWING A 1% INCREASE IN THE EFFECTIVE TAX RATE - SOUTH REGION.



3.7 IMPULSE RESPONSE FOLLOWING A 1% INCREASE IN THE EFFECTIVE TAX RATE - WEST REGION.



VITA

Jerome Segura III

Candidate for the Degree of Doctor of Philosophy

Dissertation: TWO ESSAYS IN APPLIED ECONOMICS

Major Field: Urban and Regional Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Economics at Oklahoma State University, Stillwater, Oklahoma in July, 2013.

Completed the requirements for the Masters of Arts in Economics at University of Missouri, Columbia, Missouri in December, 2007.

Completed the requirements for the Bachelors of Arts in General Business with a concentration in Economics at Southeastern Louisiana University, Hammond, Louisiana in May, 2006.

Completed the requirements for the High School Diploma at Hahnville High School, Boutte, Louisiana in May, 2001.

Experience:

Adjunct instructor at Oklahoma City University, Oklahoma City, Oklahoma in August, 2012 through current.

Graduate teaching associate at Oklahoma State University, Stillwater, Oklahoma in August, 2008 through July, 2013.

Adjunct instructor at Southeastern Louisiana University, Hammond, Louisiana in January, 2008 through July, 2008.

Graduate teaching assistant at University of Missouri, Columbia, Missouri in June, 2006 through December, 2007.

Awards:

Outstanding Graduate Teaching Associate Award in Economics, Oklahoma State University, Stillwater, Oklahoma, 2011.

Outstanding Academic Scholarship in Economics, Southeastern Louisiana University, Hammond, Louisiana, 2006.