A Thesis
entitled
Regional Growth in the United States: A Spatial Study of Convergence
Comparing Real GSP per capita and the Human Development Index

by
Noah N. Gillespie

Submitted to the Graduate Faculty as partial fulfillment of the
requirements for the Master of Arts Degree in Economics

Dr. Olugbenga Ajilore, Committee Chair
Dr. David Black, Committee Member
Dr. Oleg Smirnov, Committee Member
Dr. Patricia R. Komuniecki, Dean
College of Graduate Studies

The University of Toledo
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An Abstract of

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“Development” is a ubiquitous term that at one turn refers purely to regional or national economic growth, and at another refers to achieving a basic standard of living for all the people of the world. The dearth of reflection on these multiple meanings in the literature is further overshadowed by the absence of empirical study into the different implications of development, when considered through these various lenses.

In this thesis, I strive to provide some analysis into the prevailing trends in two separate measures among the 48 contiguous United States over the period 1997-2006: real Gross State Product per capita (GSP) representing the “economic growth” paradigm, and the Human Development Index (HDI) representing a more holistic “quality of life” conception. Using the standard convergence equation popularized and rigorously defined by Barro and Sala-i-Martin (2004), I analyze whether there is convergence, divergence or stability in the distribution of GSP and HDI over this time period. I also experiment with three different model specifications: the standard non-linear model, a random effects panel model, and a spatial error panel model with random effects. Each specification, by relaxing some of the assumptions of the previous model, is found to provide a more realistic and nuanced picture of the true data generating process.
I find that, over the study period, there is stability in GSP among the states, and that HDI is converging rapidly. I find further that all of the components of HDI are converging with the exception of the “command over resources” component, which is based on real GSP per capita. This implies that if prevailing trends continue, the quality of life experienced by the states in terms of health and education will rapidly approach equality, but that inequality in income is persistent, and should be the focus of policy aimed to increase equity among U.S. residents. I also find that there are significant spatial relationships among the states, and that controlling for these spatial effects greatly improves a model’s explanatory power.
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Preface

In this study, we aim to compare two separate criteria for economic development – on
the one hand, the presence of meaningful economic growth, on the other, a measure of
human development that takes into account additional aspects of the quality of life – to
discover if they provide the same, or at least very similar results.

We will apply the neoclassical growth framework elucidated by Barro and Sala-i-
Martin (2004) to both real GSP per capita, a measure of economic growth, and the
Human Development Index, a more holistic measure of human conditions. We will
extend the standard neoclassical framework into a spatial context, assembling panel data
from the contiguous U.S. states to examine whether convergence is present in these two
measures.

We discover that there is neither convergence nor divergence in economic growth,
indicating persistent income inequality among the states. We find evidence of inter-state
convergence in the HDI measure, indicating increasing equality among the states in
human conditions. We provide the unique result that convergence in broader socio-
economic factors is not impeded by this remaining heterogeneity in economic growth.
Chapter 1

Literature Review

The literatures on economic growth, development, convergence, and spatial econometrics are each extensive. The contributions of each are reviewed to provide a context for our study.

1.1 Real GDP per capita and Economic Growth

In the economic growth literature, real GDP per capita (hereafter GDP) is the measure of choice. Its rise as the ideal indicator really should be no surprise, given the years of effort to perfect it and to ensure the comprehensiveness, coverage, availability and comparability of its data globally and through time.

Its use also has a deep grounding in economic theory. Real GDP per capita, even though technically a measure of productivity, is taken to be statistically equivalent to average income (and much empirical evidence supports this; see Barro & Sala-i-Martin 2004, p.466, n.5). Because of GSP’s ties to productivity, GDP is seen as an excellent measure of business prospects, activity, the gains from scale and exchange, and the ability of a region or country to add value to raw materials and intermediate goods.
The dominance of GDP as the key indicator of economic growth is evidenced by the fact that few theories of growth even consider any other indicator as a dependent variable (Barro & Sala-i-Martin 2004, chapters 1-2, chapters 4-10; Heijman 1998, chapters 14-15, chapters 17-18). Few contend that any other measure is a better indicator of economic progress, economic development or economic growth (total factor productivity, or “TFP,” may be an exception). It is on account of the burgeoning literature on development, especially on the global scale and from other social sciences, that a more inclusive set of considerations are coming to the fore.

Mazumdar (2003) suggests that the inadequacy of GDP as a sole indicator of development or well-being has been known since the 1950’s and 60’s (p. 535-36). Many studies find that GDP and indicators that aim to encompass a broader conception of well-being or holistic quality of life are significantly different from one another, suggesting at the very least that these indicators measure something GDP does not. The state of Kerala in India is an example that challenges the assumption that GDP growth is a necessary condition for development, because Kerala has dramatically improved its life expectancy and education levels, and decreased its rate of population growth while nonetheless retaining a low level of average income (Parayil 1996). Of course, it is important to come to an understanding of what exactly each of these indicators does measure, to aid in their application and interpretation, and facilitate our own understanding of what we take terms like “development” and “growth” to encompass.

---

1 See McGillivray (2007) for an excellent description and exposition on a wide variety of “well-being” measures.
1.2 The Human Development Index and its Usefulness

An indicator that has risen above the rest is the Human Development Index [HDI]. This measure, introduced by the United Nations Development Programme [UNDP] in its first Human Development Report in 1990, and revised in later Reports, aims to address the need for a holistic measure of well-being while recognizing the constraints imposed by global data availability.

Several sources identify the inspiration of Amartya Sen in the construction of the HDI (Desai 1994, p. 39; Mazumdar 2003, p. 536; Noorbakhsh 1998, p. 590). Sen is known for broadening the discourse on the valuation of individual “well-being” from the all-encompassing economic concept of “utility” to recognize that individuals’ satisfaction can come from the well-being of others as well as one’s own well-being (Gasper 2007, p. 51-53). The HDI parsimoniously contains indicators intended to capture three key dimensions of well-being, reminding “us of the fact that economic development is not only about raising output or income, but also enlarging human choice and enriching human lives” (Low & Aw 1997, p. 2). The first dimension, “a long and healthy life,” is currently represented by life expectancy at birth (UNDP 2008, p. 356). The second dimension, “knowledge,” is represented by the combination of two measures: “adult literacy rate,” being the proportion of the population aged 15 or older who can read, and the “gross enrollment ratio,” being the proportion of the population having received primary, secondary or tertiary education. The literacy rate is given a 2/3 weight and the enrollment measure a 1/3 weight in the knowledge index (ibid.). The third dimension, formerly called “command over resources” and now simply called “a decent standard of living,” is represented by the natural logarithm of real (i.e. $PPP) GDP per capita. The
natural logarithm is used to account for diminishing marginal returns to income, acknowledging that, e.g., an increase in the level of real GDP per capita by $200 in Luxembourg does not provide as much additional utility as an increase of $200 in Malawi (ibid.).

Each of these levels (life expectancy, knowledge, and income) is re-scaled to fall in $[0,1]$ by being transformed into an index measure. An index measure describes the progress of an entity along a given distance, according to the formula: 

\[
I_{i,n} = \frac{L_{i,n} - \text{min}_n}{\text{max}_n - \text{min}_n},
\]

where \(L_{i,n}\) is the level of dimension \(n\) attained by individual \(i\), \(\text{min}_n\) is a lower “goalpost” for dimension \(n\) which is arbitrarily fixed, and \(\text{max}_n\) is the upper “goalpost” for dimension \(n\) which is similarly established. The three dimensions are given equal weight in the composite measure, the HDI. Thus,

\[
(1) \quad HDI_i = \frac{1}{3} \left( \frac{\text{life}_i - 25}{85 - 25} + \frac{2(\text{lit}_i - 0)}{3(100 - 0)} + \frac{\text{enroll}_i - 0}{3(100 - 0)} + \frac{\ln(\text{income}_i) - \ln(100))}{\ln(40,000) - \ln(100)} \right)
\]

where each of the goalposts are those defined by the UNDP (2008, p. 355).

1.3 Applications of the HDI

Beyond its conceptual merits, the HDI has been shown to be associated with many other positive development and well-being outcomes. Antony & Laxmaiah (2008) find that the HDI of states in India is highly correlated with their “nutritional quality of life indicator,” which values proper nutrition and penalizes for obesity as well as undernutrition. In a detailed analysis, Ranis, Stewart & Samman (2006) discover that the
HDI is a good predictor of a host of other variables encompassing well-being, freedom, social relations, and environmental and economic stability. They conclude the HDI is a more broadly applicable and inclusive measure than GDP because the latter is a poor predictor of several of these dimensions (p. 348).

Many studies now include the HDI as an accessible and trustworthy indicator. Dholakia & Kumar (2004) use a suite of measures, including the HDI, to identify the “top performing economies” of past and coming decades. Esufzai (1996) analyzes the benefits of openness to trade and foreign investment, finding that HDI is positively correlated with openness, and that openness is correlated with more beneficial levels and faster rates of improvement in both the under-five-mortality-rate and access to safe drinking water. Jha & Bawa (2006) present the encouraging finding that HDI has a significant, negative effect on the rate of deforestation in global biodiversity hotspots. This effect is strong enough that it can offset the usually enormous environmental impact of quickly growing populations (p. 910). Finally, Cooke et al. (2007) investigate the quality of life of indigenous populations in four highly-developed nations using both HDI and GDP.

1.4 Criticisms and Alternative Constructions of the HDI

The popularity of the HDI has also contributed to a substantial body of criticism in the literature. The most common criticisms relate to the accuracy of the measures used to gauge the three components, the weights assigned to each, and the consistency of the data across time and space.

Low & Aw (1997) respond to the earliest release of the HDI. They believe the measure is very much needed but point out a number of design flaws. In particular, they
contest the quality of the data used to calculate the original HDI, and the bizarre cut-off system originally used to transform GDP (p. 3, 5). However, given that the data or design of the HDI changed in nearly every early Report, their key recommendation was for the UNDP to settle on a single design for the HDI, and provide datasets that could reliably be compared over time (p. 14-15). Since the 1994 Human Development Report, the UNDP has maintained a single methodology and now provides data for 177 countries on five-year intervals from 1975-2005 (see UNDP 2008, p. 234-37).

Mazumdar (2003) recognizes the motivation for applying diminishing marginal returns to the GDP measure, but views the system applied prior to 1994 as unrealistically strict, making the gap between the poorest and wealthiest nations seem far too small (p. 539-40). This transformation also makes it difficult to compare the relative status of wealthier nations (ibid.). He proposes a “rescaled new human development index” [RNHDI] which first utilizes the natural logarithm of the level of real GDP per capita, and secondly allows the goalposts for all three dimensions to change over time, so that the measure describes a country’s progress relative to the current standing of all the world’s countries (p. 540-43). His modifications result in significant ranking changes for a number of countries, because of the greater influence of GDP in this measure (p. 544-47). The UNDP has retained its static goalposts, but has since adopted the natural logarithm of real GDP per capita as its control over resources measure (UNDP, 2008, p. 356).

Noorbakhsh (1998) highlights many shortcomings of the HDI. First, he echoes the position that the HDI does little to differentiate or allow for comparisons between wealthy countries (p. 591). Second, he finds no reason to constrain the principle of
diminishing marginal returns to income alone (ibid.). Finally, the HDI’s equal weighting scheme finds little justification because each dimension has different means and variances, and the ranges between the selected goalposts in fact serve as inverse weights (ibid.). To remedy these defects, Noorbakhsh introduces a modified HDI [MHDI] which applies diminishing returns to all three dimensions, and standardizes them according to their resulting means and variances. The MHDI pictures each of these three indices as an orthogonal vector with a length between zero and one, constituting a three-dimensional space. Then, the index value is simply the distance between the vector of a given country’s achievement and the vector that represents the ideal (p. 592-93). He applies principal component analysis to the components of MHDI to discern appropriate weights. He finds that HDI, MHDI, and the primary component that accounts for 85% of MHDI’s variation are highly correlated, and concludes that equal weighting presents no problem for any of these three potential measures (p. 602).

This conclusion that equal weights are acceptable is more strongly supported by Stapleton & Garrod (2007). They treat the UNDP’s HDI as if it were an estimator for an unobservable “true” HDI, and apply five statistics that measure goodness-of-fit while also penalizing for complexity to find the weighting scheme that renders the HDI most “parsimonious” (p. 183). These authors note that many have suggested the HDI may be sensitive to these weights, but point out that the high correlation between the three dimensions makes it less likely that different weights could generate a measure with sufficiently different values to provide any better or worse accuracy (p. 186). Testing these theoretical claims with simulation data, they find that even extremely different weights lead to very similar results. With the aid of the parsimony statistics, they
conclude that any goodness-of-fit another weighting scheme may provide is far outweighed by the statistical complexity such variation introduces (p. 187).

Nissan & Shahmoon (1993) believe that the HDI is not as useful as it could be because it is a simple average, and seek a measure that is “metric,” i.e. that measures something that is quantitative rather than a pure number. They propose an index “D” which represents the Euclidian distance between a country’s achievement and the high goalpost, representing how far that country has left to go (p. 34). They find that HDI and the corresponding value [1 – D] are highly correlated (r = 0.99) and conclude D is an acceptable and in fact superb index (p. 35). However, the near statistical equality of the indices suggests they are interchangeable.

Baliamoune-Lutz & McGillivray (2006) argue that since development is a process rather than an instantaneous achievement, and since development takes on different meanings and thus different appropriate bundles of social development amenities, “fuzzy set theory” could improve the HDI. “Fuzzy sets allow one to model a gradual transition from membership to non-membership and vice versa” and thus are particularly useful in delineating between “rather negative (dismal)” and “rather positive (there is hope) achievement[s]” (p. 169-70). By replacing the index measures of UNDP’s HDI with fuzzy measures of achievement on each dimension, a “fuzzy HDI” is calculated and used to re-rank various Asia-Pacific nations. They find that the rankings of these nations do not change much with respect to one another but typically rise relative to all the world’s countries, and suggest that HDI and fuzzy HDI consequently measure different things (p. 172, 175). This approach is certainly an interesting suggestion, but leads to several implementation problems, especially with regard to consistency, as generating the
“fuzzy” measure requires setting an arbitrary cut off between the two groups, and sacrifices much of the initial HDI’s variation by essentially transforming it into a binary variable. Finally, the interpretation of any results found using this measure is difficult because its values are so far removed from any direct observations.

A more stringent criticism of the HDI is offered by McGillivray & Pillarisetti (2004). This study uses three population-weighted inequality indices to identify the degree of dispersion among current levels of GDP, HDI, GDI, GEM\(^2\), and a restricted HDI constructed with only the knowledge and life dimensions. On the basis of the dispersion of these measures, the authors conclude that “if one is concerned with inequalities in broader, non-economic dimensions of well-being, then using indicators like the HDI, GDI and GEM tell us little or no more than the logarithm of income per capita” (p. 573). This very strong statement is not well supported by the article’s evidence, however, as the values of the dispersion statistics are quite similar between the measures the authors evaluated.

1.5 Selected Other Indices of Development and Well-Being

The success of the HDI has also contributed to the creation of a number of other indices that attempt to capture a holistic picture of development or well-being. Shortly after the release of the HDI, Sharma (1997) urged the disaggregation of all data the UNDP collects by gender, especially the HDI. Sharma emphasized the vast differences in the ways of life and issues faced by women as opposed to men in many countries. In actuality, the UNDP experimented with a number of indices that it introduced alongside

\(^2\) GDI (“Gender Development Index”) and GEM (“Gender Empowerment Measure”) are defined and described in detail in the next section.
the HDI. Further, every *Report* investigates a different global issue and includes vast amounts of data collected on that topic.

Some of the indicators the UNDP has developed to account for gender disparities include the Gender-related Development Index [GDI] and the Gender Empowerment Measure [GEM]. GDI calculates index measures separately for males and females, and combines the two index scores by calculating their harmonic mean. Then, like HDI, the composite index is the equally weighted sum of the three adjusted dimension indices (UNDP 2008, p. 358):

\[
GDI_{i,d} = \left\{[maleprop_i(maleindex_i^{-1})] + [femprop_i(femindex_i^{-1})]\right\}^{-1}
\]

*maleprop*\(_i\) is the proportion of the population who are male, and the *maleindex*\(_i\) is the index value on dimension *d* attained by the males in country *i*. *femprop*\(_i\) and *femindex*\(_i\) are similarly constructed. The interior exponents are constructed as 1–\(\epsilon\) and the outer exponent as 1/1–\(\epsilon\), where \(\epsilon\) is chosen to equal 2 to give a moderate penalty to inequality (p. 359). Ultimately, the GDI is the HDI penalized for remaining gender disparities.

The GEM digs a little deeper into a society to uncover the real opportunities women have in that society. GEM is built out of “equally distributed equivalent percentages” [EDEPs] rather than index measures, also on three dimensions gauged by four measures. Each EDEP is calculated according to Equation (2). The composite measure, GEM, is the equally weighted sum of the three dimensions. The “political participation” dimension compares the number of parliamentary seats held by women and men. The “economic participation” dimension compares first the gendered shares of legislative, managerial
and senior official positions, and second the gendered share of professional and technical positions, weighted equally. The “power over economic resources” dimension compares gendered income, as estimated from real GDP per capita (p. 360).

Scholars outside of the UNDP have also crafted interesting and useful measures. The Physical Quality of Life Index [PQLI] precedes the HDI by a decade and yet is remarkably similar to the current HDI. Introduced by Morris (1980), the PQLI is the equally weighted composite of the adult literacy rate, an adjusted infant mortality rate, and an adjusted life expectancy at age one. Though the PQLI certainly inspired the HDI, its formulation has come under great criticism due to a lack of comparability between countries and across time, its odd adjustment mechanisms, and its lack of an economic well-being dimension.

Another measure that was a contender with the HDI for UNDP’s chosen index is the series of “Life Time” measures introduced by Desai. Desai (1994) describes the construction of this index, and advocates that it be used in place of life expectancy as the health measure. Desai hoped for a measure that was linear, aggregable, and that had readily recognizable and understandable units, rather than a pure number. For this, he chose a measure that would indicate the average years remaining in the lives of the people of a country. He introduces the Future Life Time [FLT] measure, whose units are calendar years (p. 37):

\[
(3) \quad f_j = (E(L|a) - a_j); \quad F = \sum_j f_j = [\bar{L}a - \bar{a}]N; \quad FLT_i = \bar{F} = F|N = \bar{L}a - \bar{a}.
\]
In Equation (3), \( j \) represents each individual person, and \( i \), as before, represents each country or region. The FLT begins with the calculation of the “conditional life expectancy of each individual,” which is the expected total longevity given that the individual has lived to their current age. The statistic \( f_j \) is simply the expected remaining years of life for person \( j \). This is aggregated to the national level simply by finding the average remaining conditional life expectancy of the whole population (ibid.).

Unfortunately, the properties Desai desired prevent the FLT from being as useful as possible (see ibid., p. 38). He thus normalized the FLT measure with the PLT measure to create the index \( r \), which is more comparable and less biased than the FLT (p. 38):

\[
(4) \quad p_j = (T - a_j); \quad P = (T - \bar{a})N; \quad r_j = \frac{f_j}{p_j} = \frac{E(L|a_i) - a_j}{T - a_j}.
\]

This equation incorporates a constant \( T \) that is arbitrarily chosen to represent a normative maximum desired longevity. It is the national average of the normalized \( r \) that Desai proposes should replace life expectancy at birth in the calculation of the HDI (p. 41).

Finally, Osberg & Sharpe (2005) propose the Index of Economic Well-Being (IEWB) and encourage its use in place of adjusted real GDP per capita in the HDI. The IEWB combines four measures intended to capture four different conceptions of “command over resources” and “economic well-being.” Each of these four assumes either that the average citizen is representative or the population is heterogeneous, and that the present or the future matters most. These four measures are: “average flow of current income” [representative, present], “aggregate accumulation of productive stocks” [representative, future], “income inequality and poverty” [heterogeneous, present], and “insecurity of
future income” [heterogeneous, future] (p. 314). The measure has been shown to be very sensitive to the chosen weights. While the weights were altered to 0.4, 0.1, 0.25, and 0.25 respectively for a time, equal weights are most often used (Sharpe & Osberg 2006, p. 13-14). The authors acknowledge that these dimensions sometimes move in different directions, generating a largely neutral trend that can obfuscate comparison and nuanced analysis (Osberg & Sharpe 2005, p. 321).

1.6 Barro and Sala-i-Martin

A very influential study in the convergence literature is Barro & Sala-i-Martin (2004, chapters 11-12). They note that neoclassical economics assumes “conditional convergence:” that economies with similar properties and thus a similar steady-state, tend to converge toward that steady-state (p. 461). This further implies that economies farther from their steady-state have growth rates with larger absolute values. However, they caution, this should not be confused with “absolute convergence,” in which poor countries grow faster than rich countries regardless of their economic properties (ibid.).

They contrast two separate aspects of convergence. The first is “β-convergence,” defined as the property that a “poor economy tends to grow faster than a rich one, so that the poor country tends to catch up to the rich one in terms of levels of per capita income or product;” β, of course, referring to the relevant regions’ growth rates (p. 62). The second is “σ-convergence,” defined as the property that “dispersion – measured, for example, by the standard deviation of the logarithm of per capita income or product across the group of countries or regions – declines over time,” though “this process is offset by new disturbances that tend to increase dispersion” (ibid.).
Barro & Sala-i-Martin use data to empirically examine the presence of these trends. After a thorough theoretical consideration, they arrive at the following model (p. 465):

\[
\begin{align*}
\log\left(\frac{y_{i,t}}{y_{i,t-1}}\right) &= a_{i,t} - (1 - e^{-\beta}) \cdot \log(y_{i,t-1}) + \varphi_t S_t + u_{i,t} \\
\sigma_t^2 &= e^{-2\beta} \cdot \sigma_{t-1}^2 + \sigma_{u_t}^2 + S_t^2 \cdot \sigma_{\varphi}^2 + 2S_t \cdot e^{-\beta} \cdot \text{Cov}[\log(y_{i,t-1}), \varphi_t]
\end{align*}
\]

Here, \( \beta \) is the growth rate and \( S_t \) is a term controlling for known sectoral shocks. With this model, they analyze the growth patterns in the U.S. states, the Japanese prefectures, and selected European regions. In all three cases they find strong support for absolute \( \beta \)-convergence among the regions\(^3\), and evidence for \( \sigma \)-convergence disrupted by historically-predicable shocks (p. 496). They found that poorer regions experience high, positive growth rates while wealthier regions tended to level off at a constant, low, positive growth rate. In the U.S., they found a steady growth rate of 2% per year, while this growth rate was slightly smaller in Europe and closer to 3% in Japan in recent years (p. 472, 480, 478).

The distinction between absolute and conditional convergence is especially important to Cooke et al. (2007). Their study of the indigenous populations of Australia, Canada, New Zealand and the United States – four former British colonies with relatively large and arguably oppressed indigenous populations – found very interesting trends. Previous research had found that while well-being on the whole tended to improve, there were significant periods of divergence (p. 3). Using both real GDP per capita and HDI, the authors compare the status of native and non-native populations over the period 1990-
2000 (p. 6-8). They found that education and life expectancy dimensions improved the most, while the income dimension experienced the most fluctuation. Overall, the HDI converged for natives and non-natives over this short period in Canada, New Zealand and the U.S. but diverged in Australia (p. 8-9). It is interesting to note that while the indigenous populations of these countries would rank in “high” and “medium” human development, they rank far below the general population of their country as a whole (p. 10).

Cooke et. al’s study illuminates the need to carefully compare the progress of regions by not only real GDP per capita but other, more holistic measures. Further, studies like that of Barro and Sala-i-Martin could be improved by relaxing the assumption that the economies being studied are closed, and that no spatial effects are present (see Barro & Sala-i-Martin 2004, p. 461).

1.7 Spatial Methods and the Analysis of Growth in the U.S.

Ordinary panel data models carry with them the implied assumption that the individual entities are isolated or closed from one another, precluding the possibility that the effects or relationships of interest result from processes that involve interaction or spillover. Spatial panel analysis lifts this assumption by allowing for these interactions between “neighbors,” either by including a spatial term in the linear specification of the model or by allowing for spatial and/or temporal autocorrelation in the specification of the error term.
1.7.1 The Neighborhood

The critical question in setting up a spatial model is how to determine who is a “neighbor,” and what weight to give each neighbor. A relatively simple approach, called “contiguity,” is to allow every region which shares a border with a given region to have equal influence. Another form of contiguity is to make the weights equal to the proportion of the region’s border that is shared with each of its adjacent regions. Other constructs are based on the great circle distance between the geographic centers of the regions, such that all regions whose centers are within a set distance of each region are considered its neighbors.

These relationships are expressed in a square matrix C, whose dimensions equal the number of regions, where element \((i, j)\) is equal to one if region \(i\) and \(j\) are neighbors, and zero otherwise. As each region cannot be considered its own neighbor, the diagonal of this matrix contains all zero elements. And since “neighborhood” is a binary relationship (if \(A\) is a neighbor to \(B\), then \(B\) is a neighbor to \(A\); and only two entities are involved at a time), \(C\) is symmetric. It is common to “row-standardize” the matrix \(C\), by dividing each row by its sum, so that each of the rows in the resulting matrix sum to one. The resulting matrix \(W\) is a “spatial weights” matrix that assigns every region its level of impact on every other region. Thus, when \(W\) pre-multiplies any vector or matrix, the result is vector or matrix containing the neighborhood averages of the values in the original vector or matrix. For example, \(Wy\) is a vector that contains in each “row” \(i\) the “average” value of \(y\) among the neighbors of \(i\). Similarly \(WX\) is a matrix containing in each row \(i\) and column \(j\) the “average” value of each \(x_j\) among the neighbors of \(i\).
To get a better grasp of how this process works, let us examine the approach taken by Murdoch & Sandler (2004) in their analysis of the effect of civil war on economic growth. The intention of the authors is to create a variable representing the extent of nearby civil wars. They produce five different weighting schemes: contiguity, length of shared border, and when the great circle distance between the centers of a pair of countries is within 100, 300 or 800 km (p. 141).

Civil war is quantified either as a simple dummy variable indicating the presence or absence of a civil war during the study period or a continuous variable indicating the number of months a civil war has endured. The measures for own-civil-war are simply taken at their levels, but the spatial weights matrices are used to construct measures for the exposure to civil wars in neighboring countries (ibid.). The authors trust that the model with the greatest significance must be the one with the best specification (p. 142). The authors estimate a total several models, being the combinations of the five weighting schemes and the choice between dummy or continuous civil war measures. All of the models include a constant term and explanatory variables suggested in previous studies of GDP growth (p. 344). By this design, the authors isolate the effect they aim to understand.

1.7.2 Spatial Models and Estimation

Regardless of whether cross-sectional or panel data is used there are two prominent spatial frameworks. The first is the spatial autoregressive model:

---

4 It does not make a lot of sense to speak of a spatial time series, because a time series is a set of observations on a single individual/location over time.
which is simply the translation of the (serial) autocorrelation model to a spatial arena, in which values of \( y \) are highly correlated with (and in fact co-determined by) the values of \( y \) in neighboring regions (Anselin & Bera 1998, p. 246-48). The reduced form model \( y = (I - \rho W)^{-1}X\beta + (I - \rho W)^{-1}\epsilon \) is often estimated in a straightforward fashion by maximum likelihood if \( \epsilon \sim N \) (e.g., ibid., p. 255-56).

A second type of model is the spatial error model:

\[
y = X\beta + \epsilon, \quad \epsilon = \lambda W\epsilon + \nu, \quad \nu \sim IID(0, \sigma^2)
\]

in which there are unobserved factors that are spatially autocorrelated (ibid., p. 248-251). The reduced form \( y = X\beta + (I - \lambda W)^{-1}\nu \) can also be easily estimated by maximum likelihood if \( \nu \sim N \) (e.g., ibid., p. 257-58). With a suitable set of instruments, these models may also be estimated by GMM (e.g., ibid., p. 258-60).

A maximum likelihood estimator is not ideal for our relatively small dataset because maximum likelihood is known to be “overfitting,” in the sense of being very sensitive to outliers. We therefore prefer a GMM estimator.

While most GMM estimators are suspect because they assume that the chosen moment conditions hold (without any evidence to suggest they actually do), this estimator uses moment conditions only to assist in estimating the spatial parameters by minimizing the degree to which the moment conditions fail to hold. This estimator, developed by Kapoor, Kelejian & Prucha (2006), allows for the construction of models
with spatially correlated error components and random effects. The data is assumed to be generated in each period \( t \) according to: 
\[ y_N(t) = X_N(t)\beta + u_N(t), \]
where the error term \( u \) is spatially autocorrelated: 
\[ u_N(t) = \rho W_N u_N(t) + \varepsilon_N(t) \]
and the innovations are described by 
\[ \varepsilon_{i,t} = \mu_i + \nu_{i,t}, \]
\( \mu \) being the time-invariant and region-unique random effect term, and \( \nu \) being a well-behaved error term with no remaining spatial or temporal autocorrelation (p. 100). These authors define their GMM-based FGLS estimators for \( \rho \) and the variances \( \sigma^2_{\nu} \) and \( \sigma^2_{\mu} \equiv \sigma^2_{\nu} + T \sigma^2_{\mu} \), and prove their consistency. Most notably, they demonstrate with simulation data that these estimators are just as efficient as the corresponding ML estimators, but are far less computationally complex (p. 115-18). The details of the procedure are laid out in Chapter 3.
Chapter 2

Data

The sources and nature of the data are described, as well as the choice of sample and time period.

2.1 Dependent Variables

The first step in analyzing the distributions of real GSP per capita and the Human Development Index is to construct the measures for all of the U.S. states over a suitable period of time. We have obtained data on real GSP per capita for all 50 states and D.C. from the Bureau of Economic Analysis (2009), for the years 1997 – 2008 under the North American Industry Classification System (NAICS), and for the years 1990 – 1997 under the Standard Industry Classification (SIC). The change in classification should not affect the integrity of the data, conceptually, because it is a change in how the boundaries of an industry are determined, rather than a substantive change that would affect the total product aggregated across all industries within each state.

In order to construct a Human Development Index we must also gather data on the gross enrollment ratio, adult literacy, and life expectancy. For the gross enrollment ratio, we first collected data on the number of pupils enrolled within each state in primary and
secondary education from the National Center for Education Statistics (2008a) for the school years beginning in 1986 to 2006. We then divided these values by the total number of persons aged 5 to 17 as estimated by the U.S. Census Bureau (1995, 2000, 2005a, 2006, 2007a, 2008, 2009a). We have this data for all 50 states and DC.

For adult literacy, limitations on data availability by state led us to choose mean SAT Verbal scores as a proxy. We obtained data for all 50 states and D.C. for the years 1990-2004 from Math Forum (2005) and for the years 2005-2007 from the National Center for Education Statistics (2008b). The SAT Verbal section is graded on a scale from 200 (worst) to 800 (best), and is trusted by most colleges and universities as a highly accurate predictor of a potential student’s English proficiency.

Finally, in place of life expectancy at birth, we may use the age-adjusted death rate. Both statistics were obtained for all 50 states and DC from the National Vital Statistics System of the Centers for Disease Control and Prevention. Life expectancy, though it is the ideal measure as it is the specified variable in the HDI, is available for the states only every ten years. Life expectancy aims to measure how long an individual born in a given year has to live, supposing mortality trends remain the same. The age-adjusted death rate is a value representing the number of the population, out of every 100,000 persons, who die per year, adjusted to account for the age distribution in each state. We have found that, for 2000, life expectancy at birth and the age-adjusted death rate among the 51 regions had a strong negative correlation ($r = -0.96$), and we thus propose that they are interchangeable (as opposites)$^5$.

With this suite of data, we are able to construct an HDI value for each of the 51 regions by the following adjusted formula:

$^5$ See Appendix A for more information on this and other data transformations.
Take note that health is constructed as an inverse of the age-adjusted death rate, so that lower values of AADR (fewer people dying per year, controlling for the age structure of that state) contribute most to the total HDI score and higher values contribute less, and so that the final value is a positive number as we intend. Our choice of goalposts for the U.S. is described in Appendix A.

\[
\begin{align*}
  resource &= \frac{\ln(RealGSPpc) - \ln(20,000)}{\ln(65,000) - \ln(20,000)} \\
  literacy &= \frac{SATV - 350}{650 - 350} \\
  edu &= \frac{1}{3} (literacy) + \frac{2}{3} \left( \frac{enrollment}{pop5to17} \right) \\
  health &= \frac{aaDeathRt - 1200}{550 - 1200} \\
  HDI &= \frac{1}{3} (resource + edu + health)
\end{align*}
\]

2.2 Creating a Consistent Data Set

Once our data was collected, we examined the years of data coverage for the five base variables, while keeping in mind the quality of the data for each year. We narrowed the possibilities down to the years for which we would be able to have observations on all five variables, from which we chose the ten year continuous period with the best data quality. This period turned out to be 1997 – 2006. During this period, some of the measures underwent a change in definition. We analyze these changes in detail and ensure they will not adversely affect our study in Appendix A.

Considering that we also want to perform a spatial analysis, other factors must also be taken into account. First, we must ensure that there are no missing values whatsoever.
Second, as Alaska and Hawaii are not connected to the other states, and do not meet the contiguity standard that we wish to use to create our spatial weights matrix, we chose to exclude them. We also chose to exclude the District of Columbia because of our concerns with heterogeneity. Whenever a researcher works with spatial units of such differing size as the U.S. states, it is unavoidable that certain states will have much larger variance than others simply because their values are of such different magnitudes. Compare, for instance, the level of GSP in California to that of Delaware! Using real GSP per capita lessens this difficulty somewhat, but we judged that whatever explanatory power including DC may offer was outweighed by the chance of exacerbating heterogeneity.

2.3 Explanatory Variables

We included data on several measures that we did not expect to truly explain the movements in real GSP per capita or HDI, but that would be sufficient to control for the factors that are a part of the true data generating process.

A variable well known to be strongly associated with production, and thus real GSP per capita, is the size of the labor force. We have two seasonally-adjusted measures. The first is the full civilian labor force, in thousands of persons, on a monthly basis (BLS 2010). The second is the civilian non-farm labor force, in thousands of persons, also on a monthly basis (ibid.). For both variables, the yearly average of these monthly values is used.

In order to predict changes in quality of health, we included data on the percentage of people in each state who have health insurance (U.S. Census Bureau 2007b). Data on this variable was only available from 1999-2006, so we linearly interpolated it backwards.
assuming that the values of the first two years differed from each other by the average yearly change across the period in which data was available. The coefficients on health coverage found in our regressions should thus be regarded with caution.

One aspect of the quality of life that is held in high regard in the United States is access to housing, particularly owning a home. We have collected several measures intended to pick up on these affects in the U.S. states. One measure is the house price index (FHFA 2010), which measures the value of the homes being sold (and thus presumably of the whole housing stock) relative to 1980 Quarter 1, which is given the value 100 (Calhoun 1996, p. 12). As this data is given quarterly, and we wanted only annual values, we simply averaged the values over the four quarters of each year for each state. Another measure is the home vacancy rate (U.S. Census Bureau 2009b), which measures the percentage of houses that are vacant at a given time. This data is a yearly average. A similar measure is the rental vacancy rate (ibid.), which is the percentage of rental units that are vacant on average during the year. Another factor in the availability of housing is how many new houses are being constructed. The number of new private housing units authorized by building permits was obtained on a monthly basis (U.S. Census Bureau 2010), and then averaged over each year. A final determinant is the homeownership rate, which expresses what proportion of the population owns a home (U.S. Census Bureau 2005b).

Finally, a suite of relevant variables on state spending were obtained (Ajilore 2005). These measures include per capita spending on education, public welfare, hospitals, health, highways, police, corrections, natural resources, and parks and recreation. The data also include population density, the Gini coefficient, unemployment rate, state debt,
federal aid received by each state and several demographic characteristics such as the proportion of the population who are elderly, the total number of immigrants, the political ideology of both the citizenry and the sitting legislators, and the proportions who identify as White (always excluded), Black, Asian, Hispanic and Native American.

2.4. Correlations and Descriptive Statistics

The following table lists the variables by their code name, provides a description of each, and lists the mean, standard deviation, minimum and maximum value for each one. Every variable listed has 432 observations, one for each year 1997-2006 in each of the 48 states. Only nine years end up being used in any regression because the first difference of the variable to be explained is taken as the dependent variable, and its lag is included on the right-hand side. Thus, only 1998-2006 is completely free from missing values.
Table 2.1: Descriptive Statistics for all the Variables within the Sample of 48 States and 9 Years, including their Mean, Standard Deviation, Minimum and Maximum Values (n = 432)

<table>
<thead>
<tr>
<th>Code</th>
<th>Name</th>
<th>Description</th>
<th>Descriptive Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>lngsp</td>
<td>ln(real GSP per capita)</td>
<td></td>
<td>10.40239</td>
</tr>
<tr>
<td>hdi</td>
<td>Human Development Index</td>
<td></td>
<td>0.5679051</td>
</tr>
<tr>
<td>hdi_1</td>
<td>HDI Health Component</td>
<td></td>
<td>0.5567941</td>
</tr>
<tr>
<td>hdi_2</td>
<td>HDI Education Component</td>
<td></td>
<td>0.7236436</td>
</tr>
<tr>
<td>hdi_3</td>
<td>HDI Literacy Component</td>
<td></td>
<td>0.6192438</td>
</tr>
<tr>
<td>hdi_4</td>
<td>HDI Resource Component</td>
<td></td>
<td>0.4232777</td>
</tr>
<tr>
<td>citi6006</td>
<td>Citizens’ Political Ideology</td>
<td></td>
<td>49.68072</td>
</tr>
<tr>
<td>death</td>
<td>Age-adjusted Death Rate</td>
<td></td>
<td>838.0838</td>
</tr>
<tr>
<td>debt</td>
<td>State Debt</td>
<td></td>
<td>2496.859</td>
</tr>
<tr>
<td>fedaid</td>
<td>Aid from Federal Govt.</td>
<td></td>
<td>1221.361</td>
</tr>
<tr>
<td>ger</td>
<td>Gross Enrollment Ratio</td>
<td></td>
<td>0.7758435</td>
</tr>
<tr>
<td>gini</td>
<td>Gini Coefficient</td>
<td></td>
<td>0.3880787</td>
</tr>
<tr>
<td>hcover</td>
<td>Health Coverage Rate</td>
<td></td>
<td>86.66301</td>
</tr>
<tr>
<td>home</td>
<td>Homeownership Rate</td>
<td></td>
<td>70.32222</td>
</tr>
<tr>
<td>house</td>
<td>House Price Index</td>
<td></td>
<td>272.0356</td>
</tr>
<tr>
<td>house</td>
<td>House Vacancy Rate</td>
<td></td>
<td>1.779861</td>
</tr>
<tr>
<td>immig</td>
<td>New Immigrants</td>
<td></td>
<td>18893.27</td>
</tr>
<tr>
<td>inst</td>
<td>Sitting Legislators’ Political Ideology</td>
<td></td>
<td>45.95806</td>
</tr>
<tr>
<td>new</td>
<td>New Housing Units</td>
<td></td>
<td>3040.221</td>
</tr>
<tr>
<td>housing</td>
<td>Non Farm Labor Force (1000s)</td>
<td></td>
<td>2696.321</td>
</tr>
<tr>
<td>pscrct</td>
<td>Per cap. Spending on Corrections</td>
<td></td>
<td>0.1247772</td>
</tr>
</tbody>
</table>

continued on the following page
Table 2.1 (Continued): Descriptive Statistics for all the Variables within the Sample of 48 States and 9 Years, including their Mean, Standard Deviation, Minimum and Maximum Values (n = 432)

<table>
<thead>
<tr>
<th>Code</th>
<th>Name</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>psedu</td>
<td>Per cap. Spending on Education</td>
<td></td>
<td>1.396503</td>
<td>0.3316847</td>
<td>0.05752931</td>
<td>3.247636</td>
</tr>
<tr>
<td>pshlth</td>
<td>Per cap. Spending on Health</td>
<td></td>
<td>0.1486671</td>
<td>0.0689761</td>
<td>0.0405114</td>
<td>0.3911651</td>
</tr>
<tr>
<td>pshwy</td>
<td>Per cap. Spending on Highway</td>
<td></td>
<td>0.3389421</td>
<td>0.1174767</td>
<td>0.1004703</td>
<td>0.8809827</td>
</tr>
<tr>
<td>pshosp</td>
<td>Per cap. Spending on Hospitals</td>
<td></td>
<td>0.1213412</td>
<td>0.0876152</td>
<td>0</td>
<td>0.4110853</td>
</tr>
<tr>
<td>psnatr</td>
<td>Per cap. Spending on Natural Resources</td>
<td></td>
<td>0.0767869</td>
<td>0.054538</td>
<td>0.0180806</td>
<td>0.4183812</td>
</tr>
<tr>
<td>pspark</td>
<td>Per cap. Spending on Parks &amp; Recreation</td>
<td></td>
<td>0.0209304</td>
<td>0.014104</td>
<td>0.0017939</td>
<td>0.0750648</td>
</tr>
<tr>
<td>pspolice</td>
<td>Per cap. Spending on Police</td>
<td></td>
<td>0.0390753</td>
<td>0.0184836</td>
<td>0.0080351</td>
<td>0.1429111</td>
</tr>
<tr>
<td>pspwel</td>
<td>Per cap. Spending on Public Welfare</td>
<td></td>
<td>0.9627207</td>
<td>0.3260777</td>
<td>0.2639574</td>
<td>2.265729</td>
</tr>
<tr>
<td>rentvac</td>
<td>Rental Vacancy Rate</td>
<td></td>
<td>9.326852</td>
<td>3.05534</td>
<td>3.2</td>
<td>18.1</td>
</tr>
<tr>
<td>sat</td>
<td>Average SAT Verbal Scores</td>
<td></td>
<td>535.7731</td>
<td>33.8092</td>
<td>466</td>
<td>610</td>
</tr>
<tr>
<td>unemp</td>
<td>Unemployment Rate</td>
<td></td>
<td>0.0472222</td>
<td>0.0113851</td>
<td>0.02</td>
<td>0.08</td>
</tr>
<tr>
<td>elderly</td>
<td>% Pop. = elderly</td>
<td></td>
<td>0.1265</td>
<td>0.0158</td>
<td>0.0900</td>
<td>0.1800</td>
</tr>
<tr>
<td>asian</td>
<td>% Pop. = Asian</td>
<td></td>
<td>0.0269444</td>
<td>0.0312228</td>
<td>0</td>
<td>0.49</td>
</tr>
<tr>
<td>black</td>
<td>% Pop. = Black</td>
<td></td>
<td>0.1143287</td>
<td>0.1176826</td>
<td>0</td>
<td>0.62</td>
</tr>
<tr>
<td>hispanic</td>
<td>% Pop. = Hispanic</td>
<td></td>
<td>0.0901852</td>
<td>0.0940847</td>
<td>0.01</td>
<td>0.45</td>
</tr>
<tr>
<td>native</td>
<td>% Pop. = Native American</td>
<td></td>
<td>0.0139815</td>
<td>0.0232784</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>white</td>
<td>% Pop. = White</td>
<td></td>
<td>.7586111</td>
<td>0.149222</td>
<td>0.25</td>
<td>0.98</td>
</tr>
<tr>
<td>year</td>
<td>Year</td>
<td></td>
<td>2003</td>
<td>2.584983</td>
<td>1998</td>
<td>2006</td>
</tr>
</tbody>
</table>

The following table displays the correlations between the variables using the 432 observations summarized above.
Table 2.2: Correlations between all Variables within the Sample of 48 States and 9 Years (n = 432)

<table>
<thead>
<tr>
<th>Variable</th>
<th>lnspp</th>
<th>hdi</th>
<th>hdihealth</th>
<th>hdi_educ</th>
<th>hdi_lit</th>
<th>hdi_resource</th>
<th>6006</th>
<th>death</th>
<th>debt</th>
</tr>
</thead>
<tbody>
<tr>
<td>hdi</td>
<td>0.652</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>hdihealth</td>
<td>0.441</td>
<td>0.708</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>hdi_educ</td>
<td>-0.329</td>
<td>0.322</td>
<td>-0.194</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>hdi_lit</td>
<td>-0.284</td>
<td>-0.046</td>
<td>-0.104</td>
<td>0.2949</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>hdi_resource</td>
<td>1.000</td>
<td>0.652</td>
<td>0.441</td>
<td>-0.329</td>
<td>-0.284</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>citi6006</td>
<td>0.372</td>
<td>0.281</td>
<td>0.365</td>
<td>-0.240</td>
<td>-0.372</td>
<td>0.372</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>death</td>
<td>-0.441</td>
<td>-0.708</td>
<td>-1.000</td>
<td>0.194</td>
<td>0.104</td>
<td>-0.441</td>
<td>-0.365</td>
<td></td>
<td></td>
</tr>
<tr>
<td>debt</td>
<td>0.358</td>
<td>0.172</td>
<td>0.264</td>
<td>-0.310</td>
<td>-0.214</td>
<td>0.358</td>
<td>0.407</td>
<td>-0.264</td>
<td></td>
</tr>
<tr>
<td>fedaid</td>
<td>-0.023</td>
<td>-0.113</td>
<td>0.056</td>
<td>-0.207</td>
<td>0.048</td>
<td>-0.023</td>
<td>0.1191</td>
<td>-0.056</td>
<td>0.1769</td>
</tr>
<tr>
<td>ger</td>
<td>-0.271</td>
<td>0.348</td>
<td>-0.176</td>
<td>0.970</td>
<td>0.053</td>
<td>-0.271</td>
<td>-0.155</td>
<td>0.1764</td>
<td>-0.269</td>
</tr>
<tr>
<td>gini</td>
<td>0.201</td>
<td>-0.173</td>
<td>0.163</td>
<td>-0.613</td>
<td>-0.109</td>
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48 States and 9 Years
Table 2.2 (Continued): Correlations between all Variables within the Sample of 48 States and 9 Years (n = 432)

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continued below
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Table 2.2 (Continued): Correlations between all Variables within the Sample of 48 States and 9 Years (n = 432)

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Chapter 3

Methodology and Results

Three different model specifications are examined and the quality of the results are compared using Moran’s I to test for remaining spatial autocorrelation in the residuals.

3.1 Convergence in GSP and HDI

The primary question we wish to explore is whether there is convergence among the U.S. states in the levels of real GSP per capita and the Human Development Index. Following Barro and Sala-i-Martin (2004), we seek to estimate the equation

\[
\ln \frac{y_{i,t}}{y_{i,t-1}} = \alpha - (1 - e^{-\beta})y_{i,t-1} + X\gamma + \varepsilon
\]

where \( y \) is the dependent variable, either real GSP per capita or the HDI, \( \alpha \) is the constant term, \( \beta \) is the growth rate of the dependent variable, \( X \) is an NTx(K–1) matrix of explanatory and control variables, each associated with a coefficient in the (K–1)x1 vector \( \gamma \), and \( \varepsilon \) is the NTx1 vector of I.I.D. residuals. Here, \( N \) is the number of regions in the study, \( T \) the total number of time periods and \( K \) is the number of regressors, including
the constant term. If $\beta$ is significant and positive, there is evidence of convergence; if it is significant and negative, divergence is present; if it is insignificant, then the distribution of the variable in question is stable (Barro & Sala-i-Martin 2004, p. 355 ff.).

As we wish to explain a process we believe to be spatial in nature, we will provide a test of remaining spatial autocorrelation in the residuals with each regression. The most commonly used test for the final residuals $\varepsilon^*$ given a row-standardized spatial weights matrix is Moran’s I, which is given by $\frac{\varepsilon^*W\varepsilon^*}{\varepsilon^*\varepsilon^*}$, has expectation $E(I) = \left[\frac{tr(MW)}{NT-K}\right]$ and variance

$$Var(I) = \frac{tr(MWMW') + tr(MW)^2 + [tr(MW)]^2}{(NT-K)(NT-K+2)} - [E(I)]^2$$

where $M = I - X^*(X^*X^*)^{-1}X^{*'}$. It is common to test for spatial autocorrelation by transforming the Moran’s I test statistic into a z-statistic. Spatial autocorrelation is said to be present when $tcdf\left(\frac{|I - E(I)|}{\sqrt{Var(I)}}, n-1\right) > (1 - \alpha)\%$, where $\alpha$ is the tolerable probability of Type I error and $n$ is the size of the sample, here $n = N$ (Anselin & Bera 1998, p. 266-67). Rather than performing such a test for each year separately, we can test Moran’s I in all ten years jointly using the fact that the sum of the squares of $p$ independent, normally distributed variables is $\chi^2$ distributed with $p$ degrees of freedom.

We will also include the Akaike Information Criterion$^6$ for each regression as a measure of its explanatory power and parsimony.

This growth model can be estimated for both real GSP per capita and HDI using Non-linear least squares. Regressions were chosen that minimized root MSE.

$^6 AIC = 2K + NT\ln((\varepsilon^*\varepsilon^*)/NT)$ where $\varepsilon^* = y^* - X^*\beta$. 
Table 3.1: Non-Linear Least Squares Regression of the Change in Real GSP per Capita and the Human Development Index on the Explanatory Variables (n = 432)

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<td>0.0238</td>
<td></td>
</tr>
<tr>
<td>pshighway</td>
<td>0.0814***</td>
<td>0.0457*</td>
</tr>
<tr>
<td>pshospital</td>
<td>0.0371**</td>
<td></td>
</tr>
<tr>
<td>pspolice</td>
<td>0.1566**</td>
<td>-0.0045</td>
</tr>
<tr>
<td>pspubwel</td>
<td>0.0151</td>
<td></td>
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<tr>
<td>psnatres</td>
<td>-0.0347</td>
<td></td>
</tr>
<tr>
<td>pspark</td>
<td>0.3715**</td>
<td></td>
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<tr>
<td>elderly</td>
<td>-0.0341</td>
<td>-0.4621***</td>
</tr>
<tr>
<td>inst6006</td>
<td>-0.0001</td>
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</tr>
<tr>
<td>asian</td>
<td>-0.0459</td>
<td>0.0170</td>
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<tr>
<td>black</td>
<td>-0.0024</td>
<td>-0.0560**</td>
</tr>
<tr>
<td>hispanic</td>
<td>-0.0230</td>
<td>0.0431</td>
</tr>
<tr>
<td>native</td>
<td>0.0973**</td>
<td>-0.0219</td>
</tr>
</tbody>
</table>

R²                | 0.2310         | 0.3092     |
Root MSE          | 0.01734        | 0.03556    |
AIC               | -3488.70       | -2856.50   |

Joint Moran’s I Test | χ² statistic | P-value | χ² statistic | P-value |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10.8744</td>
<td>0.2844</td>
<td>15.5383*</td>
<td>0.0772</td>
</tr>
</tbody>
</table>

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

In this model, real GSP per capita is found to be stationary, and HDI is found to be converging at 33% per year. In the model for GSP, per capita police spending (0.1566) and the proportion of the population that is Native American (0.0973) are found to have
large, positive effects. The change in non-farm labor has a significant, positive small effect (0.0001). The age-adjusted death rate has a negative effect (−0.0000), as does the Gini coefficient (−0.0617), which implies that income equality within the state speeds up the convergence between states.

In the model for HDI, per capita spending on parks and recreation has a strong positive effect (0.3715), as does per capita spending on highways (0.0814). The house price index (0.0001), which measures the value of existing homes, the quantity of new housing being built (0.0000) and the home vacancy rate (0.0083), which measures how many homes are currently unoccupied and presumably available, all contribute positively to HDI growth. The homeownership rate, on the contrary, is negatively related (−0.0014). Income equality within the state also improves HDI growth (gini: −0.5613). The proportions of the population that are elderly (−0.4621) and black (−0.0560) are negatively related to growth, perhaps demonstrating some ongoing prejudice against those groups.

There are a number of issues with this model. The first is that it is forced to estimate the presence or absence of absolute convergence, when conditional convergence may be more likely. We should not split the regions up into their potential “convergence clubs” prior to estimation because this would be a function of the data and introduce endogeneity and bias.

One intermediate step that would allow for variation between the different states is to estimate a random effects panel model. In general, a random effects model posits that

\[ y_{i,t} = \alpha + \mu_i + \mathbf{x}'_{i,t}\gamma + \epsilon_{i,t} \]
in which the N \( \mu \) terms are unique to each region and do not vary over time. This amounts to there being a (potentially) unique intercept for each region, although as a practical matter \( \mu \) is often grouped together with the well-behaved error term \( \varepsilon \). The random effects estimates are presented in Table 3.2.

The random effects models, as shown by the 95% confidence intervals around \( \beta \) in Table 3.2, find convergence in both real GSP per capita and the Human Development Index: the former at about 2% per year, and the latter at 34% per year.

In the GSP regression, the unemployment rate (–0.2177) and the Gini coefficient (–0.0753) have strong, negative impacts on the growth of GSP. The age-adjusted death rate (–0.0000) and the homeownership rate (–0.0007) also have small, negative impacts. The change in the non-farm labor force (0.0001) and per capita spending on public welfare (0.0082) both have positive impacts on the GSP growth rate.

In the HDI regression, income inequality harms HDI growth (gini: –0.5627), and the homeownership rate (–0.0014), and the proportions of the population that are elderly (–0.4618) and black (–0.0604) are negatively related to HDI growth. Several factors are found to have a positive impact on HDI growth: the house price index (0.0001), the home vacancy rate (0.0109), and the quantity of new housing being built (0.0000). Also, per capita spending on highways (0.0.0714) and on parks and recreation (0.3663) significantly improve the HDI growth rate.
Table 3.2: Random Effects Panel Regression of the Change in Real GSP per capita and the Human Development Index on Explanatory Variables (n = 432)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Random-Effects (GLS) Estimates</th>
<th>95% Conf. Interval</th>
<th>95% Conf. Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δln(GSP)</td>
<td>ΔHDI</td>
<td></td>
</tr>
<tr>
<td>α</td>
<td>0.3601***</td>
<td>0.3418***</td>
<td></td>
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<tr>
<td>y_{t-1}</td>
<td>-0.0192**</td>
<td>-0.2909***</td>
<td></td>
</tr>
<tr>
<td>death</td>
<td>-0.0000***</td>
<td></td>
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</tr>
<tr>
<td>debt</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>gini</td>
<td>-0.0753***</td>
<td>-0.5627***</td>
<td></td>
</tr>
<tr>
<td>hcoverage</td>
<td>-0.0005</td>
<td>0.0013</td>
<td></td>
</tr>
<tr>
<td>homeowner</td>
<td>-0.0007***</td>
<td>-0.0014***</td>
<td></td>
</tr>
<tr>
<td>houseprice</td>
<td></td>
<td>0.0001***</td>
<td></td>
</tr>
<tr>
<td>housevac</td>
<td></td>
<td>0.0109***</td>
<td></td>
</tr>
<tr>
<td>newhousing</td>
<td>0.0000</td>
<td>0.0000**</td>
<td></td>
</tr>
<tr>
<td>Δnonfarmlabor</td>
<td>0.0001***</td>
<td>-0.0000</td>
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<td>-0.0715</td>
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<td>0.0160</td>
<td></td>
</tr>
<tr>
<td>pshighway</td>
<td>0.0193</td>
<td>0.0714**</td>
<td></td>
</tr>
<tr>
<td>pshospital</td>
<td>0.0134</td>
<td>0.0445*</td>
<td></td>
</tr>
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<td>-0.0755</td>
<td></td>
</tr>
<tr>
<td>psplakes</td>
<td>0.0551</td>
<td>0.3663**</td>
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</tr>
<tr>
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<td></td>
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<tr>
<td>pspubwel</td>
<td>0.0082**</td>
<td>0.0081</td>
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<td>inst6006</td>
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<td>immig</td>
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<tr>
<td>elderly</td>
<td>-0.1015</td>
<td>-0.4618***</td>
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<tr>
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<td>-0.0604***</td>
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<td>hispanic</td>
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<td>0.0423</td>
<td></td>
</tr>
<tr>
<td>native</td>
<td>0.0820</td>
<td>-0.0206</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>β</th>
<th>95% Conf. Interval</th>
<th>95% Conf. Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>within</td>
<td>between</td>
</tr>
<tr>
<td></td>
<td>within</td>
<td>between</td>
</tr>
<tr>
<td>β</td>
<td>0.01937</td>
<td>0.001636</td>
</tr>
<tr>
<td>R²</td>
<td>0.2112</td>
<td>0.6167</td>
</tr>
<tr>
<td>AIC</td>
<td>-3481.80</td>
<td>-2851.90</td>
</tr>
</tbody>
</table>

Joint Moran’s I Test: χ² statistic = 9.8427, P-value = 0.3634

χ² statistic = 16.8152, P-value = 0.0517

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.
Moving from the non-linear to the random effects model does not change the magnitude or significance of any of the explanatory variables in the HDI regressions very much at all. The significance and magnitude of some coefficients in the GSP regressions do change for certain variables. In the non-linear model, we excluded per capita spending on public welfare because it was never significant, but in the random effects model it is significant. Per capita spending on police and the proportion of the population who are Native American lose their significance in moving from the non-linear to the random effects model. Finally, the unemployment rate and homeownership rate are significant in the random effects model, where they had not been in the non-linear model.

It is interesting to note that in both random effects models, the random effects variance, $\sigma^2_\mu$, which measures the variance of the terms $\mu$, is zero. This means that all of the $N$ terms $\mu$ are equal to zero, and that there are no meaningful differences in intercepts between the states. This implies that there are no unique unobserved elements of any state that would prevent it from fully enjoying or participating in the process of convergence, divergence or stationarity experienced by the nation as a whole. In this context, this finding also lends support to the belief that absolute convergence among the U.S. states is reasonable, because all of them are following the same process.

Therefore, at least from the viewpoint of this model, there is absolute convergence in both real GSP per capita and the Human Development Index during this time period.

### 3.2 Spatial Analysis

The primary assumption maintained by both of the previous models is that there were no interactions between regions until convergence began, and that spontaneously, without
identifying any mechanism, convergence begins to work on the regions like gravity, pulling them all in towards a common steady state. This assumption implies that a spatial effect arises without an underlying spatial process. We can correct this by identifying an appropriate spatial model as the true data generating process.

As estimators for nonlinear spatial models are quite uncommon, we cannot directly estimate $\beta$ in the ideal model of:

$$
\ln \left( \frac{y_{i,t}}{y_{i,t-1}} \right) = \alpha - (1 - e^{-\beta}) \ln(y_{i,t-1}) + X_t \gamma + u_{i,t}
$$

$$
u_{i,t} = \rho W u_{i,t} + \epsilon_{i,t}
$$

$$
\epsilon_{i,t} = \mu_i + \nu_{i,t}
$$

where $\mu$ is a random-effects term $\sim N(0, \sigma_\mu^2)$, unique to each region and not varying over time; $\nu$ is a well-behaved error term $\sim N(0, \sigma_\nu^2)$; $\rho$ is the spatial coefficient; $W$ is an NxN spatial weights matrix; and the other variables are as previously defined. Yet as $\beta$ is the only “non-linear” term and appears only once as a component of a linear coefficient, the use of non-linear methods is convenient but not necessary.

So, when we utilize a method that does not have non-linear support, we can simply transform the point estimate and its confidence interval to obtain an estimate of $\beta$ and determine whether it is statistically significant. We thus estimate the model:

---

7 It is also acceptable for $\mu$ and $\nu$ to be independently and identically distributed, with their own parameters.
The coefficient $b$ in this model is the “marginal effect” of the previous period’s log level of the dependent variable on the change in the dependent variable. Earlier studies on convergence assumed that a negative $b$ was evidence of convergence. However, because of the nonlinear transformation that bridges $b$ and $\beta$, the significance of $b$ does not guarantee that $\beta$ is significantly different from zero.

This nonlinear transformation is derived as follows:

\[
\begin{align*}
    &b = -(1 - e^{-\beta}) \\
    &-b = (1 - e^{-\beta}) \\
    &-b - 1 = -e^{-\beta} \\
    &1 + b = e^{-\beta} \\
    &\ln(1 + b) = -\beta \\
    &\beta = -\ln(1 + b)
\end{align*}
\]

We also demonstrate that $b$ and $\beta$ always have the opposite sign:

\[
\begin{align*}
    -(1 - e^{-\beta}) &= b > 0 \\
    (1 - e^{-\beta}) &= -b < 0 \\
    -e^{-\beta} &= -b - 1 < -1 \\
    e^{-\beta} &= 1 + b > 1 \\
    -\beta &= \ln(1 + b) > \ln(1) = 0
\end{align*}
\]
\[ \beta = -\ln(1 + b) < 0 \]

It is intuitively obvious that if \( b < 0 \), \( \beta > 0 \), by simply switching the direction of the inequalities above\(^8\). It should also be evident that if \( b = 0 \), \( \beta = 0 \) as well.

To construct confidence intervals around \( \beta \) to determine its significance, we follow a procedure as follows. First, we use the standard error of the estimate of \( b \) to construct a confidence interval for \( b \): \([\hat{b} \pm 1.9659 \times \text{se}]\). This lower and upper bound is then transformed in the same way as the point estimate to define a confidence interval for \( \beta \).

We will use the FGLS procedure proposed by Kapoor, Kelejian and Prucha (2006) to estimate the model in Equation (11). This procedure has three steps. In the first step, the initial estimates \( \hat{\rho}, \hat{\sigma}_v^2 \) are obtained using only the first three of the six moment conditions. The initial estimate \( \hat{\sigma}_I^2 \) is then just a function of \( \hat{\rho} \) (p. 103-07). Two different estimators are provided for the second step, the first being the most accurate and the second being far easier to compute. We have chosen to use the second method, which first uses the initial estimators to arrive at a consistent estimate of the appropriate variance-covariance matrix \( \Sigma \), and then obtains the weighted estimates \( \hat{\rho}, \hat{\sigma}_v^2, \hat{\sigma}_I^2 \) using all six moment conditions (p. 109-10). Finally, the weighted estimates are used to create the spatially-filtered variables \( X^* = \left[ I_T \otimes (I_N - \hat{\rho}W) \right] X \) and \( y^* = \left[ I_T \otimes (I_N - \hat{\rho}W) \right] y \). The authors find\(^9\) that \( \Omega^{-1}_e = \Omega^{-1/2}_e \Omega^{-1/2}_e \) where \( \Omega^{-1/2}_e = \hat{\sigma}_v^{-1} Q_0 + \hat{\sigma}_I^{-1} Q_1 \), and use this information to construct the feasible generalized least squares estimator of the model coefficients:

\[ \hat{\beta}_{FGLS} = (X^{*\prime} \Omega^{-1}_e X^*)^{-1} X^{*\prime} \Omega^{-1}_e y^* \]. Small sample inference on these coefficients may be

---

\(^8\) In general, \( b \) should be less than one in absolute value, as otherwise the process would exhibit a unit root. This allows \( \ln(1+b) \) to be calculated when \( b \) is negative, because \( 1+b \) is still greater than zero.

\(^9\) The authors have previously defined the Q matrices. \( Q_0 = \left( I_T - \frac{I_T}{T} \right) \otimes I_N \) and \( Q_1 = \frac{I_T}{T} \otimes I_N \) where \( J_T \) is a \( T \times T \) matrix of ones (101).
based off of the approximation $\hat{\beta}_{FLGS} \sim N \left( \beta, \left( NT^{-1} \Psi \right) \right)$ where $\Psi = \left\{ \frac{1}{NT} \hat{X}^{*} \hat{\Omega}_{e}^{-1} \hat{X}^{*} \right\}^{-1}$ (p. 110-11).

We implemented this procedure in MATLAB 7.6.0, and created a well-organized text-based GUI in which to display the results. Our implementation calculated t-statistics as $\frac{\hat{\beta}_{FLGS}}{SE(\hat{\beta}_{FLGS})} \sim t(NT - K)$ and obtained P-values from the same Student’s $t$ distribution. Our implementation calculated 95% confidence intervals as $\hat{\beta}_{FLGS} \pm t_{0.975, NT-K} SE(\hat{\beta}_{FLGS})$ where $t_{0.975, NT-K}$ is the two-sided critical value from the same $t$ distribution. We use the AIC to select the best regressions\(^{10}\). The GMM estimates are presented in Table 3.3.

For real GSP per capita, we find no evidence of convergence or divergence. We do however find many interesting relationships between GSP and the explanatory variables. Of the variables whose coefficients are significant at the 5% level or higher, the unemployment rate (−0.1758) and per capita state spending on police (0.1344) have the strongest effects. Interestingly, the homeownership rate has a negative relationship with GSP (−0.0005), and the proportion of the population that is Native American is positively related (0.0810). The age-adjusted death rate has a small, significant impact. The change in non-farm labor participation has a significant, positive effect.

\(^{10}\) Note that the variable “elderly” was excluded from all spatial models, because it was found that variables that vary in only one of the time- or region-dimensions tend to result in $X^{*} \hat{\Omega}_{e}^{-1} X^{*}$ being nearly singular.
Table 3.3: GMM-Based Feasible Generalized Least Squares Regression of Real GSP per capita and the Human Development Index on Explanatory Variables (n = 432)

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\Delta \ln(GSP)$</th>
<th>$\Delta \text{HDI}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.2817***</td>
<td>0.2975***</td>
</tr>
<tr>
<td>$y_{t-1}$</td>
<td>-0.0141**</td>
<td>-0.1989***</td>
</tr>
<tr>
<td>death</td>
<td>-0.0000***</td>
<td></td>
</tr>
<tr>
<td>debt</td>
<td></td>
<td>0.0000*</td>
</tr>
<tr>
<td>ger</td>
<td>0.0063</td>
<td></td>
</tr>
<tr>
<td>sat</td>
<td>0.0000</td>
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</tr>
<tr>
<td>gini</td>
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<td>-0.3961</td>
</tr>
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<td>hcoverage</td>
<td>-0.0006*</td>
<td>-0.0001</td>
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<tr>
<td>homeowner</td>
<td>-0.0005**</td>
<td>-0.0011***</td>
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<tr>
<td>houseprice</td>
<td></td>
<td>0.0001***</td>
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<tr>
<td>housevac</td>
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<td>0.0080***</td>
</tr>
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<td>rentvac</td>
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<td>-0.0019**</td>
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<td>newhousing</td>
<td>-0.0000</td>
<td>0.0000***</td>
</tr>
<tr>
<td>$\Delta \text{nonfarmlabor}$</td>
<td>0.0001***</td>
<td>-0.0001***</td>
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<td>unemp</td>
<td>-0.1758**</td>
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<td>0.0018</td>
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<td>pshighway</td>
<td>0.017</td>
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<td>-0.0001</td>
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<td>black</td>
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<td>-0.0535***</td>
</tr>
<tr>
<td>hispanic</td>
<td>-0.0225*</td>
<td></td>
</tr>
<tr>
<td>native</td>
<td>0.0810**</td>
<td>-0.0349</td>
</tr>
</tbody>
</table>

| $\rho$ | -0.11114*** | 0.33318*** |
|        |            | (6.7727)   | (9.8436)  |
| $\sigma_v^2$ | 0.00028 | 0.00093  |
| $\sigma_1^2$ | 0.00028 | 0.00326  |
| $\sigma_a^2 = (\sigma_1^2 - \sigma_v^2)/T$ | 0.0000 | 0.0014  |

| $\beta$ | 0.014166 | 0.014166 |
|         | -0.00159 | 0.03018  |
| $R^2$   | 0.2491   | 0.2672   |
| AIC     | -3491.759 | -2852.360 |

Joint Moran’s I Test

<table>
<thead>
<tr>
<th>$\chi^2$ statistic</th>
<th>P-value</th>
<th>$\chi^2$ statistic</th>
<th>P-value</th>
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<td>11.8519</td>
<td>0.2218</td>
<td>14.5453</td>
<td>0.1042</td>
</tr>
</tbody>
</table>

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

The significance of $\rho$ was tested with an F-test between the full model and a constrained model in which $\rho = 0$, the F-statistics of which are listed below the estimates of $\rho$ in parentheses.
For the HDI, we find evidence of convergence, at a rate of about 22% per year. The significant coefficients with the strongest effects are per capita state spending on natural resources (−0.1223) and on parks and recreation (0.3021). The home vacancy rate is positively related (0.0080) and the homeownership rate is negatively related (−0.0011) to growth; however the rental vacancy rate is negatively related (−0.0019). As we might expect, the home price index (0.0001) and the number of new housing units (0.0000) are positively related to growth. Interestingly, the change in non-farm labor participation (−0.0001) and the proportion of the population that is black (−0.0535) are negatively related to growth.

There are several interesting changes in the magnitude and significance of the coefficients in the spatial error model compared to the earlier two models. In the models for GSP, per capita spending on police, and the proportion of the population that is Native American are both significant but have a lesser magnitude than in the non-linear estimation. Per capita spending on public welfare is no longer significant, while per capita spending on parks has an effect similar to that found in the random effects estimation. Here, the Gini coefficient is not significant, meaning that income inequality does not affect the growth of GSP. The coefficients on the house price index, home vacancy rate, and new housing are similar to what was estimated earlier.

In the HDI regressions, the coefficients on homeownership, home vacancy rate, and proportion of the population that is black are quite similar. We find here for the first time that per capita spending on natural resources and the rental vacancy rate have a significant, negative impact on HDI growth.
For both regressions, we find no remaining spatial autocorrelation in the residuals. Though none of the previous models had any remaining spatial autocorrelation at the 5% level, they did often have remaining spatial autocorrelation at the 10% level for HDI. By introducing a way for the spatial relationships at play to be expressed within the model, we ensured that all the spatial variation in the data was able to be explained. This finding provides strong evidence that the spatial effects we have found are very meaningful, and that controlling for them has supplied us with a much more accurate model.

3.3 Investigation into the Components of HDI

Now that we have found convergence in HDI over the time period of our study, it is interesting to investigate to what degree each of the components of HDI are converging or diverging in the same period. We present only the growth rate estimates from spatial error model regressions for each of the four variables that make up the HDI. We also report the results from regressions including year dummies. We identified appropriate year dummies by evaluating Moran’s I for the residuals of each year separately. We then considered models that included each of the following formations of year dummies: (a) the years with remaining spatial autocorrelation, (b) the years without remaining spatial autocorrelation, (c) the years immediately prior to years with remaining spatial autocorrelation, or (d) the years immediately after the years with remaining spatial autocorrelation. Only the formation with the greatest significance is included in the table below.
Table 3.4: Estimates of the Growth Rate and the Presence of Convergence for Each of the Components of the Human Development Index (n = 432)

<table>
<thead>
<tr>
<th>Component</th>
<th>β</th>
<th>ρ</th>
<th>R²</th>
<th>AIC</th>
<th>Joint Moran’s I (χ²-statistic)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>without year dummies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.5476**</td>
<td>0.3328***</td>
<td>0.3964</td>
<td>-2138.93</td>
<td>13.9914</td>
</tr>
<tr>
<td>Literacy</td>
<td>0.1375**</td>
<td>0.1112</td>
<td>0.0689</td>
<td>-2584.05</td>
<td>4.8253</td>
</tr>
<tr>
<td>Health</td>
<td>0.3008**</td>
<td>0.3332***</td>
<td>0.3398</td>
<td>-2481.32</td>
<td>12.9641</td>
</tr>
<tr>
<td>Resources</td>
<td>0.0122</td>
<td>-0.1111**</td>
<td>0.2239</td>
<td>-3637.53</td>
<td>10.8138</td>
</tr>
<tr>
<td><strong>with year dummies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>0.2236**</td>
<td>0.1104**</td>
<td>0.6112</td>
<td>-2139.94</td>
<td>15.3433*</td>
</tr>
<tr>
<td>Literacy</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Health</td>
<td>0.1148**</td>
<td>0.1112</td>
<td>0.8260</td>
<td>-3058.23</td>
<td>9.5479</td>
</tr>
<tr>
<td>Resources</td>
<td>0.0093</td>
<td>-0.1111**</td>
<td>0.3085</td>
<td>-3673.35</td>
<td>11.1793</td>
</tr>
</tbody>
</table>

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

From these results, we can conclude that the convergence found in HDI is due to its non-economic components. As we expected, the “command over resources” component is stationary over this time period, and the other components are converging at a rate similar to that of the HDI as a whole.
Chapter 4

Discussion

The implications of the results presented in the preceding chapter are elaborated upon, and suggestions for future research are given.

4.1 Interpretation of the Models

The three model specifications provide widely different results in terms of the parameter of interest, $\beta$, the growth rate of the dependent variable. As we interpret each model it is important to remember the assumptions each model makes and consider how reasonable those assumptions are. As each of the three specifications relaxes one assumption from the specification before it, each can be seen as a test of the validity of that assumption within the data available to us.

In the non-linear least squares results, we find no evidence for convergence or divergence in real GSP per capita over the period 1997-2006. We do, however, find that HDI exhibits convergence over the time period, with a “growth rate” of about 25% per year. In the random effects results, we find that both real GSP per capita and HDI are
converging, the former at the standard rate\textsuperscript{11} of about 2.8%, and almost 36% for the latter. In the spatial error model results, we find no evidence of convergence or divergence in real GSP per capita over the time period, and for HDI we find convergence at a rate of about 22% per year.

These different findings tell us something about the underlying process by virtue of the way that the elements of the true data generating process enter into each specification. When we assumed that the error terms would be free of spatial and random effects, all of the spatial autocorrelation in the underlying process introduced inconsistency. When we allowed for random effects, we were better able to control for the heteroskedacity that was left over because of the model specification’s inability to express spatial phenomena. When we finally controlled for the spatial autocorrelation in the error terms, our estimates of the parameters became (more) consistent, and had the least remaining spatial autocorrelation.

It is intriguing nonetheless that the comparison statistics (the $R^2$, AIC and Moran’s I) are remarkably similar between all three methods. This means that even though the spatial model does add noticeable explanatory power to our model, because the models in which $\rho$ was allowed to vary have significantly smaller residuals than the models in which $\rho$ was constrained to be zero, the actual impact remains very small.

\textsuperscript{11} Barro & Sala-i-Martin (2004) and others commonly find a 2% rate of convergence in real GDP per capita among industrialized regions or nations.
4.2 Findings

We have found that there is stability in the distribution of real GSP per capita and convergence in the Human Development Index over 1997-2006. The stability in GSP means that states that were relatively poorer at the beginning of the time period have remained so, and that wealthier states have retained their rank as well. This implies that income inequality is persistent, and should be the focus of policy aimed at increasing equity among U.S. residents.

The convergence in HDI, and in particular its non-economic components, is extremely encouraging. It shows that, in terms of factors such as access to education, literacy, and health, the states are rapidly approaching equality, and that we do not need to be greatly concerned that any original discrepancies will last.

We also found that the random effects terms in most models were uniformly zero. This means that there are no significant differences between the states that would lead an individual state or set of states to experience a level of income or a quality of life that is noticeably above or below the level experienced nationally. Thus, the only differences the states should experience, if these trends continue, would be due to random and temporary shocks.

Finally, we have found that there are underlying spatial processes at work, in which each state has a meaningful influence on its neighbors. It is reasonable to think that such factors exist for real GSP per capita because production, and hence its growth, is highly dependent on the factors of production within each state. While the stock of capital may be relatively fixed over a ten year period, such as the one we have examined, with investment nearly equal to depreciation, labor and human capital are very dynamic and
quite mobile. Service-sector businesses and young workers, for instance, are known to
easily move from one place to another in response to economic stimuli.

For real GSP per capita, these spatial effects exhibit a negative spatial autocorrelation
\( \rho = -0.11 \). This means that states with relatively high (low) economic growth tend to be
surrounded by states with relatively poor (strong) economic growth. This indicates that
certain states are likely absorbing the factors that contribute most to production from their
neighbors, benefiting at the cost to the regions around them. Such affects could be due to
mobile individuals and businesses with high productive capacity, such as the younger,
technologically-savvy generation and budding service-sector industries, who move
readily to the states that offer the best business environment, amenities or other prospects.

The spatial relationships are positive for HDI \( (\rho = 0.33 \text{ or } 0.11) \), meaning that states
with relatively high (low) quality of life tend to be surrounded by states that also have
relatively strong (poor) quality of life. This indicates that there is “clustering” in HDI,
where there are centers of high/low levels of quality of life scattered amid more moderate
levels. This positive spatial interaction may also assist the convergence process, as
regions tend to pull their neighbors along with them as they rise up.

4.3 Suggestions for Future Research

Many improvements can be made in continuing this line of research. First, data on the
variables that neoclassical growth theory says are related to GDP should be obtained for
all the regions and time periods, such as the saving rate, depreciation rate, flow of
investment, population growth rate (if GDP is not in per capita terms), etc. Similarly, data
on variables that bear a stronger theoretical relationship to the other components of HDI should also be included.

Second, the U.S. states are a highly aggregated unit of analysis. It would be better to collect data for much smaller spatial units that are closer to the actual units within the data generating process. For income and human development, it may be the case that the individual is the appropriate unit, because individuals are the economic actors who drive the economy as a whole, generate production, and receive income; and it is also individuals who invest in their own human capital (education, health, adaptability) and thereby raise their own opportunity. It may also be acceptable to use geographic units that best conform to the regional economies in which these exchanges take place. For instance, labor mobility occurs when workers go from working within one labor market to working in another. If data were aggregated only to the level of labor markets, a spatial error model could describe the impact of this mobility, or this mobility could be modeled directly.

Finally, while we have discovered that spatial effects are at work, we were unable in this study to delve into the processes themselves. Now that these spatial effects have been identified, their mechanisms should be explored so that we can better understand how the regions interact with one another.
Chapter 5

Conclusions

In this study, we have compared two separate criteria for economic development, represented by real Gross State Product per capita, and the Human Development Index, and have discovered that they present very different results.

We applied the neoclassical growth framework elucidated by Barro and Sala-i-Martin (2004) to these two measures while also extending this framework to allow for underlying spatial processes.

We have found that in the period from 1997-2006 in the 48 contiguous U.S. states, there is neither convergence nor divergence in economic growth. Reducing the persistent income inequality this finding represents should be the chief aim of any policy intended to increase the well-being of Americans. We have also found evidence of inter-state convergence in the HDI measure. This increasing equality among the states in human conditions is not impeded by the remaining heterogeneity in economic growth.

We have also demonstrated that allowing for spatial effects has greatly increased the explanatory power of our results, and may indicate that Barro and Sala-i-Martin’s conclusion that convergence existed among the U.S. states may have turned out differently if they had incorporated these spatial measures.
References


Appendix A

Data Transformations and HDI Goalposts

The testing and transformations that ensured our data set was consistent are described, as well as the process by which the goalposts for our American HDI were determined.

A.1 Filling in Missing Health Coverage Values

Data on health coverage rates is available only from 1999 onward, and so we linearly interpolated the two missing values for each state by assuming that the average yearly change in health coverage in each state over the eight years we had data was true of the two missing years as well:

\[
h = \frac{1}{7} \sum_{m=1998}^{2006} (h_{\text{coverage}}_m - h_{\text{coverage}}_{m-1})
\]

The missing values for each state \( i \) were then filled in a straightforward fashion:

\[
h_{\text{coverage}}(1997, i) = h_{\text{coverage}}(1999, i) - 2*h
\]

\[
h_{\text{coverage}}(1998, i) = h_{\text{coverage}}(1999, i) - h
\]
A.2 Redefinition of the Age-Adjusted Death Rate

One transition that impacts the chosen period is the change in the way data on age-adjusted death rates were reported that took place from 1999 onward. The later data is more reliable and more apparently consistent, in that the values observed from one year to the next appear very continuous. The data from 1998 and earlier contains two possible sets of observations. One labeled “death rate,” which many times but not always appears closer to the values reported for later years, and another labeled “age-adjusted death rate” that in many cases is far smaller than the values reported in later years – sometimes as little as one-half of the value we would expect. To help us think about whether this change is meaningful, we will compare the correlation across the break (1998 – 1999) to the correlation within the break (1999 – 2000) in Stata 10.1:

Table A.1: Correlation Coefficients between Different Years and Definitions of the Variable “Death Rate” in the Original Sources (n = 51).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>death2000</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>death1999</td>
<td>0.9835</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;death&quot;1998</td>
<td>0.5211</td>
<td>0.5556</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>&quot;AADR&quot;1998</td>
<td>0.9483</td>
<td>0.9644</td>
<td>0.5565</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

We find that the “age-adjusted death rates” of 1998 are preferred to the “death rates” of the same year because they move in the same direction as the trustworthy values reported in 1999 and even 2000. However, since the values of the age-adjusted death rate are quite different in the two periods, we must adjust the values in the earlier years to be on the same scale as those in the later period.
Table A.2: Mean and Standard Deviation of the Variable “Death Rate” Before Adjustment, Using the Preferred Sources (n = 48 per year)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>475.7042</td>
<td>51.94415</td>
</tr>
<tr>
<td>1998</td>
<td>481.3687</td>
<td>53.15384</td>
</tr>
<tr>
<td>1999</td>
<td>793.1229</td>
<td>75.39423</td>
</tr>
<tr>
<td>2000</td>
<td>813.1750</td>
<td>77.24587</td>
</tr>
<tr>
<td>2001</td>
<td>815.7417</td>
<td>77.97395</td>
</tr>
<tr>
<td>2002</td>
<td>846.0146</td>
<td>80.30692</td>
</tr>
<tr>
<td>2003</td>
<td>856.2417</td>
<td>82.38915</td>
</tr>
<tr>
<td>2004</td>
<td>860.4354</td>
<td>82.87491</td>
</tr>
<tr>
<td>2005</td>
<td>884.4938</td>
<td>85.88178</td>
</tr>
<tr>
<td>2006</td>
<td>892.3854</td>
<td>92.37025</td>
</tr>
</tbody>
</table>

To create a basis of the true trend in the age-adjusted death rate, we regress the means and standard deviations of the eight trustworthy years on time ($t = year - 1997$) and a constant term.

Table A.3: Regressions of the Distribution Parameters of the Variable “Death Rate” on Time and a Constant Term to Describe the True Trend (n = 8)

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Regression Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean(death)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>766.9088***</td>
</tr>
<tr>
<td>$t$</td>
<td>14.23499***</td>
</tr>
<tr>
<td>R²</td>
<td>0.9748</td>
</tr>
</tbody>
</table>

The strong explanatory power of these regressions suggests that even this simple model can reliably describe the time-path of the distribution parameters of the age-adjusted death rate process, so that we can determine the appropriate distribution parameters for the first two years. Using these models to estimate the mean and standard deviation of the true process in the first two years we find:
Table A.4: Point Estimates of the Mean and Standard Deviation of a Consistent “Death Rate” Process

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>766.9088</td>
<td>70.01116</td>
</tr>
<tr>
<td>1998</td>
<td>781.1438</td>
<td>72.15205</td>
</tr>
</tbody>
</table>

If the age-adjusted death rate is distributed normally in each year, then we can transform the data from the original sources to have values that are more in line with the expected distribution that retain the full unique character of their time and location, by using the following formula:

\[
\text{death}_1 = \left(\frac{\text{death}_0 - \text{mean}_0}{\text{sd}_0}\right) \times \text{sd}_1 + \text{mean}_1
\]

where the variables with subscript zero are the original values, and the variables with subscript one are the desired values.

We first test whether the age-adjusted death rate is in fact close to a normal distribution, using the `sktest` command available in Stata 10.1, which tests the skewness and kurtosis of a given variable for departures from normality:

Table A.5: Test for Normality of the Variable “Death Rate” in each of the Ten Years

<table>
<thead>
<tr>
<th>Year</th>
<th>Pr(skewness)</th>
<th>Pr(kurtosis)</th>
<th>(\chi^2) statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>0.097</td>
<td>0.307</td>
<td>4.00</td>
<td>0.1357</td>
</tr>
<tr>
<td>1998</td>
<td>0.062</td>
<td>0.422</td>
<td>4.26</td>
<td>0.1186</td>
</tr>
<tr>
<td>1999</td>
<td>0.132</td>
<td>0.053</td>
<td>5.69</td>
<td>0.0580</td>
</tr>
<tr>
<td>2000</td>
<td>0.139</td>
<td>0.071</td>
<td>5.27</td>
<td>0.0716</td>
</tr>
<tr>
<td>2001</td>
<td>0.090</td>
<td>0.108</td>
<td>5.28</td>
<td>0.0713</td>
</tr>
<tr>
<td>2002</td>
<td>0.076</td>
<td>0.132</td>
<td>5.26</td>
<td>0.0721</td>
</tr>
<tr>
<td>2003</td>
<td>0.069</td>
<td>0.171</td>
<td>5.07</td>
<td>0.0793</td>
</tr>
<tr>
<td>2004</td>
<td>0.034</td>
<td>0.399</td>
<td>5.11</td>
<td>0.0777</td>
</tr>
<tr>
<td>2005</td>
<td>0.026</td>
<td>0.680</td>
<td>5.01</td>
<td>0.0817</td>
</tr>
<tr>
<td>2006</td>
<td>0.057</td>
<td>0.317</td>
<td>4.65</td>
<td>0.0979</td>
</tr>
</tbody>
</table>
As all of the P-values are greater than our chosen probability of Type I error, 5%, we fail to reject the null hypothesis of normality for all ten years. We therefore used the technique described in the formula on the previous page to replace the values of the age-adjusted death rate obtained from the original sources with values that followed the expected distribution. Doing so prevents the occurrence of spurious correlations on account of the sharp jump in values in 1999.

A.3 Investigating the SIC/NAICS Break

A transition that should not affect our sample is the adoption of the NAICS for aggregating GDP across sectors of production, as opposed to the previous SIC. We know that this change should not affect our accuracy because we are concerned with the aggregate amount of production, not how it is distributed among the various sectors. We find that in 1997, the year in which both are reported, the values of the two series are highly correlated ($r = 0.9926$). We can more rigorously test for group differences using a paired t-test:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.E.</th>
<th>Std. Dev.</th>
<th>95% Conf. Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAICS$^{1997}$</td>
<td>32036.63</td>
<td>1506.861</td>
<td>10761.14</td>
<td>29010.01 35063.25</td>
</tr>
<tr>
<td>SIC$^{1997}$</td>
<td>31511.27</td>
<td>1452.618</td>
<td>10380.91</td>
<td>28591.6  34430.95</td>
</tr>
<tr>
<td>difference</td>
<td>525.3529</td>
<td>187.3516</td>
<td>1337.958</td>
<td>149.0462 901.6597</td>
</tr>
</tbody>
</table>

$t$ statistic: 2.8041***

The $t$-statistic of 2.8041 exceeds the critical value of 1.6759, leading us to conclude that the measures are different, even when looking at aggregate production. The NAICS
reports significantly higher levels of GSP, on average, than does SIC. Yet, since this difference is no more than 3%, and most likely only 1% of the level of GSP in any given period, we would gain no advantage by rescaling the values of earlier years.

A.4 Setting the Goalposts for an American HDI

The United Nations Development Programme has set the goalposts used in the global HDI, and kept them the same since they finalized the design of the HDI in 1994 (UNDP 2008). Nonetheless, these values are arbitrary and in large part represent a merely subjective view of what levels of each of the components are feasible for any country to experience in the near future. As many of the authors cited in Chapter 1, Section 4 contend, the weighting system applied globally leaves little room for comparison among industrialized regions.

We therefore adopted a different set of weights that would serve the same function of projecting the values found in our data within [0, 1], but would allow for a broader subset of that range to actually be realized. Since the goalposts serve as a set of weights, as long as the weights are consistent, no problems should arise: the value of coefficients in regressions will change, but not their significance.

We maintained the [0, 100] goalposts for the gross enrollment index, because it is a percentage. However, we modified the other goalposts. With respect to the log of real GSP per capita, the global goalposts are [ln(100), ln(40000)], however, the lowest per capita GSP found in our data is about $22,419, and the highest is just under $60,000. We chose [ln(20,000), ln(60,000)] as our new goalposts to ensure no values of the resource index would exceed one, and to allow the resource index to dip fairly close to zero.
If we had a direct measure for the adult literacy rate, we would have kept its goalposts at $[0, 100]$ because that rate is also a percentage. However, we are working with SAT Verbal scores. We know that the scores can range from 200 to 800, but that average scores within a state will vary much less. In selecting our new goalposts, we strove only to recognize the symmetric property of the SAT values, and to choose an interval that would best stretch from zero to one after being transformed. We settled on $[350, 650]$, which amounts to a $6^{th}$ to $91^{st}$ percentile score group (College Board 2007).

In constructing goalposts for the health component, we had the advantage of having data on both the desired and proxy variable in a single year. We were able to regress the age-adjusted death rate on life expectancy to obtain a benchmark of their relationship:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Regression Results</th>
<th>death</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>5234.515***</td>
<td></td>
</tr>
<tr>
<td>life</td>
<td>$-56.56077^{***}$</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.9315</td>
<td></td>
</tr>
</tbody>
</table>

Using these results, it is simple matter to verify that the global goalposts of $[25, 85]$ would translate into age-adjusted death rates of $[3820, 486]$. However, the largest (worst) age-adjusted death rate in our sample is 1074, and the smallest (best) is 668. We therefore chose $[1200, 550]$ to better encapsulate the range of death rates reasonable within the United States.
Appendix B

Efficiency of the KKP Estimator

The GMM-based FGLS estimator for spatial error panel models is quite efficient. In a 1000-trial Monte Carlo simulation, data was constructed according to the data generating process described on page 18. The true parameters from which the data was generated, and the mean error and standard deviation of the error of the model’s estimates over the 1000 iterations is shown:

Table B.1: Average Error in the GMM-based FGLS Estimates of a Spatial Error Model with Random Effects (reps = 1000, n = 48, t = 9)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>True DGP Coefficient</th>
<th>Mean Error</th>
<th>Std. Dev. of Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>60.543</td>
<td>−0.0552</td>
<td>5.3014</td>
</tr>
<tr>
<td>x1</td>
<td>2.2</td>
<td>−0.0002</td>
<td>0.0735</td>
</tr>
<tr>
<td>x2</td>
<td>−0.5</td>
<td>0.0015</td>
<td>0.0417</td>
</tr>
<tr>
<td>x3</td>
<td>−0.17</td>
<td>0.0005</td>
<td>0.0258</td>
</tr>
<tr>
<td>x4</td>
<td>12</td>
<td>0.0000</td>
<td>0.0164</td>
</tr>
<tr>
<td>x5</td>
<td>1.05</td>
<td>−0.0002</td>
<td>0.0099</td>
</tr>
<tr>
<td>ρ</td>
<td>0.25</td>
<td>−0.0241</td>
<td>0.0809</td>
</tr>
<tr>
<td>σu²</td>
<td>2.00</td>
<td>−0.0061</td>
<td>0.1479</td>
</tr>
<tr>
<td>σ²</td>
<td>10.19</td>
<td>−0.4681</td>
<td>2.0412</td>
</tr>
</tbody>
</table>

P-value of F-stat for ρ

<table>
<thead>
<tr>
<th>P-value of F-stat for ρ</th>
<th>Average P-value</th>
<th>Std. Dev. of P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0000</td>
<td>0.0342</td>
<td>0.1534(^{12})</td>
</tr>
</tbody>
</table>

\(^{12}\) 77 of the 1000 P-values were greater than 5%.
This simulation suggests that the estimator proposed by Kapoor, Kelejian and Prucha (2006) is indeed unbiased and consistent, and will work very well when the true data generating process is similar to their theoretical model. In a more limited number of trials, we found that the FGLS procedure was far more accurate than either the random effects panel estimator or a non-linear least squares estimator. For these reasons, we are confident that this estimator will prove useful in our study.
Appendix C

Selected Source Code

This study used three software packages: Stata 10.1, Matlab 7.6.0, and MasterMatrix, a new software package written for this project. As all of the work in Stata used built-in commands, we will include here the source code of the most useful Matlab commands, and a description of the MasterMatrix program, which was written in C#.

C.1 Matlab Source Code

The programming in Matlab featured creating an implementation of the procedure outlined by Kapoor, Kelejian and Prucha (2006). Other functions were created, as needed, to facilitate the data management tasks and other computational needs that arose.
function [gmmestimates, spatparms, mortest, resid] = kkpgm(y,Xlist,W,prec,rhobound,snubound,sonebound)
%
% KKPGM Generalized Method of Moments estimator for a Spatial Error Model
% based on Kapoor, Kelejian, Prucha (2006).
% y is a bracketed string with the variable name of the ntx1 vector of independent variable
% Xlist is a bracketed string with the variables names of the components of the ntxk set of exogenous variables
% the data should be stacked time-wise (time the slow-running index)
% W is the nxn spatial weights matrix
% rhobound is a 2x1 vector of bounds for rho
% snubound is a 2x1 vector of bounds for sigma-squared-nu (random-effects variance)
% sonebound is a 2x1 vector of bounds for sigma-squared-one (other effects variance)
%
% *** CHECKS *** %
if (nargin >= 3)

[N,dw2] = size(W);
N;
if (N == dw2)

% y and X given as strings, compute actual matricies
displayy = removebrackets(y);
y = evalin('base',y);
% save text before conversion
displayx = removebrackets(Xlist);
Xlist = removebrackets(Xlist);
nox = counttokens(Xlist);
for nx = 1:nox
    X(:,nx) = evalin('base',gettoken(Xlist,nx,0));
end

end

[dx1,K] = size(X);
if isequal(isnan(X),zeros(dx1,K))

[dy1,dy2] = size(y);
if dy1 == dx1

T = dx1/N;
if nargin < 7
    sonebound = [0; 1e7];
end

if nargin < 6
    snubound = [0; 1e7];
end

if nargin < 5
    rhobound = [-1; 1];
end

end

end

k kp g m m
end

if nargin < 4
    prec = 1e-4;
end

% *** PRELIMINARY BETA; ASSUME X's are demeaned and scaled *** %

beta_ols = inv(X'*X)*X'*y;

Qzero = kron(eye(T) - ones(T)/T, eye(N));
Qone = kron((ones(T)/T), eye(N));

usq = y - X*beta_ols;
itbywn = kron(eye(T), W);
usqf = itbywn*usq;
usqs = itbywn*usqf;

% *** CALCULATE CONSTRAINT MATRICES *** %
Geo = zeros(3,3);
Gwon = zeros(3,3);
geo = zeros(3,1);
gwon = zeros(3,1);

Geobase = 1/(N*(T-1));

Geo(1,1) = (2*Geobase)*usq'*Qzero*usqf;
Geo(1,2) = (-1*Geobase)*usqf'*Qzero*usqf;
Geo(1,3) = 1;

Geo(2,1) = (2*Geobase)*usqs'*Qzero*usqf;
Geo(2,2) = (-1*Geobase)*usqs'*Qzero*usqs;
Geo(2,3) = (1/N)*trace(W'*W);

Geo(3,1) = Geobase*(usq'*Qzero*usqs + usqf'*Qzero*usqf);
Geo(3,2) = -Geobase*usqf'*Qzero*usqs;
Geo(3,3) = 0;

geo(1,1) = Geobase*usq'*Qzero*usq;
geo(2,1) = Geobase*usqf'*Qzero*usq;
geo(3,1) = Geobase*usq'*Qzero*usqf;

Gwon(1,1) = (2/N)*usq'*Qone*usqf;
Gwon(1,2) = (-1/N)*usqf'*Qone*usqf;
Gwon(1,3) = 1;

Gwon(2,1) = (2/N)*usqs'*Qone*usqf;
Gwon(2,2) = (-1/N)*usqs'*Qone*usqs;
Gwon(2,3) = Geo(2,3);

Gwon(3,1) = (1/N)*(usq'*Qone*usqs + usqf'*Qone*usqf);
Gwon(3,2) = (-1/N)*usqf'*Qone*usqs;
Gwon(3,3) = 0;
gwon(1,1) = (1/N)*usq'*Qone*usq;
gwon(2,1) = (1/N)*usqf'*Qone*usqf;
gwon(3,1) = (1/N)*usq'*Qone*usqf;

size(Qzero);
size(Qone);

% *** OPTIMIZE xioh'*xioh RETURN rhosq sigma2nusq *** %
xioh = zeros(3,1);
rhosq = 0;
sigma2nusq = 0;
mincrit = Inf;
rinterval = ((rhobound(2,1)-rhobound(1,1))/9);
sinterval = ((snubound(2,1)-snubound(1,1))/9);
rbound = rhobound;
sbound = snubound;

while or(rinterval > prec, sinterval > prec)
    for rest = rbound(1,1):rinterval:rbound(2,1)
        for sest = sbound(1,1):sinterval:sbound(2,1)
            xioh = Geo*[rest, rest^2, sest]' - geo;
            ssr = xioh'*xioh;
            if ssr < mincrit
                mincrit = ssr;
                rhosq = rest;
                sigma2nusq = sest;
            end
        end
    end
    rbound = [rhosq-rinterval; rhosq+rinterval];
    sbound = [sigma2nusq-sinterval; sigma2nusq+sinterval];
    rinterval = ((rbound(2,1)-rbound(1,1))/9);
    sinterval = ((sbound(2,1)-sbound(1,1))/9);
end

sigma2onesq = gwon(1,1) - Gwon(1,1) - Gwon(1,2);

% *** STEP TWO *** %
ups = zeros(2);
ups(1,1) = (1/(T-1))*(sigma2nusq)^2;
ups(2,2) = (sigma2onesq)^2;
Upsilon = kron(ups, eye(3));
Upsiloninv = inv(Upsilon);

% *** OPTIMIZE xin'*Upsiloninv*xin RETURN rhod sigma2nud sigma2oned ***

xin = zeros(6,1);
ninterval = ((snubound(2,1)-snubound(1,1))/9);
ointerval = ((sonebound(2,1)-sonebound(1,1))/9);
rbound = rhobound;
nbound = snubound;
obound = sonebound;

while or(rinterval > prec, or(ninterval > prec, ointerval > prec))
    for rest = rbound(1,1):rinterval:rbound(2,1)
        for nest = nbound(1,1):ninterval:nbound(2,1)
            for oest = obound(1,1):ointerval:obound(2,1)
                xioh = Geo* [rest rest^2 nest]' - geo;
                xiwon = Gwon * [rest rest^2 oest]' - gwon;
                xin = [xioh; xiwon];
                ssr = xin'*Upsiloninv*xin;
                if ssr < mincrit
                    mincrit = ssr;
                    rhod = rest;
                    sigma2nud = nest;
                    sigma2oned = oest;
                end
            end
        end
    end
end

rbound = [rhod-rinterval; rhod+rinterval];
nbound = [sigma2nud-ninterval; sigma2nud+ninterval];
obound = [sigma2oned-ointerval; sigma2oned+ointerval];
rinterval = ((rbound(2,1)-rbound(1,1))/9);
ninterval = ((nbound(2,1)-nbound(1,1))/9);
ointerval = ((obound(2,1)-obound(1,1))/9);
end

% *** FGLS *** %

startransform = kron( eye(T), eye(N) - rhod*W );
ystar = startransform*y;
Xstar = startransform*X;
Oehalf = ( sigma2nud^(-0.5) * Qzero + sigma2oned^(-0.5) * Qone);
Omegaepsiloninv = Oehalf*Oehalf;

beta_fgl =
    inv(Xstar'*Omegaepsiloninv*Xstar)*Xstar'*Omegaepsiloninv*ystar;
cov_fgl = ((1/(N*T)))*inv((1/(N*T)))*(Xstar'*Omegaepsiloninv*Xstar));
se_fgl = sqrt(diag(cov_fgl));
spatparms = [rhod; sigma2nud; sigma2oned];

% real answer

outputtext = zeros(K,6);
outputtext(:,1:2) = gmmestimates(:,1:2);
outputtext(:,3) = gmmestimates(:,1) ./ gmmestimates(:,2);
outputtext(:,4) = 1 - tcdf(abs(outputtext(:,3)),N*T-K);
\[
\text{outputtext}(:,5) = \text{outputtext}(:,1) - (tinv(0.975,N*T - K) * \text{outputtext}(:,2));
\]
\[
\text{outputtext}(:,6) = \text{outputtext}(:,1) + (tinv(0.975,N*T - K) * \text{outputtext}(:,2));
\]
\[
\text{ml} = \text{maxtokenlength(displayx)};
\]
\[
\text{err} = \text{ystar} - \text{Xstar} \ast \text{beta_fglgs};
\]
\[
\text{ssy} = (\text{ystar} - \text{mean(ystar,1)})''(\text{ystar} - \text{mean(ystar,1)});
\]
\[
[\text{fm}, \text{pm}] = \text{jointmoran(\text{err}, \text{W}, \text{Xstar}, \text{K})};
\]
\[
\text{mortest} = [\text{fm}, \text{pm}];
\]
\[
\text{resid} = \text{err};
\]
\[
\text{sa} = \text{sprintf('\%s', 'Kapoor-Kelejian-Prucha (2006) GMM/FGLS Spatial Error Model ')};
\]
\[
\text{sb} = [\text{sprintf('\%s\%3d', N: 'N: ', N) blanks(10) sprintf('\%s\2.5f', rho: 'rhod) blanks(10) sprintf('\%s\1.6f', R2: '1 - (err*err / ssy)) ];
\]
\[
\text{sc} = [\text{sprintf('\%s\%3d', T: 'T) blanks(10) sprintf('\%s\2.5f', s2nu: 'sigma2nu) blanks(10) sprintf('\%s\4.5f', AIC: '2*K + N*T*log(err*err/(N*T))) ];
\]
\[
\text{sd} = [\text{sprintf('\%s\%3d', K: 'K) blanks(10) sprintf('\%s\2.5f', s2one: 'sigma2oned) blanks(10) ];
\]
\[
\text{s1} = \text{sprintf('\%s', [blanks(ml-length(displayy)) displayy ' ' beta std. err. t-stat p-val [conf. interval]']);
\]
\[
\text{s15} = \text{sprintf('\%s', [hyphens(ml) ' ' '-----------------------------------------------']);
\]
\[
\text{disp(sa)};
\]
\[
\text{disp(sb)};
\]
\[
\text{disp(sc)};
\]
\[
\text{disp(sd)};
\]
\[
\text{disp(blanks(1))};
\]
\[
\text{disp(s1)};
\]
\[
\text{disp(s15)};
\]
\[
\text{for } \text{ik} = 1:K
\]
\[
\quad \text{disp(strcat(sprintf('\%s', gettoken(displayx,ik,ml), ' | ')), sprintf('\%10.4f', outputtext(ik,:))));
\]
\[
\text{end}
\]
\[
\text{disp(s15)};
\]
\[
\% \text{fake answers upon error}
\]
\[
\text{else}
\]
\[
\quad \text{gmmestimates} = \text{zeros}(K,2);
\quad \text{spatparms} = \text{zeros}(3,1);
\]
\[
\text{end}
\]
\[
\text{else}
\]
\[
\quad \text{gmmestimates} = \text{zeros}(K,2);
\quad \text{spatparms} = \text{zeros}(3,1);
\]
\[
\text{end}
\]
\[
\text{else}
\]
\[
\quad \text{gmmestimates} = \text{zeros}(K,2);
\quad \text{spatparms} = \text{zeros}(3,1);
\]
\[
\text{end}
\]
\[
\text{else}
\]
\[
\quad \text{gmmestimates} = \text{zeros}(K,2);
\quad \text{spatparms} = \text{zeros}(3,1);
\]
\[
\text{end}
\]
function [beta] = calcbeta(gmme, rownumber)
  b_hat = gmme(rownumber,1);
  seb = gmme(rownumber,2);
  if 1+b_hat > 0
    beta_hat = -log(1+b_hat);
  else
    beta_hat = -Inf;
  end
  blow = b_hat - 1.9659*seb;
  bup = b_hat + 1.9659*seb;
  if 1+blow > 0
    beta_low = -log(1+blow);
  else
    beta_low = -Inf;
  end
  if 1+bup > 0;
    beta_up = -log(1+bup);
  else
    beta_up = Inf;
  end
  if beta_low > beta_up
    beta_temp = beta_low;
    beta_low = beta_up;
    beta_up = beta_temp;
  end
  ml = 11;
  disp(sprintf('%s', [blanks(ml) ' ' ' coef. std. err. t-stat p-val [conf. interval]']));
  disp(sprintf('%s', [hyphens(ml) ' ' '-----------------------------------' ' ' ' ' ' ' ' ' ' ' ' ' ' '']));
  disp(sprintf('%s%10.6f%s%s%4.4g%s%4.4g', 'beta | ', beta_hat, ' ',' ',' ',' ', beta_low, blanks(1), beta_up));
  disp(sprintf('%s' , [hyphens(ml) ' ' '-----------------------------------' ' ' ' ' ' ' ' ' ' ' ' ' ' '']));
  beta = beta_hat;
end

function [fstat, pval] = kkpftest(rcomplete, rconstrained, gmmestimates)
  ftop = rconstrained'*rconstrained - rcomplete'*rcomplete;
  fbot = rcomplete'*rcomplete/(432-size(gmmestimates,2));
  fstat = ftop/fbot;
  pval = 1 - fcdf(fstat,1,432-size(gmmestimates,2));
end
moran.m

function [istat, pval] = moran(vect,W,M,K)
N = length(vect);
if size(W,1) == N
mor = (vect'*W*vect)/(vect'*vect);
emor = trace(M*W)/(N-K);
vmor = (trace(M*W*M*W')+trace((M*W)^2)+(trace(M*W))^2)/((N-K)*(N-K+2));
zstat = (mor-emor)/sqrt(vmor);
pval = 1 - tcdf(abs(zstat),N-1);
istat = mor;
else
    istat = NaN;
pval = Inf;
end

jointmoran.m

function [chistat, pval] = jointmoran(vect,W,X,K)
N = size(W,1);
T = length(vect)/N;
M = zeros(N,N);
if floor(T) == T
    zstat = zeros(T,1);
    emor = zeros(T,1);
    vmor = zeros(T,1);
    for t = 1:T
        Xs = X( (t-1)*N+1:t*N,:);
        M = eye(N) - Xs*inv(Xs'*Xs)*Xs';
        emor(t) = trace(M*W)/(N-K);
        vmor(t) = (trace(M*W*M*W')+trace((M*W)^2)+(trace(M*W))^2)/((N-K)*(N-K+2));
        v = vect(N*(t-1)+1:N*t,1);
        mor = (v'*W*v)/(v'*v);
        zstat(t) = (mor-emor(t))/sqrt(vmor(t));
    end
    chistat = sum(zstat.^2);
pval = 1 - chi2cdf(chistat,T);
else
    chistat = NaN;
pval = Inf;
end
Miscellaneous Functions

**counttokens.m**

```matlab
function [ct] = counttokens(varlist)

ml = 0;
while true
    [tok, varlist] = strtok(varlist);
    if isempty(tok), break;
    else
        ml = ml+1;
    end
end
tct = ml;
```

**cut.m**

```matlab
function [cvar] = cut(input, delay, N, T)
% remove the first 'delay' time periods from an N*T vector of observations
% that are ordered by N, then T, both ascending

cv = NaN(N*(T-delay),1);
for dn = 1:N
    for dnn = 1: T-delay
        cv((T-delay)*(dn-1)+dnn,1) = input(T*(dn-1)+dnn+delay, 1);
    end
end
cvar = cv;
```

**gettoken.m**

```matlab
function [vari] = gettoken(varlist,index,balancedlength)
% get token #'index' from space-delimited 'varlist', and return it
% left-padded with spaces so its length is 'balancedlength'

iind = 0;
while true
    [tok, varlist] = strtok(varlist);
    iind = iind+1;
    if isempty(tok), break;
    elseif iind == index,
        if balancedlength ~= 0
            vari = [blanks(balancedlength-length(tok)), tok];
            return;
        else
            vari = tok;
            return;
        end
    end
end
```
**hyphens.m**

```matlab
function [str] = hyphens(len)
    s = '-'
    for si = 2:len
        s = [s ' - ']
    end
    str = s;
```

**lag.m**

```matlab
function [linput] = lag(input, N, T)
    li = NaN(N*T,1);
    for dn = 1:N
        for dnn = 2 : T
            li( (dn-1)*T+dnn, 1) = input( (dn-1)*T+dnn-1, 1);
        end
    end
    linput = li;
```

**maxtokenlength.m**

```matlab
function [maxl] = maxtokenlength(varlist)
    ml = 0;
    while true
        [tok, varlist] = strtok(varlist);
        if isempty(tok), break;
        elseif length(tok) > ml,
            ml = length(tok);
        end
    end
    maxl = ml;
```

**removebrackets.m**

```matlab
function [str] = removebrackets(text)
    s = strrep(text,'[', '');
    s = strrep(s,']',' ');
    str = s;
```
C.2  C# Source Code for MasterMatrix

The purpose of the MasterMatrix program is to reorganize large sets of data from whichever format it may appear in the original data source into a single, consistent dataset that can be imported into a software package of choice. MasterMatrix manipulates files in the comma-separated value file format according to instructions in programmatic text files. This program proved invaluable as even the most careful copying, pasting, and double-checking of values in Excel or Stata proved to introduce too many errors to be trustworthy. C# is a programming language created by Microsoft that can be compiled and then run on any computer that has the .NET Runtime installed. We would have liked to have included the full source code here, but the 1762 lines of code proved too voluminous. Therefore, we note that the source code will be available from the author by request.