Growing at Your Neighbor's Expense? A spatial examination of growth in the Americas

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Abstract: This paper extends the literature on international spatial economic growth by employing a clear procedure for model selection and highlighting the importance of using time fixed effects that are region specific. Using a sample of countries in the continental Americas, and after capturing common shocks to the region, estimates of spatial effects are negative and significant, in contrast to most of the existing literature. The net economic value of these spatial effects is of a magnitude similar to the value of the initial growth, and failing to account for growth spillovers is shown to bias estimates of the effectiveness of growth altering policies.

I. Introduction

In a global environment where economies are increasingly interdependent, it seems logical that the growth experience of one country might be importantly related to the growth experience of other countries. In spite of this, most models of economic growth examine countries in isolation, ignoring the potential for spillover effects from growth in neighboring countries. A better understanding of the channels through which economies influence one another's growth experience could enlighten policymakers about how to achieve consistent, stable growth.

Spatial growth spillovers could have important policy implications for developed and developing countries alike. If spatial effects are positive, coordinated efforts among neighbors might be able to jumpstart growth for an entire region. Given knowledge of the pattern of growth spillovers, the best way to create growth in a region may be to target one or two specific countries for aid or intervention and to allow the resulting effects to spread through spatial channels. Alternatively, if spatial effects are negative, policymakers would want to know the mechanisms through which these occur to find ways to circumvent these spillover effects. The existence of un-modeled spillovers, either positive or negative, would also lead to biased estimation of the impacts of the myriad programs targeting growth. In all of these cases, identifying the sign and existence of spatial effects in the growth process is a necessary first step.

Using a panel of countries in continental North, Central, and South America over a thirty year period, this paper estimates a Spatial Durbin Model of the growth process, finding evidence of statistically significant negative growth spillovers. These results are robust to other spatial weighting schemes and to changes in the spatial model used. Using the estimated spatial effects from the preferred model, a simulated shock to growth in a single country is seen to have spillover effects that are economically meaningful as well.

This paper extends the current literature on spatial models of international growth in three ways. First, few spatial models of international growth engage in any clear, empirical model selection procedure. This paper follows the approaches of Elhorst (2010) and LeSage and Pace (2009) to determine the appropriate spatial model. Second, many existing papers use panels which contain countries from all over the globe but have only limited coverage in most regions. Spatial effects are likely to be localized, making a global focus questionable. Shocks which are common to groups of countries within a region may be heterogeneous across regions and difficult to account for using global time fixed effects. By focusing on only a single region (the continental Americas) and having almost complete coverage, this study can address these concerns. Third, this paper distinguishes clearly between common shocks to countries and actual growth spillovers. Failure to account for common shocks can lead to an upward bias in estimates of spatial relationships. The standard panel data approach to dealing with common shocks is to include time-period fixed effects. In spite of this, few spatial models of international growth have incorporated fixed effects, in part because doing so in spatial models leads to biased estimates of model parameters. This paper includes time period fixed effects, but also employs the bias correction procedure of Lee and Yu (2010).

The rest of this paper is structured as follows. Section II introduces the most common spatial models and reviews the existing literature. Section III discusses the model selection process and the data which is used in the empirical analysis. Section IV presents the results of the empirical estimation and checks the robustness of results to alternative models and spatial weighting matrices. Section V estimates the magnitude of spatial growth effects and provides an example of how these effects could bias policy evaluation if not properly modeled. Section VI revisits the existing literature on growth spillovers to examine how previously accepted results change when a model takes into account the suggestions of this paper. This section also addresses the question of whether negative spillovers are unique to the Americas. Section VII suggests future directions of research and concludes.

II. The Direction of Growth Spillovers, Common Spatial Models, and Existing Literature

The Direction of Spillovers

An inspection of international growth rates within regions suggests that spatial correlations among growth rates are positive. Countries in North America and Western Europe have typically experienced positive growth rates. At the same time, Sub-Saharan African countries have almost universally performed significantly worse. It is easy to assume that these positive correlations across countries' growth rates are due to positive spillovers of growth. However, theories about how spillovers operate do not unambiguously suggest that spillovers should be positive. Consider trade as a channel for potential spillovers. Growth in country A might lead to increased trade between A and B. Frankel and Romer (1999) suggest that this would in turn lead to growth in country B, a positive spillover. On the other hand, another plausible story is that growth in A might make A's goods cheaper in international markets, causing reduced growth in A's competitor, country C (a negative spillover).

As another example, consider a model where country leaders learn by watching policy outcomes of their neighbors. If country A implements a policy which generates positive growth, neighboring country B might choose to emulate the policy, growing as well (a positive spillover). Alternatively, country A could just as easily adopt a policy which might hinder growth. Country B, observing this, might avoid similar policies, or even choose opposing ones, leading to a better outcome (a negative spillover). With ambiguity about the theoretically predicted direction of spillovers, solid empirical evidence is essential.

There are multiple potential channels for spatial growth effects, and some of these channels suggest that spillovers could be negative, e.g., channels where countries are in competition with each other. The lack of a conclusive theoretical prediction about the direction of these effects highlights the need for empirical investigations of the issue. The next two subsections will introduce the most common models used to investigate spatial effects and will examine several attempts in the existing literature to identify and quantify spatial growth effects across countries.

Common Spatial Models

Three of the most common panel spatial models originate from a standard panel regression form, as in (1).[1]

$$y_{i,t} = x_{i,t}\beta + \mu_{i,t} \tag{1}$$

Here, x is a vector of k explanatory variables and $\mu_{i,t}$ is independently distributed $N(0, \sigma^2)$. The first spatial model relaxes the assumption that the error terms are independently distributed. Instead, it is assumed that there is some correlation of the error terms across space according to (2).

$$\mu_{i,t} = \lambda \sum_{j=1}^{N} w_{i,j}\, \mu_{j,t} + \varepsilon_{i,t} \tag{2}$$

The parameter $w_{i,j}$ is the row i, column j element of the matrix W, which is known as a spatial weight matrix. This matrix describes the level of "relatedness" across the sample of observations.

[1] The following is simply a brief overview of the most common spatial models.For a more thorough and in-depth description of spatial modeling, the reader should refer to Anselin, Le Gallo, and Jayet (2008) or LeSage and Pace (2009).

The choice of a spatial weighting matrix is at the researcher's discretion, but common forms reflect physical distance between observations or physical contiguity of particular observations, with zeros along the diagonal. The λ term captures the extent to which shocks to one country spill over to another country, given their level of relatedness. The model resulting from a combination of (1) and (2) is known as the Spatial Error Model (SEM). The SEM is appropriate when it is believed that the correlation across dependent observations results from spatial correlation in the shocks to the data generating process.

The second common spatial model expands upon (1) to allow for a direct spatial relationship among dependent variable observations. The model does so by including a spatially weighted vector of the dependent variable as an explanatory term. The resulting model is known as the Spatial Autoregressive (SAR) model or the Spatial Lag model.

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{i,j} + x_{i,t}\beta + \mu_{i,t} \tag{3}$$

In this case, neighboring values of the dependent variable are weighted according to a spatial weighting matrix. The SAR model is appropriate when it is believed that the spatial dependence is inherent in the dependent variable.

A third common model of spatial dependence is the Spatial Durbin Model (SDM). The SDM expands upon the SAR model in (3) by allowing for a spatial relationship not only in the dependent variable, y, but also in the independent variables, x. The inclusion of this additional term results in the specification in (4).

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{j,t} + x_{i,t}\beta + \sum_{j=1}^{N} w_{i,j} x_{j,t}\gamma + \mu_{i,t} \tag{4}$$

Here, both β and γ are $\mathrm{k} \times 1$ vectors of parameters. Both the SEM and SAR models can be viewed as special cases of the SDM given appropriate restrictions on parameters.

As with non-spatial panel models, the SER, SAR, and SDM models can be augmented with time and/or spatial fixed effects. Time fixed effects are of particular interest in spatial models because the existence of common, un-modeled shocks across time would lead to an upward bias in the estimates of the spatial parameters of interest. Lee and Yu (2010) point out that time fixed effects may be especially relevant for growth theory.

The next subsection examines the existing spatial literature on international growth, focusing on the each paper's choice of countries used in the sample, the model used in estimation along with model selection process, and the choice to include or omit time fixed effects in estimation. The process for model selection among the three candidates above will be addressed in section IV.

A Review of the Literature on Growth Spillovers

While a very limited number of other papers have examined international growth spillovers, within this literature there is sizeable variability in model choice, sample analysis period, and dataset coverage. The existing literature almost universally finds evidence of positive growth spillovers among countries.

Of the papers on international spatial growth effects, three look exclusively at a spatially autoregressive process, as in (3). Easterly and Levine (1997), one of the earliest and best known works allowing for spillovers, studies the African growth experience in an SAR framework without fixed effects. They find evidence of positive spatial effects across countries, and from their results they conclude that policy changes which affect growth are more powerful when coordinated with policy changes in neighboring countries.

Behar (2008), also using an SAR model, finds evidence of positive spatial effects in a global panel. Spatial effects are found to be strongest in smaller regions and weaker in larger regions or globally. Time fixed effects are included in the global models, but Behar points out that it is difficult to distinguish between spillovers and common shocks in his specification.

Roberts and Deichman (2011) also use an SAR model to look at long-run spatial growth effects, focusing on how these effects may vary across a global sample of countries and how this heterogeneity may be systematically related to infrastructure. They find that positive spatial effects are magnified by higher levels of transportation and communication infrastructure. They highlight, additionally, the negative effects of low transportation infrastructure and being landlocked on spatial effects. The SAR model used includes country fixed effects, but because they focus on long-run growth rates, they only have a single cross section of average growth rates and cannot include time fixed-effects.

In addition to the three aforementioned papers which utilize only an SAR framework to examine spatial growth effects internationally, three additional papers examine these effects using a combination of models. Both Moreno and Trehan (1997) and Abreu, de Groot, and Florax (2004) examine spatial growth effects using a combination of SAR and SEM models. Moreno and Trehan find positive spatial effects on a global sample of countries using their SAR model, and then find further evidence of common "shocks" to countries in an SEM framework. Abreu, de Groot, and Florax use both models to test for spatial effects and spillovers on Total Factor Productivity across countries, again finding evidence of positive effects in their global sample. Weinhold (2002) applies an SAR model of spatial growth effects to a global sample. She finds positive spatial effects in her model, which includes country and time fixed effects. Weinhold then extends her model to a limited SDM model where one of her explanatory variables (a TFP residual) also has a spatial effect on other countries. Weinhold is somewhat different from other works, in that her models only allow for spatial effects among either developed or developing countries. Her results indicate the existence of positive spatial growth effects.

A final paper uses tests for spatial model selection to choose the appropriate spatial framework for analyzing spatial growth effects. Ertur and Koch (2007) extend the Augmented Solow Model of Mankiw, Romer, and Weil (1992) to a spatial setting. Their tests indicate that the data is best represented by a Spatial Durbin Model. The resulting estimates of spatial growth effects are positive in a model including neither country nor time fixed effects, again estimated on a global sample.

Section III moves on to a full discussion of the model employed here. After introducing the data, the model selection procedure will be discussed along with its results. Special attention is given to the importance of choices regarding the inclusion of fixed effects. Lastly, the estimation approach of the selected spatial model will be outlined.

III. Data, Model Selection, and Estimation

Growth and Growth Spillovers

Economies across countries are interrelated to differing degrees. Examining the different pathways in which spatial effects may be transmitted provides insights into the potential importance of these effects as well as into the ability of policymakers to manipulate, magnify, or avoid spatial effects on growth.

For the purposes of this paper, growth (positive or negative) will refer to the year over year percentage changes in per-capita GDP in a country, while "growth spillovers" will be the net spatial effects of growth in one country on other countries, regardless of the source of the initial growth. It is important to distinguish between two scenarios. The first is one in which a change in country A's growth causes a change in country B's growth. A scenario like this is the type of growth spillover which this paper focuses on, and would be captured by the ρ parameter in an SAR model or an SDM. The second scenario is one in which a change in some other variable in country A, such as an indicator of war, leads to simultaneous changes in growth in both country A and country B. This type of effect is what would be captured by the γ parameter in an SDM framework. While it may be important to control for this second type of scenario, because the initial shock was not in country A's growth, this is not the primary effect of interest here.

The Data

To reiterate, the goal of this paper is to identify any spatial effects of the growth of one country on its relevant neighbors, regardless of the source of the initial growth. To isolate any such effects, the model includes a set of variables in the X vector intended to control for other common sources of growth variations. In this paper, the vector of control variables will consist of physical capital growth rates, changes in terms of trade, and an indicator of war within a country's borders.

Like Easterly and Levine, who focused exclusively on Africa, I examine spatial growth effects within a single, clearly defined region: the continental Americas. This provides several advantages over global models. First, I have almost universal data coverage for the sovereign states in the region. From the 22 nations in the continental Americas, I form a 29 year panel including 19 countries (the three omitted countries are Belize, Guyana, and Suriname). The second benefit of focusing on a single geographical region is that spillovers should be pronounced within this region. The continental Americas are geographically isolated from other areas, and a large percentage of trade from these countries is within region as well (approximately 20% over the sample period according to the IMF's DOTS). The third benefit is that, as was pointed out by Roberts and Deichman (2011), spillovers may be heterogeneous across regions, so looking across multiple regions at once may muddle estimates.

Data on GDP growth and capital stock growth rates come from the Penn World Tables version 7.1. Capital stock growth rates are calculated from the investment series using a perpetual inventory method with an assumed five percent depreciation rate. Terms of trade data are from the World Development Indicators, and the war indicator represents the sum of civil and international indicators for political violence from the Major Episodes of Political Violence dataset maintained by Monty Marshall at the Center for Systemic Peace. Table 1 provides summary statistics for these variables.

[Insert Table 1 here]

All data are collected for the 19 countries in the continental Americas which have complete coverage during the 30 year period from 1978-2007.

The Spatial Weight Matrix

All of the potential spatial models require that a spatial weight matrix be chosen. An appropriate spatial weight matrix reflects the level of "relatedness" of all observations in the sample, but the exact form is up to the researcher. Initially, a common form of this matrix reflecting the physical distance between spatial units will be used here. In a later section, the robustness of results to alternative specifications of this matrix will be examined as well.

The precise form of the primary weighting matrix is as follows. The diagonal elements of the weighting matrix are all zero. Geographic distance is defined as the straight-line distance between the centers of countries. Because nearer countries are hypothesized to have stronger spillovers, the geographic distance is inverted so that larger values correspond to closer countries. Because spillovers create feedback loops (where growth from A spills over to B, but then this growth change in B spills back to A and so on), an infinite series of spatially weighted growth effects is created in the process of estimation. To guarantee the necessary convergence of this series, each row of the spatial weighting matrix must be normalized so that the entries sum to one[2]. Earlier works, like Easterly and Levine (1997), used more basic weighting matrices which treated all countries as potential neighbors, but re-weighted the observations by country size. While the intuitive power of such a weighting scheme is clear, it lacks the mathematical properties necessary to ensure convergence.

Model Selection

[2] Matrices of this particular form have also been used by Roberts and Deichman, Moreno and Trehan, Abreu, de Groot and Florax, Ertur and Koch, and Weinhold.

The process for selecting among competing spatial models, proposed in Elhorst (2010), begins with a test of whether spatial effects are even appropriate. The non-spatial model is compared to SAR and SEM alternatives using Lagrange multiplier tests. A test of a hypothesis that this paper's data exhibits no spatial lag is rejected with a p-value of 0.018. A test of the hypothesis that the data exhibits no spatial error is also rejected, with a p-value of 0.008. Given that these tests indicate that both spatial models are preferred to the non-spatial alternative, the selection process then involves estimation of a Spatial Durbin Model, which can be viewed as the most general of the three spatial models discussed. The SAR model in (3) can be seen as a special case of the SDM where $\gamma=0$. The SEM model is a special case of the SDM as well, the case where $\gamma+\rho\beta=0$ (Burridge, 1981). Testing these two hypotheses via likelihood ratio tests is then an appropriate method of choosing among the three models. If the two hypotheses are rejected, the SDM model is the most appropriate. If the first hypothesis cannot be rejected, the appropriate model is the SAR, and if the second hypothesis cannot be rejected, the SEM model is appropriate. If these hypothesis tests do not point conclusively to either the SAR or the SEM model, the more general SDM model is deemed appropriate.

A likelihood ratio test comparing the SDM and SAR model is unable to reject the hypothesis that the SDM can be reduced, and that the SAR is appropriate (p-value of 0.308). Similarly, a likelihood ratio test of the hypothesis that the SDM can be reduced to an SEM cannot be rejected (p-value of 0.247). Following Elhorst (2010), when these tests fail to indicate that only one of the more simple models is appropriate, the general SDM is the appropriate choice.[3]

IV. Model Estimation and Empirical Results

Having settled on a Spatial Durbin Model, the expression in (4), can be modified to include time and/or spatial (country) fixed effects:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{j,t} + x_{i,t}\beta + \sum_{j=1}^{N} w_{i,j} x_{j,t}\gamma + \theta_i + \tau_t + \mu_{i,t} \tag{5}$$

[3] Each individual test fails to reject a hypothesis that the general model can be reduced to a simpler one. Given these results that either simpler model may still be appropriate, it seems somewhat clumsy that the standard approach is to stick with the general model. One could instead argue that a much larger rejection region is appropriate for these tests if neither test is able to reject the null at standard levels, even a rejection region as large as 0.4 or 0.5. In that case, both tests indicate that the SDM is more likely than the simpler alternatives.

The inclusion of the Wy term on the right hand side of the equation introduces simultaneity issues, making the use of OLS inappropriate for estimation. However, the dependent variable can algebraically be solved for in matrix notation as:

$$Y = (I - \rho W)^{-1}(X_i\beta + WX\gamma + \theta_i + \tau_t) + (I - \rho W)^{-1}\mu \tag{6}$$

Under the assumed classical structure of the underlying error term μ, equation (6) can then be estimated via maximum likelihood.

Lee and Yu (2010) discuss how standard estimation of any spatial model, like that expressed in (5), which contains spatial and/or time fixed effects will lead to biased estimates of some model parameters. They propose correction procedures for eliminating these biases, which are of particular importance when the breadth and/or length of the sample are small. In the case of spatial models with spatial fixed effects, but not time fixed effects, the estimate $\hat{\sigma}^2$ will be biased downward and needs to be corrected by a factor of $\frac{T}{T-1}$. In the case of spatial models with time fixed effects but not spatial fixed effects, the estimate of $\hat{\sigma}^2$ needs to be corrected by a factor of $\frac{N}{N-1}$. In the case of a spatial model with both time and spatial fixed effects, all parameter estimates are biased. The correction procedure in a model with both types of fixed effects is significantly more complex, and the reader is referred to Lee and Yu (2010) or Elhorst (2010) for a full discussion. All estimation results are reported after the implementation of the appropriate bias correction procedures.

Coefficient Interpretation

In a traditional non-spatial model (as in (1)), the partial derivative $\frac{\partial y}{\partial x}$ is simply going to be the parameter β associated with x. In a Spatial Durbin Model, $\frac{\partial y}{\partial x}$ is more complicated. This is due to the feedback loops whereby a change in x in country A not only has a primary effect on y in country A, but also potential effects on y in all other countries in the sample and then secondary effects on y in country A. LeSage and Pace (2009) outline a system for measuring the average *direct effects* of a change in x, along with the average *indirect effects* of the change. Under their system, the *direct effect* of a change in a variable represents the average effect of a change in x_i on y_i for all countries. This direct effect would be analogous in interpretation to the single parameter β associated with x in a non-spatial framework. The *indirect effect* of a change in x would be the average effect of a change in x_i on y in all other countries. For the purposes of interpreting the marginal effects of control variables and testing their significance in the model, the appropriate questions relate to the magnitude of direct and indirect effects and whether or not these effects are statistically significant, not on the magnitude or significance of the specific β or γ parameters. Therefore, all regression results will report these results instead of specific parameter estimates.

[Insert Table 2 here]

Table 2 reports the estimation results from a variety of spatial models. The first column contains results from a Spatial Durbin Model with both time and spatial fixed effects. A joint significance test of the year fixed effects finds them significant with a p-value less than 0.01. Similarly, a joint test of the country fixed effects finds them significant with a p-value less than 0.01. Therefore, I adopt this specification as the preferred model. The primary parameter of interest is ρ, reflecting the spatial growth effect this paper seeks to address. In this specification, the estimate of ρ is negative and statistically significant, indicating that a positive growth shock in one country actually leads to a significant decrease in growth rates of neighboring countries. Of course, the magnitude of this negative spatial effect will be heterogeneous across neighbors, as determined by the spatial weight matrix. Intuitively, the magnitude of the shock dissipates the farther away neighbors are from the origin country. As I will highlight in the next section, this negative coefficient estimate does not necessarily mean that growth is a "zero sum" game. While a growth shock in one country will, according to these estimates, lower neighboring growth rates, the spillover to any one country is much smaller than the initial shock.

The direct effect of an increase in the capital stock is positive and quite significant, as would be expected. Increased capital stocks have no significant indirect effects on neighboring growth rates. Positive terms of trade shocks do not have any direct effect on GDP growth, but do have a significant indirect effect on neighboring GDP growth. A one percent increase in a country's terms of trade would lead to an average reduction in neighboring GDP growth of approximately a tenth of a percentage point. The warscore variable is significant in its direct effects. A one unit increase in the score for a country leads to a third of a percentage point decrease in growth rates in the same country. While there is an estimated average decrease in neighbors' growth rates of a little more than a percent, this effect is not statistically significant.

Columns two and three from Table 2 highlight the relative importance of the time and spatial fixed effects in the estimation. Column two provides results from a Spatial Durbin Model without spatial fixed effects. While the omission of the spatial fixed effects changes the magnitude of the estimated spatial growth effect, the estimated parameter is still negative and significant. Column three, however, shows the more drastic impact of removing the time fixed effects. This change causes the primary spatial effect to have a positive and significant estimated effect. The omission of time fixed effects to account for common shocks is thus a likely explanation for the difference between the positive spatial effects found in most of the literature and the negative effects observed here.

The final Column in Table 2 has estimates from an SAR model with both spatial and time fixed effects. While the model selection process indicated that the SDM was preferred, the negative and significant sign on the primary spatial parameter in the corresponding SAR model indicates that the choice of model is not the driving factor in the finding of negative spatial growth effects.

[Insert Table 3 here]

LeSage and Pace (2010) point out that in a well specified spatial model, changes in the weighting scheme actually have very little effect on parameter estimates. Still, it cannot hurt to verify that the results presented here are not being driven by the choice of the spatial weight matrix. Table 3 provides perspective on this issue. The first column reproduces the results from the preferred model, which uses the geographic distance between countries to weight the spatial growth effects. The second column has results from the same Spatial Durbin Model, but this time the geographic weighting matrix is replaced by a matrix capturing the "economic distance" between countries. Following Buera et al. (2008), who discuss how countries engage in policy observation of similar neighbors, spatial growth effects should be strongest among countries which are closest in their level of development. They suggest measuring economic distance as the absolute value of the difference in the natural logs of GDPs of the countries. This creates a matrix which is decreasing in the level of economic similarity. Again, because the elements of a weighting matrix should be increasing in the strength of spillovers, this value is inverted to form the weighting matrix of economic distance. Consistent with the spatial literature, this matrix is also row-normalized before being included in regressions. The similarity of results across the columns, especially the negative and significant coefficient on the spatial parameter of interest, suggests that the findings are not being driven by the choice of weighting scheme.

V. The Economic Significance of Spillovers and Policy Evaluation

The Real Economic Value of Spillovers

Having made an argument for the existence of negative growth spillovers and their statistical significance, it is important to also determine their economic relevance. Do these spillovers actually matter in practice? As a thought exercise, suppose that every country in the Americas was holding constant at their year 2000 GDPs, when an initial 2% growth shock occurs exogenously in a single country, Argentina. Table 4 outlines the effects of this hypothetical shock.
[Insert Table 4 here]

First, notice that the spatial feebacks magnify this initial 2% shock slightly. The dollar value of this net shock to Argentina would be approximately $6.3 billion. The estimates from the preferred SDM with spatial and time fixed effects indicates that spatial growth effects would cause GDP to contract in a number of other countries by over a fifth of a percentage point. Some countries would actually see positive net spatial effects as the negative spillover from the initial Argentinean shock is outweighed by secondary positive spillovers from the resulting decreases in other neighbors' GDPs. The real value of the spatial growth effects ranges from an almost $17 billion loss in the United States to a $56 million increase in Chilean GDP. The net *absolute value* of spatial growth effects is estimated to be over $20 billion. The net change in the combined GDP of all countries is sensitive in an exercise such as this to the location and number of countries in which the initial shock originates.

Un-modeled spillovers and policy effects

While this paper and others suggest that spatial growth effects might be impacting how neighboring countries grow in relation to each other, most papers examining growth policies do not currently account for these effects. It is worthwhile to understand how the exclusion of spatial growth effects from a model might change estimates of other parameters in growth regressions. To highlight this problem, consider a counterfactual situation where all the countries in the sample are holding steady at zero growth, when the 10 member states of Mercosur (Argentina, Brazil, Paraguay and Uruguay are full members, Venezuela, Bolivia, Chile, Colombia, Ecuador, and Peru are associate members), a South American customs union, implement a policy which, before the effects of any growth spillovers, would lead to a 2% increase in growth for its member states and have no effect elsewhere. Table 5 shows what the estimated growth effects of this policy would be after taking into account the spatial effects estimated by the preferred Spatial Durbin Model.

[Insert Table 5 Here]

While a spatial model would be able to isolate out the 2% growth effect of the policy on the 10 member states and the zero independent growth of the remaining sample, a regression which does not account for spatial effects would fail to capture the true policy effect and ultimately estimate a constant growth rate of about -1.25% and a policy effect of about 3.0% increased growth. Therefore, not only does a model which omits spillover effects have biased estimates of the policy effect in question, it also biases the estimates of the average growth rates of other nations.

VI. Revisiting existing literature

Using a spatial model which 1) focuses on a single region and 2) includes year fixed effects, this paper finds evidence of significant negative spatial growth spillovers. However, the existing literature on growth spillovers points exclusively to the existence of positive effects. Can this difference be explained solely by these two factors? To shed some light on this question, I re-examine an existing work while incorporating the regional focus and year fixed effects. From the perspective of this paper, Behar (2008) provides an ideal starting point for this exercise. Behar's work is the best option for this type of comparison because, like this paper, he uses annual growth rates to examine short-run spillovers. Additionally, Behar employs models both with and without time dummies, but at the global level rather than regionally. Using Behar for comparison allows for evaluation of the effects of the regional focus, the effects of the yearly dummies, and the effects of the combination of both.

While Behar uses a variety of models which allow for spillovers at the neighborhood level, the regional level, and the global level, his starting point is a basic SAR model of the form:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{i,j} + \mu_{i,t}$$

This model is estimated for 134 countries for up to 25 years. The spatial weighting matrix assigns a value of 1 for every pair of countries within 1000 km of each other, as measured by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). This model is reproduced over the same time period for the 76 countries for which complete data could be found. Behar's results, along with the results of the replication exercise, can be found in Table 6.

[Insert Table 6 here]

Comparing the Behar results in column 1 with the replicated results in column 2, the sign and significance of the estimated spillovers is preserved in the replication exercise. The same can be said comparing columns 4 and 5, which are Behar's results from a model adding in a regional spillover and this model's respective replication. The similarities of the replicated results to their counterparts imply that sample differences do not seem to be creating vastly different parameter estimates. Columns 3 and 6 of Table 6 examine how Behar's model behaves when spillover effects are the same across regions, but each region is allowed to have its own yearly fixed effects. Column 3, corresponding to Behar's model with only neighborhood spillovers, has a much smaller estimated spatial effect. In fact, the spatial effect is no longer statistically significant, with a p-value of 0.968. Column 6, corresponding to Behar's model with both neighborhood and regional effects, again has a much smaller estimated neighborhood spillover which is statistically indistinguishable from zero (p-value of 0.891), while the estimated regional spillover becomes negative and highly significant.

The absence of the yearly fixed effects seems to be responsible for an upward bias of the spillover coefficient, as would be predicted. Moreover, the inclusion of a universal yearly fixed effect in the model was not sufficient to account for the common shocks which seemingly heterogeneous across regions and are thus better modeled at the regional level. As long as shocks occur at a regional level, the inclusion of year fixed effects in a model extending beyond the region will not be able to properly account for these shocks and they will instead continue to create an upward bias in spillover estimates.

Growth Spillovers outside the Americas

This paper uses a spatial model in a specific region and incorporates time fixed effects. In contrast to the existing literature, this model produces evidence of statistically significant negative growth spillovers across countries. This effect is robust to alternative spatial models and alternative weighting schemes. It is also robust to the exclusion of spatial fixed effects. Looking at another work which found evidence of positive spillovers, it has been shown that re-estimation using region specific time fixed effects yields either statistically insignificant or negative growth spillovers. All of this evidence supports the conclusion that negative growth spillovers exist in the Americas and that the finding of negative spillovers, in contrast with the findings in the existing literature, is the result of key modeling choices.

At the same time, it is also possible that negative growth spillovers exist only in the Americas, and this is why previous studies have all found evidence that spillovers are positive. I directly address this possibility by estimating my preferred model over two other regions, Europe and Sub-Saharan Africa. These regions have less complete data coverage (both in the number of countries and in the length of the sample) and are not as clearly defined geographically. This makes these regions less suitable for the primary analysis than the Americas, but they are useful for comparing results. Table 7 shows the results of estimating the preferred model in each of the three regions.

[Insert Table 7 here]

The warscore variable does not vary at all in the European sample over the limited timeframe, so it is excluded from the regression. In all three regressions, the estimated growth spillover is negative. The estimate is statistically significant in the African sample, as it was in the main model. The coefficient on physical capital growth is positive and statistically significant in all three samples, and the warscore coefficient is significant in both the main model and the African sample, although the sign changes. None of the indirect effects achieves individual statistical significance in any model. With evidence of negative growth spillovers in all three samples, these results suggest that the unique finding is the result of the modeling choices rather than anything specific about the American sample.

VII. Conclusion

While spatial growth models are well established at sub-national levels, there has been much less investigation of growth spillovers internationally. International models which do examine spatial growth effects often fail to include time fixed effects or, if they do include time fixed effects, these models may use global samples instead of focusing on specific regions. This makes common temporal shocks harder to capture. Together, these two factors may lead to upward biases in estimates of spatial growth effects. As a result, previous papers may be capturing correlations across growth rates rather than estimating a causal relationship.

This paper adds to the spatial growth literature by estimating a carefully selected spatial model over a clearly defined sample of countries. When time fixed effects are included in this model, estimated spatial growth effects are shown to be negative and significant. These effects are robust to a range of choices concerning spatial weighting matrix and to a set of standard spatial models. These results are also evident for regions other than the Americas. The economic importance of spatial growth effects is highlighted as well. Failure to properly include spatial growth effects in growth models then leads to incorrect estimates of policy effects in growth models. Recognizing the existence of negative spatial growth effects is an important step in understanding how best to implement and evaluate growth targeting policies. Determining if these effects are a result of the competitive nature of countries in international trade or due to other factors is an important direction for future research.

References

Abreu, M., de Groot, H. L., & Florax, R. J. (2004). Spatial Patterns of Technology Diffusion: An Empirical Analysis using TFP. Tinbergen Institute Discussion Paper.

Anselin, L., Le Gallo, J., & Jayet, H. (2008). Spatial Panel Econometrics. In L. Matyas, P. Sevestre, & 3rd (Ed.), *The Econometrics of Panel Data* (pp. 625-660). Springer.

Behar, A. (2008). *Neighborhood growth effects: an annual panel data approach.* Centre for the Study of African Economies. Oxford: University of Oxford.

Buera, F. J., Monge-Naranjo, A., & Primiceri, G. E. (2008). Learning the Wealth of Nations. *NBER Working Paper*.

Burridge, P. (1981). Testing for a common factor in a spatial autoregression model. *Environment and Planning, 13,* 795-800.

Easterly, W., & Levine, R. (1997). Troubles with the Neighbors: Africa's Problem, Africa's Opportunity. *Journal of African Economies*, 120-142.

Elhorst, J. P. (2010). Matlab Software for Spatial Panels. *Presented at the IVth World Conference of the Spatial Econometrics Association*, (pp. 1-22). Chicago.

Ertur, C., & Kock, W. (2007). Growth, Technological Interdependence and Spatial Externalities: Theory and Evidence. *Journal of Applied Econometrics*, 1033-1062.

Frankel, J. A., & Romer, D. (1999). Does Trade Cause Growth? *The American Economic Review, 89*(3), 379-399.

Lee, L. F., & Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics, 154*, 165-185.

LeSage, J., & Pace, R. (2010). The Biggest Myth in Spatial Econometrics. *SSRN Working Paper*.

LeSage, J., & Pace, R. K. (2009). *Introduction to Spatial Econometrics.* Boca Raton, FL: CRC Press.

Mankiw, G., Romer, D., & Weil, D. (1992). A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics, 107*, 407-37.

Moreno, R., & Trehan, B. (1997). Location and the Growth of Nations. *Journal of Economic Growth*, 399-418.

Roberts, M., & Deichmann, U. (2011). International Growth Spillovers, Geography and Infrastructure. *The World Economy*, 1507-1533.

Weinhold, D. (2002). The Importance of Trade and Geography in the Pattern of Spatial Dependence of Growth Rates. *Review of Development Economics*, 369-382.

Table 1

Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$\%\Delta y_{i,t}$	551	1.02	4.96	-41.11	35.91
$\%\Delta k$	551	2.21	2.62	-9.1	11.93
$\%\Delta ToT$	551	0.86	12.47	-46.65	97.61
Warscore	551	0.78	1.64	0	6

Table 1 provides summary statistics for the growth rates of the countries in the sample and the three control variables used in the regressions.

Table 2
Comparisons of various model specifications

		Spatial Durbin Model with Time and Spatial Fixed Effects	Spatial Durbin Model with only Time Fixed Effects	Spatial Durbin Model without Fixed Effects	Spatial Autoregressive Model with Time and Spatial Fixed Effects
	Weighted Neighbors' Growth	-0.54 ***	-0.92 ***	0.30 ***	-0.55 ***
		(-3.65)	(-6.33)	(3.21)	(-3.83)
Direct Effects	%Dk	0.86 ***	0.80 ***	0.77 ***	0.82 ***
		(8.50)	(9.79)	(9.96)	(8.65)
	%DToT	0.02	0.02	0.03 *	0.02
		(0.95)	(1.02)	(1.68)	(1.47)
	Warscore	-0.34 *	-0.21 *	-0.27 **	-0.22
		(-1.73)	(-1.75)	(-2.42)	(-1.23)
Indirect Effects	%Dk	0.10	0.10	-0.01	-0.28 ***
		(0.21)	(0.30)	(-0.07)	(-4.84)
	%DToT	-0.11	-0.09	-0.06	-0.01
		(-1.34)	(-1.32)	(-0.91)	(-1.39)
	Warscore	-1.23	0.08	-0.60	0.08
		(-1.52)	(0.17)	(-1.42)	(1.19)
	R-squared:	0.370	0.364	0.220	0.363
	Obs:	570	570	570	570

Table 2 provides a series of regression results. The dependent variable in all specifications is GDP growth. T-stats are in parentheses.
Panel 1 has results from the preferred specification, an SDM model with both time and spatial fixed effects.
Panel 2 allows for comparison with a model which omits the spatial fixed effects. This omission doesn't substantively alter results.
Panel 3 allows for a comparison with a model which no longer has time fixed effects. This change causes the estimate of the primary spatial effect to change sign. Panel 4 allows for comparison between an SDM model and an SAR model.

* p-value <0.1 **p-value<0.05 ***p-value<0.01

Table 3
Comparison of Weighting Matrices

		SDM with both fixed effects, Geographic Distance Weighting	SDM with both fixed effects, Economic Distance Weighting
Direct Effects	Weighted Neighbors' Growth	-0.54 ***	-0.33 ***
		(-3.65)	(-2.79)
	%Dk	0.86 ***	0.82 ***
		(8.50)	(8.32)
	%DToT	0.02	0.03 *
		(0.95)	(1.78)
	Warscore	-0.34 *	-0.23
		(-1.73)	(-1.21)
Indirect Effects	%Dk	0.10	-0.17
		(0.21)	(0.22)
	%DToT	-0.11	0.05
		(-1.34)	(0.51)
	Warscore	-1.23	-0.67
		(-1.52)	(-0.71)
	R-squared:	0.370	0.347
	Obs:	570	570

Table 3 provides a comparison of regressions with different spatial weight matrices. The dependent variable in all specifications is GDP growth. T-stats are in parentheses.
Panel 1 is the preferred specification using a geographic weighting matrix. Panel 2 uses an economic distance weighting matrix instead.
* p-value <0.1 **p-value<0.05 ***p-value<0.01

Table 4
Effects of a growth shock in Argentina

Spillovers to:		New Growth Rate	Value of Spatial Growth Effect (millions of $)
	Argentina	2.07%	6,290
	Bolivia	0.01%	2
	Brazil	-0.02%	-242
	Canada	-0.14%	-1,244
	Chile	0.05%	56
	Colombia	-0.13%	-252
	Costa Rica	-0.20%	-65
	Ecuador	-0.11%	-58
	El Salvador	-0.21%	-59
	Guatemala	-0.20%	-108
	Honduras	-0.21%	-37
	Mexico	-0.17%	-1,568
	Nicaragua	-0.21%	-20
	Panama	-0.18%	-30
	Paraguay	0.04%	7
	Peru	-0.05%	-55
	United States	-0.17%	-16,600
	Uruguay	0.05%	12
	Venezuela	-0.13%	-183
	Initial Shock Value:		6,290
	Net Absolute Spillovers to other nations:		20,598

Table 4 shows the total growth rate effects, along with their dollar value, from a hypothetical 2% growth shock to Argentinean growth. These values are calculated using the parameter estimates from Table 2, panel 1.

Table 5
Effects of a growth shock in MERCOSUR countries

Spillovers to:		Initial Growth Shock	Net Growth Rate
	Argentina	2%	1.95%
	Bolivia	2%	1.97%
	Brazil	2%	1.87%
	Canada	0%	-1.12%
	Chile	2%	1.93%
	Colombia	2%	1.38%
	Costa Rica	0%	-1.20%
	Ecuador	2%	1.49%
	El Salvador	0%	-1.35%
	Guatemala	0%	-1.36%
	Honduras	0%	-1.35%
	Mexico	0%	-1.28%
	Nicaragua	0%	-1.31%
	Panama	0%	-1.06%
	Paraguay	2%	1.99%
	Peru	2%	1.72%
	United States	0%	-1.26%
	Uruguay	2%	1.95%
	Venezuela	2%	1.37%

Table 5 shows the post-spillover growth rates of the countries in the sample from a hypothetical exercise where the Merosur countries are assumed to each experience a pre-spillover 2% growth shock.

Table 6
Replicating Behar (2008) and adding region-specific year FE

	Behar's Results (Table 2, Panel 1)	Replication of Behar (Table 2, Panel 1) on modified sample	Replication of Behar (Table 2, Panel 1) with region specific year FE	Behar's Results (Table 2, Panel 5)	Replication of Behar (Table 2, Panel 5) on modified sample	Replication of Behar (Table 2, Panel 5) with region specific year FE
Weighted Neighbors' Growth Rate	0.111 ***	0.281 ***	0.002	0.068 ***	0.161 ***	0.007
Regional Growth Rate				0.189 **	0.191 *	-5.05 ***
Obs:	1390	1824	1824	1390	1824	1824
Country FE:	Yes	Yes	Yes	Yes	Yes	Yes
Yearly FE:	No	No	Region Specific	Global	Global	Region Specific

Table 6 provides results from Behar (2008), replicated versions of these results on a slightly modified sample, and replicated versions of these results when region specific yearly fixed effects are added to the models. T-statistics are not reported in Behar, and so are omitted here as well.
* p-value <0.1 **p-value<0.05 ***p-value<0.01

Table 7
Comparison of results in the Americas, Europe, and sub-Saharan Africa

		Preferred Model for the Americas (from Table 2)	Preferred Model for Europe	Preferred Model for Africa
Direct Effects	Weighted Neighbors' Growth	-0.54 ***	-0.21	-0.667 ***
		(-3.65)	(-.97)	(-3.37)
	%Dk	0.86 ***	0.9619 ***	0.3887 ***
		(8.50)	(9.90)	(4.42)
	%DToT	0.02	0.0228	0.0345
		(0.95)	(0.553)	(1.39)
	Warscore	-0.34 *		3.386 **
		(-1.73)		(2.80)
Indirect Effects	%Dk	0.10	0.5947	0.1531
		(0.21)	(0.398)	(0.17)
	%DToT	-0.11	-0.6175	0.0172
		(-1.34)	(-1.28)	(0.096)
	Warscore	-1.23		-5.16
		(-1.52)		(-0.501)
	R-squared:	0.370	0.369	0.2042
	Obs:	570	390	465

Table 7 applies the preferred model to Europe and Sub-Saharan Africa for comparison with the results from Table 2 examining the preferred model in the Americas. The European countries in the sample had no violent conflict during the sample time period, meaning the Warscore variable was necessarily omitted.

* p-value <0.1 **p-value<0.05 ***p-value<0.01