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Institutions, Geography, Trade, and Income per Capita

A Spatial-Simultaneous Equation Approach

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ABSTRACT

This paper tests a series of prominent hypotheses regarding how institutions, geography, and trade interact to influence income per capita using a novel spatial econometric approach to control for both spillovers among neighboring countries and spatially correlated omitted variables. Simultaneous equations are used to identify alternative channels through which country characteristics might affect income through trade and institutions, and then to test the robustness of those effects. Evidence indicated that both institutions and trade influence growth. Geographical factors such as whether a country is landlocked and its distance to the equator influence income, but only through trade. Data covering 95 countries across the world from 1960 through 2002 was used to construct a pooled dataset of 5-year averages (9 in all) centered on 1960, 1965, and so on through 2000. Both limited and full information estimators, partly based on a generalized moments (GM) estimator for spatial autoregressive coefficients, were used. These allow for spatial error correlation, correlation across equations, and the presence of spatially lagged dependent variables.

Keywords: economic growth, geography, institutions, trade, spatial econometrics, simultaneous equations

JEL codes: C31, C33, I18, O13, R12

1. INTRODUCTION

How institutions, geography, and trade interact to influence per capita income has been an intriguing question for development economists (Frankel and Romer 1999, Dollar and Kraay 2002, Pritchett 2003). Following North (1990) and others, economists such as Acemoglu et al. (2001) have argued that income depends primarily on economic and political institutions. This view emphasizes the role of property rights, market infrastructure, and price incentives as the key causes of differences in investment and economic growth. These institutions may correspond to national government policies, but they may arise and spread in other ways as well. An alternative approach championed in recent years by Diamond (1997) and particularly by Sachs (2001) uses location-specific geographic and technological factors to explain income differences. This approach argues that geographic obstacles to improving some determinant of economic growth, such as transportation infrastructure, could explain intercountry differences in average incomes and perhaps also help account for intercountry differences in economic institutions.

Trade, on the other hand, affects income per capita through various channels, including specialization, comparative advantage, exploitation of increasing returns from larger markets, exchange of ideas through communication and travel, and spread of technology through investment and exposure to new goods. How trade interacts with institutions and geography to influence economic income becomes more evident with the gravity equation model (Tinbergen 1962, Anderson 1997). Despite advances in understanding this question using the influential gravity model, what remains a challenge is finding best estimates and testing for the effects of institutions, geography, and trade on income per capita (Pritchett 2003).

A principal difficulty in disentangling the effects of institutions, geography, and trade on income per capita is endogeneity. Any observed correlation of institutions, geography, or trade with income could be due to reverse causality or to omitted variables that affect both items under investigation. Frankel and Romer (2002) proposed an insightful construction of instrumental variables for trade with which the endogeneity problems could be addressed. Yet the multiplicity of instruments introduced may result in inefficiency since the instruments suggest more ignorance than knowledge (Amavilah 2003).

Collinearity between these explanatory variables in a cross-section is a second fundamental challenge when separating the partial effect of institutions, geography, and trade to explain income per capita. Dollar and Kraay (2002), for instance, addressed this issue using a dynamic framework relating decadal changes in growth rates within countries to decadal changes in variables of interest. They used fewer instruments in each of their equations, but as they changed instruments from one equation to another their results changed greatly, making any conclusion about institutions and income difficult to reach (see Pritchett 2003).

Spatial correlation is a third important issue in testing the effects of institutions, geography, and trade on income per capita. This issue has not been addressed sufficiently in the literature. There are obvious geographic clusters of rich countries and poor ones. Geographic clustering could be due to spatially correlated attributes, such as climate or access to transport, or to interactions among neighbors, such as trade or migration. For recent reviews, see Magrini (2004) and Abreu, de Groot, and Florax (2005). Recent literature has dedicated much attention to endogeneity and multicollinearity as ways to capture the partial effects of institutions, geography, and trade in explaining income per capita. But less has been done to address the spatial dependency that might exist across cross-sectional units. Such spatial autocorrelation could be due to spillover across neighbors or to shared characteristics among neighbors. Spatial spillover can be understood as unobservable flows that may exist between neighboring spatial units (countries) because they are close to each other. These flows can be trade, investment, or knowledge. The shared characteristics can be unobserved social institutions or climate, either of which may explain a similarity in neighboring countries' development outcomes.

Trade, for instance—through agreements among neighboring countries, such as NAFTA and the European Union—may link the growth processes of different countries in a region. Technology diffusion can also illustrate how neighboring countries' growth processes could be linked to each other. It has been argued, for instance, that technology diffuses more easily across areas with similar climate characteristics (Diamond 1997). In such a case the level of technology that fosters higher income levels in each country would depend not only on externalities created by capital formation within the country but also on the technology level of its neighbors with a similar climate.

Using a similar but updated and extended dataset, as used by Dollar and Kraay (2002), this paper builds on the spatial estimator developed by Kelejian and Prucha (2004). This method is intended to control for very general kinds of neighborhood and spatial spillover effects while allowing for endogeneity of key regressors. Doing so raises the bar for each hypothesis by testing it against alternative processes.

The remainder of this paper is organized as follows: Section 2 discusses the model specification. Section 3 presents the data and provides an exploratory empirical assessment of the dynamics over space and time of the key variables in the system. Section 4 presents econometric methods and compares results for alternative specifications. Section 5 provides conclusions.

2. MODEL MIS-SPECIFICATION AND CONSEQUENCES

In the standard linear regression model, spatial dependence can be incorporated either as an additional regressor in the form of a spatially lagged dependent variable or as part of the error structure or in both ways. The former method is referred to as a spatial lag model and is appropriate when the focus is the assessment of the existence and strength of spatial interaction. This is interpreted as substantive in the sense that it can be given an economic interpretation. Spatial dependence in the regression disturbance term—a spatial error model—is appropriate when the concern is with correcting for the potentially disturbing influence of spatial autocorrelation due to the use of spatial data (Anselin 1988). Equations (1) and (2) provide a specification for a spatial lag and spatial error respectively:

$$y = \rho Wy + X\beta + \mu \tag{1}$$

and

$$y = X\beta + (I - \lambda W)^{-1} \mu , \tag{2}$$

where y is an ($n \times 1$) vector of observations on the dependent variable, X an ($n \times k$) matrix of nonstochastic regressors, W an ($n \times n$) spatial weights matrix that represents the topology of the spatial system, μ an ($n \times 1$) vector of iid errors, β a ($k \times 1$) vector of regression coefficients, and ρ and λ spatial autoregressive parameters.

In general, a simple linear regression such as $y = X\beta + \mu$ is "topologically invariant" in the sense that the geography of the spatial system does not matter, but it does matter in equations (1) and (2) because they allow for spillovers and spatial autocorrelation in the error term respectively. Consequently, when sampled data have a locational component but spillover is not accounted for in the model, ordinary least squares (OLS) estimators may not be optimal among all linear unbiased estimators; furthermore, some of the Gauss-Markov theorem assumptions are violated. It can be shown, for instance, that when the sampled data-generating process is spatially lagged but a simple linear regression is used instead of equation (1), the OLS estimator is biased, with $E[(X'X)^{-1} X' \rho Wy]$ representing the omitted spatial lag variable (see Appendix A for details). In the same way, it can be shown that the covariance expression in equation (1) is $\mathrm{cov}(\widetilde{\beta}) = (X'X)^{-1} X' E[(\rho W + v)'(\rho W + v)] X (X'X)^{-1}$.

Similarly, it can be shown that if there is a spatial error component in the data but a simple linear specification is used instead, the variance associated with the OLS estimates will not be of the form $\sigma^2 (X'X)^{-1}$. Rather, the variance will be a more involved function of the parameter λ, of the form $E\left[\beta - \hat{\beta}\right]\left[\beta - \hat{\beta}\right]' = \sigma^2 (X'X)^{-1} X'[(I - \lambda W)'(I - \lambda W)]^{-1} X (X'X)^{-1}$ (see Appendix A for details).

This implies that when sample data have a locational component, two problems arise: (1) spatial dependence may exist between the observations, and (2) spatial heterogeneity may be relevant for the relationships being modeled. With these two problems, it is not clear anymore whether OLS estimators are optimal among all linear unbiased estimators, since some of the Gauss-Markov theorem assumptions are violated.

Consequently, when data have a spatial component and spatial spillover is ignored in the specification as an additional explanatory factor, then an important explanatory variable has been omitted, leading to biased coefficients. Equivalently, when the data have a spatial error component and spatial error is ignored in the specification, this corresponds to mis-specification in the error term structure, leading to a biased standard error (Anselin 1996).

This paper allows for different types of spatial autocorrelation processes to affect institutions and trade and also to affect income through other means. For this purpose, it adopts an explicit three-stage least squares (3SLS) approach with panel data in a system of simultaneous equations. By identifying the entire system, it tests the role of each endogenous determinant of income (each institution and trade) through an association with particular exogenous variables. Our identification strategy rests on that exogeneity, together with the exclusion restrictions by which those variables are tied to particular development channels (Klein and Vella 2005). These identifying assumptions are plausible but are not tested here.

The particular system of equations used specifies institutions and trade as the only two endogenous variables that jointly influence income. The exogenous variables in the system include those of Dollar and Kraay (2002), notably, whether a country is landlocked, its distance to the equator, its population, the fraction of the population speaking English, and the fraction of the population speaking a European language.

The resulting system of equations is presented below. The implied exogeneity and exclusion restrictions are plausible but, as noted above, specification and robustness are not tested. Here, our goal is to estimate this representative system, taking into account neighborhood effects through spatially correlated omitted variables and spatial spillover effects from the dependent variables. Time dummies are used for each five-year period to absorb any global trends in each equation.

Equation (3) captures determinants of international trade:

$$trade_{it} = a_1 + \beta_{11} income_{it} + \beta_{12} landlockness_i + \beta_{13} Disteq_i + \beta_{14} population_{it} + \delta_{1t} + \varepsilon_{1it} \,. \tag{3}$$

In equation (3), trade can be driven by economywide income, whether a country is landlocked, distance to the equator, and population size.

The following equation uses social history to identify exogenous determinants of a country's institutions:

$$institqual_{it} = a_2 + \beta_{21} income_{it} + \beta_{22} Engfrac_i + \beta_{23} Eurfrac_i + \delta_{2t} + \varepsilon_{2it} \,. \tag{4}$$

Equation (4) links an index of institutional quality (constructed from data reported by Freedom House [2005] and ICRS [2006]) to economywide income and to social history (defined using the prevalence of English and European languages that were spread from Europe across Asia, Africa, and Latin America through migration and military conquest).

The last equation, equation (5), brings the two endogenous variables together, with no additional exogenous variables:

$$income_{it} = \alpha_3 + \beta_{31} institqual_{it} + \beta_{32} trade_{it} + \delta_{3t} + \varepsilon_{3it} \,. \tag{5}$$

This system of equations can be estimated using 3SLS, but the results are likely to be biased, inefficient, or both, due to spatial processes beyond those captured in the regressors. Equations (3) through (5) may share spatially autocorrelated errors due to one of three factors: spatially correlated omitted variables, spatially correlated measurement error, or interaction among neighboring countries as detailed by Anselin (1996).

This paper accounts for spatially correlated residuals in a system of equations by allowing each endogenous variable to be subject to spatial dependence and also to a spatial autoregressive process in the error term (that is, a spatial autoregressive models with autoregressive disturbances model, called spatial ARAR model). To accomplish this, I use a recently developed full information estimator based on instrumental variable (IV) and general moments (GM) estimators, a process that simultaneously allows for correlation across equations (Kelejian and Prucha 2004).[1] Here I start by comparing the nonspatial replication of income regression with institutions and trade from Dollar and Kraay (2002) to spatial lag

[1] Kelejian and Prucha (2005) developed an extended estimator that incorporates heteroskedasticity as well, which can be incorporated in future work.

models that use the same specifications used by Dollar and Kraay. To do so, I start by replicating Dollar and Kraay's estimation, using the new data. Then I estimate a simple OLS on each of the four specifications proposed by Dollar and Kraay, adding exploratory analysis in order to detect any eventual spatial dependence. Next, I estimate a spatial-lag maximum likelihood and a spatial-lag instrumental variable model for each equation that I compared with the Dollar and Kraay replications. Finally, I estimate the new proposed model using Kelejian and Prucha's (2004) method. Again, I start with an exploratory OLS and then estimate the system.

3. DATA AND SOME EXPLORATORY RESULTS

The data are updated from the dataset used by Dollar and Kraay (2002), but the approach chosen here is different from Dollar and Kraay's in various ways. First, Dollar and Kraay started by using data in levels; then, to address the collinearity issue, they moved to data taken as changes of a variable of interest. This approach might be problematic. In fact, one should not compare levels-on-levels results with growth-on-growth results since the dynamics are different in getting back to the levels-on-levels coefficient (Pritchett 2003). This paper uses data only in levels. First, using a cross-section of 181 countries for year 1999, I replicate Dollar and Kraay's results for income regression with institutions and trade. Second, I construct 2panel data in which, for all time-variant data, I use observations at five-year intervals around 1960, 1965, and so on through 2000. In most cases, these observations are an average of five annual observations centered on the year indicated (that is, 1963–1967 for 1965, 1968–1972 for 1970, and so forth).

Economic data are drawn from the Penn World Tables 6.2 for national income (real GDP per capita, chain indexed, in 2000 U.S. dollars) and for the trade share (exports plus imports as a fraction of GDP) (Summers et al. 2006).

The variable for the quality of national institutions is a time-varying index, constructed by me, from data reported by Freedom House (2005) and International Country Risk Services (ICRS 2006). The Freedom House data are an average of the organization's measures for a country's political rights and civil liberties, and the ICRS index is an average of ICRS's measures of a country's degree of corruption, military in politics, religion in politics, law and order, and democratic accountability. Data from the two sources are rescaled for comparability and combined to construct a continuous time series from 1960 to 2000.

All exogenous variables, except population, are drawn from Dollar and Kraay (2002). Whether a country is landlocked is a dummy variable taking the value one if the country is landlocked and zero otherwise. Distance to the equator is measured as the absolute latitude of the capital city. Both the fraction of the population that speaks English and the fraction that speaks a major European language come originally from Hall and Jones (1999) as extended using Grimes (1996). Population data are drawn from Penn World Tables 6.2 and represent the total number of people.

Overall, the dataset comprises 5-year averages (9 in all) pertaining to 1960 through 2000 for 95 countries. Variable definitions and descriptive statistics for the panel dataset are provided in Table 3.1, with a complete list of countries provided in Appendix B. Our coverage includes all of North and South America except for Belize, Suriname, French Guiana, and some islands in the Caribbean. In order to build a consistent data series, several African countries, such as Morocco, Libya, Ethiopia, Nigeria, and Chad, could not be included in the sample. Switzerland and Germany as well as most of the central and eastern European countries are excluded, as well as Russia, Mongolia, and some smaller countries in Southeast Asia.

The distance between countries is captured through a spatial weights matrix, which is defined a priori and exogenously on the basis of arc distances between the geographical midpoints of the countries considered. It is an inverse-distance matrix, whereby elements are coded $1/d_{ij}$ if the distance between countries (d_{ij}) is less than or equal to 2,500 miles. Following convention, I standardize by forcing row sums to be equal to 1 and by setting the diagonal elements to 0 (see, for example, Bell and Bockstael 2000, for an explanation). The resulting spatial weight matrix for a single time slice has dimension 95, with 17 percent of the weights being nonzero. The minimum and maximum numbers of links between countries are 1 and 26, respectively, with an average of 16. The minimum cutoff distance required to ensure that each country would be linked to at least 1 other country would have been 1,812 miles. In our weight matrix, the connectivity structure is such that there is no direct link between North America and Europe, although some countries in South America are directly linked to Africa. The weight matrix for the pooled dataset is defined as an 855 × 855–block diagonal matrix, with the sequence of 9 matrices, each 95 × 95, on the diagonal. I assume spatial autocorrelation to be strictly contemporaneous.

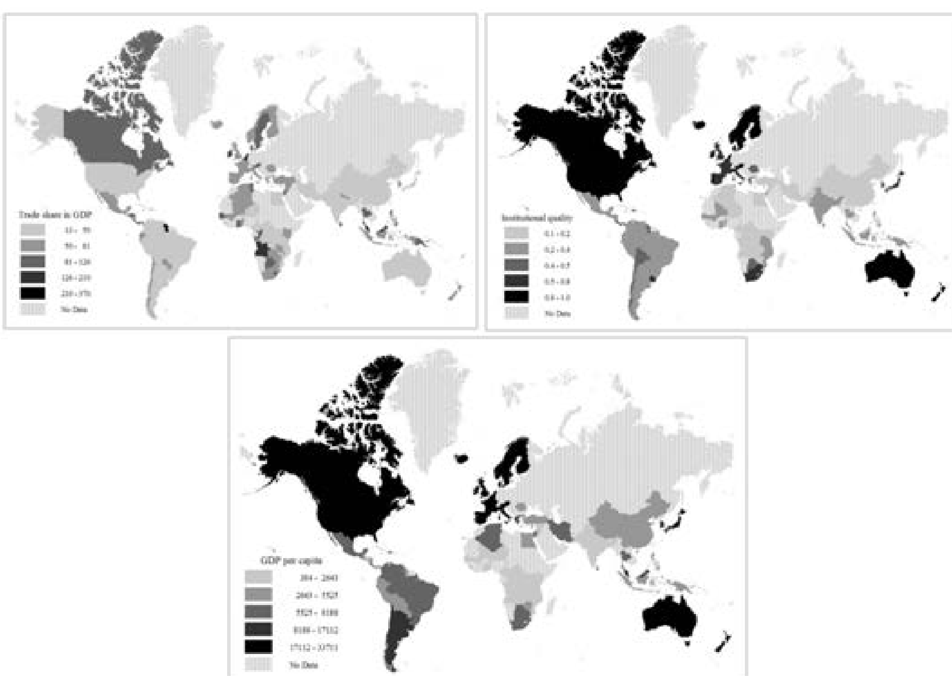
Table 3.1—Descriptive statistics

Variable/statistic	Mean	Variance	Minimum	Maximum	Skewness	Kurtosis
Trade	65.5499	2491.081	2.891	360.947	2.198	10.019
Income (´ 1000)	6345.0310	4.25E+07	353.011	34278.070	1.483	4.455
Institutional quality	0.4033	0.086	0.143	1.000	1.143	2.856
Landlocked	0.1684	0.140	0.000	1.000	1.772	4.140
Distance to equator	23.2000	282.849	0.000	64.000	0.538	2.248
Fraction of population speaking English	0.0973	0.073	0.000	1.000	2.626	8.080
Fraction of population speaking European language	0.2956	0.167	0.000	1.004	0.797	1.772
Population	37909.7300	1.61E+10	42.295	1249134.000	6.637	50.664
Time dummies	0.0000	0.2225	-1.0000	1.0000	0.0000	4.5000

Source: Author's calculations from data sample.
Note: Based on 95 countries, 5-year averages from 1960 through 2000.

Figure 3.1 represents key information for 2000 in choropleth maps, specifically for the dependent variables in the system of equations developed in Section 2. The spatial distribution of the trade share in GDP shows a scattered picture. Apart from a city-state such as Singapore, which is hard to see on the map, countries with relatively high trade shares include Guyana and Malaysia as well as Ireland, Belgium, and the Netherlands. The spatial distribution of institutional quality exhibits a concentration of high-quality institutions in North America, northern Europe, and Australasia; southern Europe constitutes an intermediate zone. GDP per capita, measured in constant U.S. dollars of 2000, is highest in North America, Europe, Australia, and Japan, and is relatively low in South America, Asia, and especially the African continent.

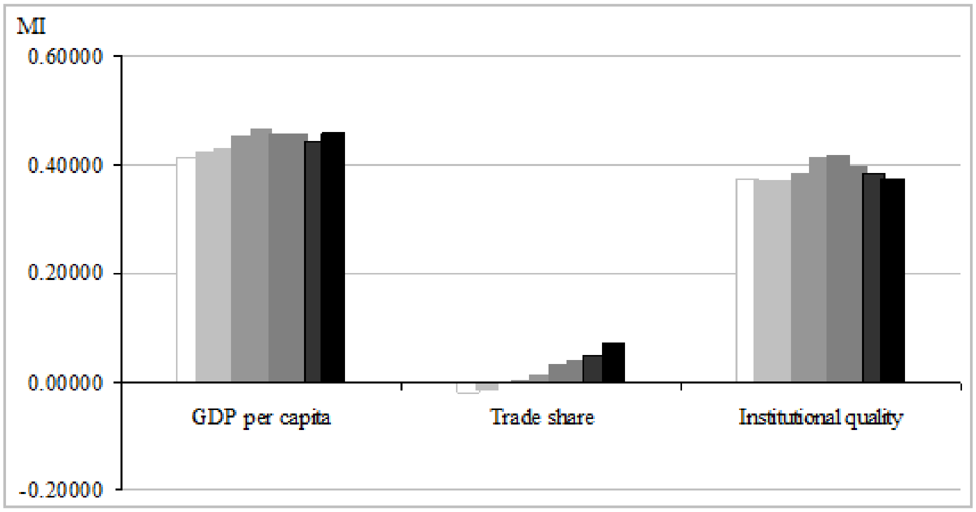
Figure 3.1—Maps of trade share, institutional quality, and GDP per capita, in 2000 U.S. dollars



Source: Constructed by author using world GIS data and data on country income, institutional quality and trade.

Figure 3.2 summarizes the level of and changes in spatial clustering for the endogenous variables using Moran's *I* statistic, defined as the degree of correlation between each country's value and that of its neighbors.[2] Global values for GDP per capita have a high degree of spatial clustering at the start of the period, suggesting strong neighborhood effects, with a small further increase in clustering during the 1970s and 1980s. The trade share has even lower spatial clustering, which increases over time but remains very close to zero. Institutional quality starts with fairly high levels of clustering in the early 1960s, but spatial clustering of institutional quality actually declines slightly from its peak in the 1980s through the 1990s.

Figure 3.2—Moran's *I* grouped by dependent variable from 1960 (left) through 2000 (right)



Source: Constructed by the author's from data sample.

[2] With a standardized weights matrix, Moran's *I* is defined as $I = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x}) / \sum_{i=1}^{n}(x_i - \bar{x})^2$, where x is measured in deviations from its mean, and w_{ij} are the elements of the weights matrix. The expected value of Moran's *I* equals $-1/(n-1)$ under the null hypothesis of no spatial autocorrelation, which is approximately –0.01 for our sample and signals a random spatial allocation of the attribute values contained in x. We use the normal distribution assumption for statistical inference. Extensive details and principles for statistical inference are available in Cliff and Ord (1981) and Tiefelsdorf (2000).

4. NEW ECONOMETRIC METHOD AND ESTIMATION RESULTS

In the current paper I follow the approach outlined in Kelejian and Prucha (2004), using a spatial econometric specification that is less restrictive in terms of spatial correlation than that used in previous work and accommodates endogeneity at the same time. In terms of spatial autocorrelation, the specification allows for spatial spillover effects through the dependent variable as well as for a spatial autoregressive error structure. This specification is known as the spatial ARAR model. For a single equation this specification reads as

$$\begin{aligned} y &= \rho W y + X\beta + \varepsilon, \\ \varepsilon &= \lambda W \varepsilon + \mu, \end{aligned} \tag{6}$$

where y is an $(n \times 1)$ vector of observations on the dependent variable, X an $(n \times k)$ matrix of nonstochastic regressors, W an $(n \times n)$ spatial weights matrix that represents the topology of the spatial system, μ an $(n \times 1)$ vector of iid errors, β a $(k \times 1)$ vector of regression coefficients, and ρ and λ spatial autoregressive parameters. Substitution and rearrangement of terms in equation (6) leads to

$$y = (I - \rho W)^{-1}\left(X\beta + (I - \lambda W)^{-1}\mu\right), \tag{7}$$

which shows that equation (6) implies a rather complex form of spatial autocorrelation evoked by nested spatial multiplier processes pertaining to the observable and the nonobservable part of the model (see also Anselin 2003). The spatial complexity of the model notwithstanding, testing for spatial autocorrelation is rather straightforward and can be based on a Lagrange multiplier test for which the asymptotic distribution has been derived in a maximum-likelihood framework. This test is generally known as the SARMA test, but since Lagrange multiplier tests cannot distinguish between locally equivalent autoregressive (AR) and moving average (MA) processes (Godfrey 1988), the SARMA test can also be used to detect an ARAR process.[3]

Instead of a purely cross-sectional dataset, I use a panel dataset comprising nine time slices centered on 1960, 1965, and so on through 2000. I do not investigate the temporal dynamics and associated serial autocorrelation but simply treat the data as independent replications of the cross-sectional data. I do, however, include fixed effects for the different time periods, thus accommodating a possible time trend. Given that some data offer yearly observations, richer models incorporating spatio-temporal dynamics are feasible, but I leave those for future research (see Anselin, Le Gallo, and Jayet 2006).

A distinct advantage of the Kelejian and Prucha (2004) system approach is that it explicitly allows for endogeneity to be taken into account. The endogeneity is not necessarily restricted to spatial spillover effects, but it can also include the usual system feedback effects. Kelejian and Prucha (2004) derived a full-information generalized spatial-systems estimator (GS3SLS) in a sequential estimation procedure using limited information IV and GM estimation to provide initial estimates of the spatial autoregressive parameters. The setup and the estimators involved are described concisely as follows.

Consider a simultaneous system of m spatially interrelated cross-sectional equations indexed by j $(= 1, 2, \ldots, m)$ and defined as

$$Y = \overline{Y}\mathrm{P} + Y\Gamma + X\mathrm{B} + U, \tag{8}$$

where $Y = (y_1, y_2, \ldots, y_m)$, with y_j as the $(n \times 1)$ vector of observations on the dependent variable; where $\overline{Y} = (\overline{y}_1, \overline{y}_2, \ldots, \overline{y}_m)$ has the same dimension and contains the spatial lags of the endogenous variables

[3] Anselin and Kelejian (1997) discussed testing for spatial autocorrelation in a model with endogenous regressors, where the endogeneity is caused by systems feedback or by spatial interaction of an endogenous variable. In the empirical application we initially use OLS-based tests, although this ignores the endogeneity of some of the regressors. Testing for spatial autocorrelation can also be based on the general results for Moran's I obtained by Kelejian and Prucha (2001).

defined as $\overline{y}_j = Wy_j$, $X = (x_1, x_2, \ldots, x_k)$, with x_l as the $(n \times 1)$ vector of observations on the exogenous variable l; and where $U = (u_1, u_2, \ldots, u_m)$, with u_j as the vector of errors in the jth equation. Further, W is an $(n \times n)$ spatial weights matrix of known constants, and P is an $(m \times m)$, Γ an $(m \times m)$, and B a $(k \times m)$ parameter matrix. In addition to the spatial spillovers in the endogenous variables, the errors are also allowed to include a spatial autoregressive process:

$$U = \overline{U}\Lambda + E, \tag{9}$$

with $E = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m)$, where ε_j denotes the $(n \times 1)$ vector of innovations. Analogous to the spatial lag operations above, $\overline{U} = (\overline{u}_1, \overline{u}_2, \ldots, \overline{u}_m)$ are the spatially correlated errors with $\overline{u}_j = W\overline{u}_j$, and the spatial autoregressive parameters are given by $\Lambda = \mathrm{diag}_{j=1}^{m}(\lambda_j)$.

One should note that the coefficient matrix P, referring to the spatially lagged endogenous variables, is not necessarily diagonal, and hence the specification allows for the jth endogenous variable to depend on its own spatial lag as well as on spatial lags of other endogenous variables. I leave this generalization to future work. The coefficient matrix Λ is also assumed to be diagonal, implying that the errors are spatially correlated within an equation, but they are not spatially correlated across equations.[4] The generality of the system approach and the suggested estimator is also evident from the fact that the exogenous regressors are allowed to depend on n, and hence form triangular arrays, which implies that the specification may also contain spatially lagged exogenous variables (Kelejian and Prucha 2004, 30). As a final observation I note that using the feasible GS3SLS estimator makes Wald tests available to test restrictions on the (spatial autoregressive) parameters.[5]

In order to determine the marginal effects of changes in the exogenous variables I use the notation and the line of reasoning introduced in Kelejian and Prucha (2004, 30–31). Define $\mathrm{y} = \mathrm{vec}(Y)$ and corresponding operations to define $\overline{\mathrm{y}}, \mathrm{x}, \mathrm{u}, \overline{\mathrm{u}},$ and $\varepsilon.$ Given that $\overline{\mathrm{y}} = (I_m \otimes W)\mathrm{y}$, the system defined by equations (8) and (9) can be written as

$$\begin{aligned} \mathrm{y} &= \Gamma^* \mathrm{y} + \mathrm{B}^* \mathrm{x} + \mathrm{u}, \\ \mathrm{u} &= \Lambda^* \mathrm{u} + \varepsilon, \end{aligned} \tag{10}$$

where $\Gamma^* = (\Gamma' \otimes I_n) + (\mathrm{P}' \otimes W)$, $\mathrm{B}^* = \mathrm{B}' \otimes I_n$, and $\Lambda^* = \Lambda \otimes W = \mathrm{diag}_{j=1}^{m}(\lambda_j W)$. The reduced form of (10) then follows from rearranging terms as

$$\mathrm{y} = (I_{nm} - \Gamma^*)^{-1}[\mathrm{B}^* \mathrm{x} + (I_{nm} - \Lambda^*)^{-1}\varepsilon], \tag{11}$$

where I_{nm} has dimension $(nm \times nm)$. Marginal effects of changes in one or more of the exogenous variables follow from

$$\frac{\partial \mathrm{y}}{\partial \mathrm{x}'} = (I_{nm} - \Gamma^*)^{-1}\mathrm{B}^* = [I_{nm} - (\Gamma' \otimes I_n) - (\mathrm{P}' \otimes W)]^{-1}\mathrm{B}^*. \tag{12}$$

This equation shows that the impact of a shock to one or more of the exogenous factors leads to spatial feedback via the endogenous regressors (through the term $\Gamma' \otimes I_n$) and depends on the

[4] The GS3SLS estimator allows for error correlation across equations, but this correlation does not have a spatial dimension.

[5] As far as the spatial variables are concerned, this is only feasible for the spatially lagged endogenous variables and eventually the spatially lagged exogenous variables. A Wald test on spatially autocorrelated errors is not possible because the values of λ_j are merely used in the Cochrane–Orcutt transformation. The latter can be tested using Moran's I (see Kelejian and Prucha 2001) or the Lagrange multiplier principle (see Anselin and Kelejian 1997). Also see footnote 3.

geographical location and the spatial connectedness of the place where the exogenous shock occurs (which is contained in the term $\mathrm{P}' \otimes W$). The weights matrix *W* defines the extent of each country's neighborhood and hence the limits of these spatial feedback effects. In our application, the definition of *neighborhood* is extremely broad in order to capture a wide range of spillovers, with all countries within a 2,500-mile radius linked to each other. Further work could test more restrictive specifications.[6]

In a concise form, I can write (8) and (9) as a system of cross-sectional equations indexed by *j* = (1, 2, …, *m*):

$$\begin{aligned} y_j &= Z_j \delta_j + u_j, \\ u_j &= \lambda_j W u_j + \varepsilon_j, \end{aligned} \tag{13}$$

where $Z_j = (\overline{Y}_j, Y_j, X_j)$ and $\delta_j = (\rho'_j, \gamma'_j, \beta'_j)'$. The full information estimator derived in Kelejian and Prucha (2004) is obtained in the following four steps:

1. Apply two-stage least squares (2SLS) to each equation and estimate δ_j as $\widetilde{\delta}_j = (\widetilde{Z}'_j Z_j)^{-1} \widetilde{Z}'_j y_j$, where $\widetilde{Z}_j = P_H Z_j$, $P_H = H(H'H)^{-1} H'$, and *H* is a matrix of instruments formed as a subset of the linearly independent columns of $(X, WX, W^2X, ...)$.
2. Based on $\widetilde{\delta}_j$, compute the 2SLS residuals $\widetilde{u}_j = y_j - Z_j \widetilde{\delta}_j$ and use the generalized moments procedure suggested by Kelejian and Prucha (1999) to estimate λ_j, the spatial autoregressive parameter of the error process for each equation.
3. Use a Cochrane–Orcutt transformation to define the suitably transformed variables $Z^*_j = Z_j - \widetilde{\rho}_j W Z_j$ and $y^*_j = y_j - \widetilde{\rho}_j W y_j$, and apply a feasible generalized spatial 2SLS (FGS2SLS) estimator to obtain $\hat{\delta}^{F2SLS}_j = (\hat{Z}'^*_j Z^*_j)^{-1} \hat{Z}'^*_j y^*_j$, where $\hat{Z}^*_j = P_H Z^*_j$.
4. Stack the equations as $y^* = Z^* \delta + \varepsilon$, where $y^* = (y'^*_1, y'^*_2, \ldots, y'^*_m)'$, $Z^* = \mathrm{diag}^m_{j=1}(Z^*_j)$, and $\delta = (\delta'_1, \delta'_2, \ldots, \delta'_m)'$. Obtain the full information results by using the FGS3SLS estimator to calculate $\hat{\delta}^{F3SLS} = (\hat{Z}'^* (\hat{\Sigma}^{-1} \otimes I_n) Z^*)^{-1} \hat{Z}'^* (\hat{\Sigma}^{-1} \otimes I_n) y^*$, where $\hat{\Sigma}$ is estimated as an (*m* × *m*) matrix whose *j*th–*l*th element is $\hat{\sigma}_{jl} = n^{-1} \widetilde{\varepsilon}'_j \widetilde{\varepsilon}_l$, with $\widetilde{\varepsilon}_j = y^*_j - Z^*_j \hat{\delta}^{F2SLS}_j$. Kelejian and Prucha (2004) proved that the small sample distribution of the FGS3SLS estimator can be approximated by $\hat{\delta}^{F3SLS} \stackrel{.}{\sim} \mathrm{N}(\delta, [\hat{Z}'^* (\hat{\Sigma}^{-1} \otimes I_n) \hat{Z}^*]^{-1})$.

The asymptotic properties of the above estimator critically depend on the assumption of homoskedastic innovations. In future work I will extend the application to the ARAR estimator, allowing for heteroskedasticity along the lines developed by Kelejian and Prucha (2005).

Let us now turn to estimation results. The first step in this paper was to replicate Dollar and Kraay's (2002) results using the new cross-section sample. The results are similar, but all variable coefficients seem to be smaller in magnitude. The signs for different coefficients remain the same, with a few exceptions. As shown in Table 4.1 Population coefficients become positive in the instrumental variable equation (Eq3IVr) and negative in the least square regression equation (Eq4OLS). But, again, these results raise concerns pointed out by Pritchett (2003). For all the coefficients, the results change in unacceptable ways as I move from one specification to another and from simple OLS to IV estimation.

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[6] An alternative approach uses direct representation of a distance-decay process for spatial spillovers, in a parametric or nonparametric fashion (see, for example, Conley and Ligon 2002). Some work has also pursued endogenizing the spatial weights matrix (Kelejian and Prucha 2005). However, neither approach can circumvent the occurrence and relevance of the modifiable areal unit problem (MAUP; see, for example, Anselin 1988).

Table 4.1—Income regression with institution and trade: Replication

	Eq1OLS	Eq1IV	Eq2OLS	Eq2IV	Eq3OLS	Eq3IV	Eq3IVr	Eq4OLS	Eq4IV	Eq4IVr	Eq5IV	Eq6IV
Rule of law	0.213*	0.681*			0.204**	1.102**	0.025	0.079	0.246	-0.743	3.309**	3.664
	(0.086)	(0.414)			(0.083)	(0.500)	(0.723)	(0.065)	(0.363)	(0.778)	(1.445)	(1.857)
Ln(trade/GDP)			0.694***	1.696***	0.694***	0.816	2.017**	0.414**	-0.213	0.712		-1.132
			(0.138)	(0.442)	(0.129)	(0.668)	(0.794)	(0.130)	(0.527)	(0.784)		(1.749)
Landlocked								-0.863***	-0.832***	0.041***		
								(0.143)	(0.173)	(0.008)		
Distance from equator								0.037***	0.040***	-0.068		
								(0.004)	(0.007)	(0.130)		
Ln(population)			0.026	0.177**	0.031	0.107	0.251**	-0.069**	-0.163	-1.019***		-0.044
			(0.043)	(0.076)	(0.042)	(0.120)	(0.120)	(0.037)	(0.095)	(0.268)		(0.367)
Constant	8.517***	8.525***	5.294***	-0.32	5.262***	4.107	-2.436	6.570***	10.013***	5.132	8.489***	13.579
	(0.086)	(0.096)	(0.828)	(2.461)	(0.783)	(3.855)	(4.406)	(0.726)	(2.928)	(4.373)	(0.387)	(9.925)
R-square	0.025	.	0.106	.	0.129	.	.	0.425	0.326	.	.	.
Observations	181	172	181	181	181	172	168	181	172	168	68	68
Instruments:		Eng-frac Eur-frac		Frankel–Romer (2002)		Eng-frac Eur-frac	Eng-frac Eur-frac Frankel–Romer (2002)		Eng-frac Eur-frac	Eng-frac Eur-frac	Settler Mortality	Settler Mortality Frankel–Romer (2002)
Omitted:							U.S. Canada Australia New Zealand			U.S. Canada Australia New Zealand		

Source: Author's results from models estimation.

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, with standard errors in parentheses.

The next step consists of a naïve exploratory OLS of the four Dollar and Kraay (2002) specifications. Table 4.2 presents results of this naïve OLS for these four specifications, without any control for endogeneity or spatial dependence. Results show how income is closely correlated with the two endogenous regressors, notably trade and institutional quality. Each of them is in turn also correlated with income, when controlling for other important determinants. The mis-specification test results shown here are also only heuristic, since they are derived without accounting for the endogeneity of some of the regressors. The condition number shows that multicollinearity does not impair the results. The results for the Jarque–Bera test indicate that the null hypothesis of normally distributed errors is rejected for nearly all equations. This provides another reason for interpreting the Lagrange multiplier diagnostics cautiously. It does not, however, have any major implications for the system estimator, because the estimator does not require the disturbances to be normal. The Breusch–Pagan test results, with random coefficient variation as the alternative hypothesis, show that homoskedasticity is not rejected in all the equations. The spatial diagnostics show for all the four equations that there is spatial autocorrelation.

Table 4.2—Income regression with institutions and trade, OLS with diagnostics for spatial effects[1]

Variable	Eq1	Eq2	Eq3	Eq4
Rule of law	0.212**		0.204**	0.113
	(0.089)		(0.084)	(0.0789)
Ln(trade/GDP)		0.695***	0.694***	0.574***
		(0.157)	(0.155)	(0.144)
Landlocked				-0.738***
				(0.185)
Distance from equator				0.273***
				(0.058)
Ln(population)		0.026***	0.031	-0.006
		(0.047)	(0.047)	
Constant	8.517***	5.294***	5.263***	5.483***
	(0.086)	(0.951)	(0.939)	(0.861)
Condition number	1	25	25	29
Jarque–Bera	6.612**	3.861	2.823	0.871
Breusch–Pagan	0.484	1.664	1.461	3.401
Moran's *I*	16.061***	15.553***	14.795***	10.729***
LM-error	235.021***	208.305***	188.218***	92.251***
Robust LM-error	14.837***	0.009	1.032	0.031
LM-lag	253.062***	234.757***	228.236***	137.351***
Robust LM-lag	32.877***	26.460***	41.050***	45.130***
SARMA	267.899***	234.765***	229.268***	137.381***
R^2-adjusted	0.0254	0.11	0.13	0.27
AIC	569.7	555.157	551.262	521.57
Log-likelihood	-282.85	-274.578	-271.631	-254.785

Source: Author's results from model estimation.
Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, with standard errors in parentheses. The Jarque–Bera and the Breusch–Pagan tests are asymptotically χ^2 distributed and test for normality of the errors and homoskedasticity with random coefficient variation as the alternative hypothesis, respectively. In cases where the null hypothesis of the Jarque–Bera test is rejected, the Koenker–Bassett variant instead of the Breusch–Pagan version is reported. For details on the spatial mis-specification tests see Anselin (1996).
[1]LM in the table stands for Lagrange Multiplier.

Accounting for spatial spillover in the Dollar and Kraay (2002) equations produces results that can be summarized as follows. Allowing for spatial dependence changes the results in Dollar and Kraay in important ways. First, after controlling for the observed variables I find significant spatial lags among all of the endogenous variables. As one can see in Table 4.3 for trade, institutional quality, and income, the spatial lag variable coefficients are positive and significant. With the procedure controlled for unobserved spillovers, the measured variables shown in Table 4.3 reveal several interesting correlations. Unlike the nonspatial estimation, including the spatial lag variables in each and every equation produces more consistent results in terms of both magnitude and signs. As one can see in Table 4.3, as I move from one spatial maximum likelihood to another or from one spatial instrumental variable to another, all signs remain consistent and correspond to the expected sign. The institutional quality variable, however, remains insignificant in all spatial instrumental variable regressions.

Table 4.3—Income regression with institutions and trade, spatial-lag estimator

	Eq1SRA-ML	Eq1SAR-IV	Eq2SRA-ML	Eq2SAR-IV	Eq3SRA-ML	Eq3SAR-IV	Eq3ISAR-IV	Eq4SRA-ML	Eq4SAR-IV	Eq4ISAR-IV
W_{income}	0.899***	1.393***	0.889***	1.157***	0.883***	1.24***	1.230***	0.846***	1.072***	0.841***
	(0.039)	(0.163)	(0.041)	(0.174)	(0.043)	(0.133)	(0.195)	(0.048)	(0.120)	(0.197)
Rule of law	0.122**	0.073			0.115**	0.079	0.112*	0.084*	0.075	0.079
	(0.346)	(0.064)			(0.060)	-0.061	(0.064)	(0.065)	(0.060)	(0.062)
Ln(trade/GDP)			0.408***	0.322***	0.410***	0.295**	0.407***	0.394***	0.346***	0.400***
			(0.112)	-0.123	(0.111)	(0.118)	(0.126)	(0.109)	(0.112)	(0.116)
Landlocked								-0.499***	-0.435***	-0.568***
								(0.143)	(0.144)	(0.155)
Distance from equator								0.065	0.011	0.014**
								(0.004)	(0.053)	(0.006)
Ln(population)			-0.014	-0.026	-0.011	-0.028	-0.024	-0.016	-0.018	-0.046
			(0.034)	(0.034)	(0.034)	(0.034)	(0.040)	-0.033	(0.033)	(0.040)
Constant	0.874***	-3.28**	-0.684***	-2.482*	-0.656	-3.055***	-3.483	-0.319	-1.868***	-0.200
	(0.346)	(1.382)	(0.765)	(1.348)	(0.760)	(1.110)	(1.499)	(0.776)	(1.050)	(1.679)
R^2	0.31		0.38	0.55	0.39	0.64	0.53	0.425	0.60	0.53
Observations	182		172	181	181	172	168	181	181	168
Omitted:							U.S. Canada Australia New Zealand			U.S. Canada Australia New Zealand

Source: Author's results from model estimation.
Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, with standard errors in parentheses.

Tables 4.4 and 4.5 show results for the new system approach proposed in the paper. Table 4.4 presents results for a naïve OLS with exploratory analysis performed equation by equation for the three equations in the system. These results, however, do not have any implication for the system. Again, the condition number shows that multicollinearity does not impair the results. The results for the Jarque-Bera test indicate that the null hypothesis of normally distributed errors is rejected for the trade equation but not for the institutions and income equations. This provides another reason for interpreting the Lagrange multiplier diagnostics cautiously. The Jarque–Bera results do not, however, have any major implications for the system estimator because the estimator does not require the disturbances to be normal.

Table 4.4—Regression income, equation-by-equation estimation, OLS with diagnostics for spatial effects

Variable	Trade	Institutional quality	Income
Trade			-0.042
			'(0.033)
Institutional quality			1.195***
			'(0.037)
Income	-0.107** *	0.411***	
	(0.025)	'(0.015)	
Landlocked	-0.369***		
	(0.063)		
Distance to equator	0.032**		
	(0.017)		
Fraction of population speaking English		0.482***	
		'(0.061)	
Fraction of population speaking European languages		0.071*	
		'(0.043)	
Population	-0.212***		
	(0.013)		
Constant	4.548***	-4.590***	9.757***
	'(0.223)	'(0.122)	'(0.137)
D_{1965}	-0.292***	0.043	-0.206***
	(0.061)	'(0.040)	'(0.067)
D_{1970}	-0.166***	-0.015	-0.061
	(0.061)	'(0.040)	'(0.067)
D_{1975}	-0.082	-0.070*	0.07
	(0.061)	'(0.040)	'(0.067)
D_{1980}	0.022	-0.058	0.104
	(0.061)	'(0.040)	'(0.067)
D_{1985}	0.012	-0.036	0.097
	(0.061)	'(0.040)	'(0.067)
D_{1990}	0.143**	0.011	0.073
	(0.061)	'(0.040)	'(0.067)
D_{1995}	0.303***	0.002	0.117*
	(0.061)	'(0.040)	'(0.067)
D_{2000}	0.406***	0.036	0.116*
	(0.061)	'(0.040)	(0.068)
Condition number	30	27	17
Jarque–Bera	46.302***	3.109	1.953
Breusch–Pagan	104.989***	64.416***	48.860***
Moran's *I*	3.452***	-0.654	72.033***
LM-error	6.123**	1.82	188.218***
Robust LM-error	0.235	10.408***	21.639***
LM-lag	6.656***	1.629	53.373***
Robust LM-lag	0.768	10.211***	2.979*
SARMA	6.892**	12.038***	75.012***
R^2-adjusted	0.27	0.60	0.57
AIC	1641.26	912.54	1804.59
Log-likelihood	-807.629	-444.271	-891.294

Source: Author's results from model estimation.
Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, with standard errors in parentheses

The Breusch–Pagan test results, with random coefficient variation as the alternative hypothesis, show, contrary to the cross-section case, that homoskedasticity is rejected in all equations. This finding implies that addressing this issue in future work would be highly relevant. The spatial diagnostics are fairly mixed. For trade and income equations there is evidence that a higher-order model is appropriate. There is, however, no clear indication of spatial autocorrelation for the institutional quality equation.

The system approach has the advantage of controlling not only unobserved spillovers but also regional characteristics. The measured variables shown in Table 4.5 again reveal several interesting correlations. As in the cross-section case, after controlling for the observed variables I find significant spatial lags in trade and income but not in institutional quality. With the procedure controlled for unobserved spillovers and regional characteristics, trade is positively correlated with income and distance to equator, as expected, and negatively correlated to whether a country is landlocked and its population. The institutions variable is strongly explained by income per capita and one of the historical tie variables. But these are of less importance. And in our final equation, these two endogenous variables have independent correlation with income, with trade showing a weak but significant correlation with income.

In sum, when controlling for spatial processes in this model, I maintain support for the ability of institutions, geography, and trade to explain income per capita. Geographic factors, such as whether a country is landlocked and its distance to the equator, are found to have significant independent effects on the system, influencing trade but not completely determining it, and a country's trade share does have an independent role in income.

Table 4.5—Regression output, system estimation, full information estimator for the ARAR specification

Variable	Trade	Institutional quality	Income
W_{trade}	-0.069*		
	(0.033)		
$W_{institutional\ quality}$		-0.062	
		(0.048)	
W_{income}			0.104*
			(0.049)
Trade			0.005*
			(0.002)
Institutional quality			1.527***
			(0.061)
Income	-0.109**	0.607***	
	(0.034)	(0.020)	
Landlocked	-0.476***		
	(0.065)		
Distance to equator	0.044**		
	(0.014)		
Fraction of population speaking English		0.081**	
		(0.030)	
Fraction of population speaking European language		0.008	
		(0.022)	
Population	-0.905***		
	(0.014)		
D_{1965}	-0.172**	0.065	-0.087
	(0.058)	(0.038)	(0.061)
D_{1970}	-0.1	0.006	-0.009
	(0.058)	(0.038)	(0.061)
D_{1975}	-0.02	-0.05	0.064
	(0.058)	(0.038)	(0.061)
D_{1980}	0.023	-0.052	0.068
	(0.058)	(0.038)	(0.061)

Table 4.5—Continued

Variable	Trade	Institutional quality	Income
D_{1985}	0	-0.04	0.053
	(0.058)	(0.038)	(0.061)
D_{1990}	0.066	-0.011	0.017
	(0.058)	(0.038)	(0.061)
D_{1995}	0.172**	-0.021	0.028
	(0.058)	(0.038)	(0.061)
D_{2000}	0.225**	-0.006	0.011
	(0.058)	(0.038)	(0.061)
Constant	4.020***	-6.220***	9.156***
	(0.310)	(0.199)	(0.428)
Implicit I^{b}	0.146***	0.313***	0.392***
	(0.053)	(0.005)	(0.049)

Source: Author's results from model estimation.
Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively, with standard errors in parentheses.

5. CONCLUSION

This paper uses panel data in a system of simultaneous equations, controlling for spatial spillovers and unobserved spatial heterogeneity, to explore how measured country trade, geography, and institutions might be linked to real income per person. This approach offers a new kind of test for how particular institutional and geographic characteristics interact with trade to affect income, and then tests the robustness of each variable against various kinds of neighborhood effects.

The endogenous variables associated with income are institutional quality (as measured by a combination of Freedom House [2005] and ICRS [2006] indexes) and trade (import plus export as percentage of GDP). The exogenous variables represent geographic characteristics (which plausibly affect only trade), social history ties (only through institutions, and population size (through international trade). With this specification, after the process is controlled for spatial proximity, all of the variables have some independent effect on income. This result provides strong empirical support for how institutions, geography, and trade interact to explain income per capita. Geographic variables such as whether a country is landlocked and its distance to the equator have strong independent effects on income by facilitating trade through easy access and proximity to larger markets. Institutional quality also has a strong independent link to income, even when one controls for reverse causality and neighborhood effects.

Most notably, accounting for these country characteristics still leaves large residual spatial lags. This result suggests that my specification has only begun to capture the relevant spillovers and spatial heterogeneity among countries. Understanding these spatial correlations will require more precise measurement of the unobserved factors driving flows associated with trade.

Throughout this paper I indicate potential extensions and variations to be addressed in future work. Among those are testing for exogeneity and exclusion restrictions, incorporating heteroskedasticity following the procedures developed in Kelejian and Prucha (2005), assessing parameter heterogeneity, and applying other robustness checks.

APPENDIX A: DIFFERENCES IN RESULTS FOR NONSPATIAL VERSUS SPATIAL SPECIFICATION

To assess differences in results due to differences in nonspatial versus spatial specification, the analysis is restricted to three models commonly used in this kind of research, and two cases of mis-specification are considered to illustrate the point: first, the aspatial model, which is commonly estimated by OLS, comprising stacked cross-sectional and regional observations that read as follows:

$$y = X\beta + \mu ; \tag{A1}$$

second, the spatial autoregressive error model, as follows:

$$y = X\beta + (I - \lambda W)^{-1} \mu ; \tag{A2}$$

and third, the spatial lag model, as follows:

$$y = \rho W y + X\beta + \mu , \tag{A3}$$

where W is the weight matrix representing the strength of the potential interaction between countries.

The first equation (A1) is "topologically invariant" in the sense that the geography of the spatial system does not matter; the second and third are not. The second equation (A2) introduces spatial autocorrelation in the error term, while the third equation (A3) allows for spillovers.

Equation (A2) would correspond to the situation in which unobserved variables that are assumed to be part of the error term follow a spatial stochastic process, such that

$$\varepsilon = (I - \lambda W)^{-1} \mu , \tag{A4}$$

where $(I - \lambda W)^{-1}$ is the spatial multiplier (Anselin 2002).

In a growth model, the spatial error pattern is due to some shared unobservable characteristics among neighbors. If such characteristics exist, the error term will exhibit a spatial structure, leading to a nonspherical error variance–covariance matrix. The variance–covariance matrix of ε in this case is given by

$$\begin{aligned} E[\varepsilon\varepsilon'] &= \sigma^2 (I - \lambda W)^{-1}[(I - \lambda W)^{-1}]' \\ &= \sigma^2[(I - \lambda W)'(I - \lambda W)]^{-1} . \end{aligned} \tag{A5}$$

This variance–covariance matrix is a full matrix, meaning that shocks at any location have an impact on all other locations. Through the spatial multiplier effect, this is also referred to as "global interaction" (Anselin 2003). This spatial interdependence, however, is only in terms of spatial diffusion effect. That is, it occurs through the error term. In fact, equation (A2) can be rewritten as follows:

$$y = X\beta + (I + \lambda W + \lambda^2 W^2 + \ldots)^{-1} \mu , \tag{A6}$$

showing that an exogenous shock in a given spatial unit affects the dependent variable in exactly the same way as in the first model, but the structure of the error term is different.

The variance associated with the OLS estimates will not be of the form $\sigma^2 (X'X)^{-1}$. It will rather be a more involved function of the parameter λ. In this case, while the OLS estimates remain unbiased, inference based on the usual variance estimates may be misleading. Formally, the bias is

$$E[\beta - \hat{\beta}] = (X'X)^{-1} X'E(\varepsilon) = 0 \quad \text{(A7)}$$

but the associated variance is

$$E\left[\beta - \hat{\beta}\right]\left[\beta - \hat{\beta}\right]' = \sigma^2 (X'X)^{-1} X'[(I - \lambda W)'(I - \lambda W)]^{-1} X(X'X)^{-1}. \quad \text{(A8)}$$

The model in equation (A2) represents a first-order spatial autoregressive lag model, where W is the spatial weight matrix. The reduced form of this equation is

$$y = (I - \rho W)^{-1} X\beta + (I - \rho \mathrm{W})^{-1} \mu, \quad \text{(A9)}$$

where ρ is the spatial autoregressive coefficient and μ an iid error term. Into an infinite form, this can be written as

$$y = (I + \rho W + \rho^2 W^2 + ...)X\beta + (I + \rho \mathrm{W} + \rho^2 W^2 + ...)\mu. \quad \text{(A10)}$$

In equation (A10), the first term on the right-hand side represents the spatial multiplier effect, showing that in every location, y depends on the observations at the same location but also on the observations in any other location. The second term on the right-hand side represents the spatial diffusion effects. Here the convergence rate will be different from that of the first model in that it will incorporate the multiplier effect.

Let us assume that instead of equation (A3), equation (A1) is estimated. That is, we assume that the correct specification is a spatial lag model, $y = \rho Wy + X\beta + \mu$, but we omit Wy and estimate instead $y = X\beta + \mu$. Let the estimator β for equation (A1) be $\tilde{\beta}$, defined as

$$\tilde{\beta} = (X'X)^{-1} X'y. \quad \text{(A11)}$$

Since the true model is given by equation (A5), let us substitute y with its true representation,

$$\begin{aligned} \tilde{\beta} &= (X'X)^{-1} X'(\rho Wy + X\beta + \mu) \\ &= (X'X)^{-1} X'\rho Wy + \beta + (X'X)^{-1} X\mu. \end{aligned} \quad \text{(A12)}$$

Introducing the expected value operator, (A12) can be written as follows:

$$\begin{aligned} E[\tilde{\beta} - \beta] &= E[(X'X)^{-1} X'\rho Wy] + (X'X)^{-1} XE\mu \\ &= E[(X'X)^{-1} X'\rho Wy] + 0 \\ &= E[(X'X)^{-1} X'\rho Wy]. \end{aligned} \quad \text{(A13)}$$

$E[(X'X)^{-1} X'\rho Wy]$ represents the omitted spatial lag variable bias. In the same way, it can be shown that the covariance expression in equation (A1) is

$$\mathrm{cov}(\tilde{\beta}) = (X'X)^{-1} X'E[(\rho W + v)'(\rho W + v)]X(X'X)^{-1}. \quad \text{(A14)}$$

APPENDIX B: LIST OF COUNTRIES INCLUDED IN THE SAMPLE

Algeria	Ghana	Pakistan
Angola	Greece	Panama
Argentina	Guatemala	Papua New Guinea
Australia	Guinea-Bissau	Paraguay
Austria	Guyana	Peru
Bangladesh	Haiti	Philippines
Barbados	Honduras	Portugal
Belgium	Iceland	Romania
Benin	India	Rwanda
Bolivia	Indonesia	Senegal
Botswana	Iran	Seychelles
Brazil	Ireland	Sierra Leone
Burundi	Israel	Singapore
Cameroon	Italy	South Africa
Canada	Jamaica	Spain
Central African Republic	Japan	Sri Lanka
Chile	Jordan	Sweden
China	Kenya	Syria
Colombia	Korea, Republic	Tanzania
Congo, Democratic Republic	Lesotho	Thailand
Congo, Republic of Congo	Malawi	Togo
Costa Rica	Malaysia	Trinidad and Tobago
Cyprus	Mali	Tunisia
Denmark	Mauritius	Turkey
Dominican Republic	Mexico	Uganda
Ecuador	Mozambique	United Kingdom
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