Measuring the World Economy

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Abstract: This paper provides an empirical assessment of whether the world economy has become smaller in terms of economic distance over the last decades. We adopt a cross-sectional spatial econometric approach, relating domestic output volatility to (distance-weighted averages of) other countries' output volatility, using a sample of 135 countries and rolling 10-year time windows over the period 1955 to 2006. Using descriptive measures, test statistics, and spatial econometric estimates, we find that cross-country interdependence was virtually insignificant in the early post-war period but has increased strongly from the mid-1960s to the mid-1980s and remained at a high level since then. Results for the most recent period suggest that common shocks to output volatility have a magnified impact and roughly quadruplicate through spillover effects and the associated repercussions, which are transmitted through both trade and financial openness.

Keywords: financial openness, spillovers, trade, output volatility

JEL No: C21, E32, F15, F40

I. Introduction

Over the last decades there has been a sizeable increase in trade and financial openness, triggered by current and capital account liberalization as well as improvements in transport and communication technologies. As a consequence, the importance of spillover effects is likely to have increased at all levels of aggregation: among firms, industries, regions, and even countries. In other words, the relevance of geographic distance should have decreased over time, a view that has been popularized as 'the death of distance' by Cairncross (1997).

Yet there is little overall quantitative evidence by how much globalisation has reduced economic distance between countries. A related albeit more specific strand of the literature considers either directly the evolution of trade costs over time or the sensitivity of trade flows to distance in gravity models. In their survey of the empirical trade literature, Leamer and Levinsohn (1995) conclude that the effect of distance on trade patterns has not diminished over time. More recently, Jacks et al. (2009) find that the role of distance has declined dramatically in the 19^{th} century, but not over the period since 1950. Another strand of the literature related to the subject of the present paper considers the synchronisation of business cycles across countries. While there are some well-established stylized facts such as the great moderation of US business cycle volatility since the mid-1980s, the results regarding the occurrence, magnitude and timing of moderations in output volatility vary considerably across countries (Stock and Watson, 2005).

This paper takes an alternative approach in addressing the question whether the world has become smaller in terms of economic distance. Instead of focussing on the transmission of single shocks (which requires high frequency data) or confining the analysis to a particular channel of interdependence (such as trade), it provides a bird-eye's perspective, using a large cross-section of 135 countries and considering how cross-country interdependence of output volatility has evolved over the period 1955 to 2006. From a methodological perspective, we adopt a spatial econometric approach, relating a country's output volatility to (distance weighted averages of) other countries' output volatility, using descriptive measures, test statistics, and econometric estimates of cross-country interdependence. We also suggest a new method to approximate (unobserved) bilateral data from observed aggregate data in order to assess the importance of alternative channels of interdependence, in particular that of trade versus financial openness.

We find that cross-country interdependence increased significantly till the mid 1980s and remained at high levels since then. In quantitative terms, estimation results for the most recent period suggest that a uniform shock to output volatility in the world economy roughly quadruplicates through spillover effects and the associated repercussions, which are equally transmitted through both trade and financial linkages.

The remainder of the paper is organized as follows. Section II outlines the empirical framework. Section III describes the evolution of the world economy's output volatility in the post-war period. Section IV presents estimates of cross-country interdependence of output volatility over time, whereas section V attempts to assess the role of trade and financial openness as transmission channels for cross-country spillover effects. Section VI summarizes the results and concludes.

II. Model Specification and Data

1. Empirical Framework

Focussing on a quantitative assessment of cross-country interdependence, we specify a cross-sectional model, which is repeatedly estimated for alternative time periods. Since increasing interdependence will be reflected in an increased propagation of both positive and negative shocks, it is natural to consider some measure of volatility as dependent variable. In particular, we consider the volatility of GDP per capita growth over (rolling) time periods of 10 years. As it is standard in skedastic regressions, the natural log is used to rule out negative predicted values. For reasons of both data availability and parsimony, the baseline specification includes (a constant) and as single explanatory variable the (log of) initial GDP per capita as an indicator of economic development and institutional quality, which we expect to be negatively related to output volatility. Hence, for a given time period *t*, our cross-section model reads

$$\sigma_{i,t} = \alpha_t + \beta_t \, y_{0,i,t} + u_{i,t} , \tag{1}$$

where σ_i is the log of country *i*'s standard deviation of output growth over a 10-year period, calculated as standard deviation of the residuals from a regression of the log of GDP per capita on a time trend over the period t to $t-10$; y_0 is the log of country *i*'s initial GDP per capita, referring to the starting year of the period considered ($t-10$). GDP is measured in million 1990 international Geary-Khamis dollars. All data are taken from Maddison (2010), yielding the most comprehensive sample with 135 countries over the period 1955 to 2006. Since we consider 10-year intervals, our first observation refers to $t = 1965$ and covers the period 1955 to 1965; we then move forward in time, using a moving 10-year time window, such that the most recent observation refers to $t = 2006$, which covers the period 1996 to 2006. Hence, the total number of cross-sections considered is 42, each of them referring to a particular 10-year time period. [1]

[1] Actually, data would be available for the first half of the 1950 as well, but its use yielded implausible estimation results throughout the paper (such as a significant positive effect of GDP per capita on output volatility, huge changes in the estimates from moving the time window by one year). Hence, we confine our analysis to data starting in 1955. Apart from data quality, the most likely explanation is

To estimate the strength of cross-sectional interdependence, we adopt a spatial econometric approach. As most general specification we consider a spatial autoregressive model with spatial autoregressive disturbances. In matrix notation (using boldface acronyms to denote matrices and vectors), the model reads

$$\boldsymbol{\sigma}_t = \alpha_t + \beta_t \mathbf{y}_{0,t} + \lambda_t \mathbf{W}\boldsymbol{\sigma}_t + \mathbf{u}_t \text{, with} \tag{2a}$$

$$\mathbf{u}_t = \rho_t \mathbf{W}\mathbf{u}_t + \boldsymbol{\varepsilon}_t , \tag{2b}$$

where the $N \times N$ spatial weights matrix $\mathbf{W} = (w_{ij})$ reflects the structure and the spatial autoregressive parameters λ and ρ measure the strength of cross-country interdependence. As outlined in more detail below, the elements of the weights matrix are specified as decreasing function of geographical distance between countries *i* and *j*. Since the weights matrices are time-invariant, we expect a reduction in economic distance (an increase in strength of cross-country interdependence) to be reflected in an increase in the spatial regressive parameters λ and ρ.

Using the definitions $\bar{\boldsymbol{\sigma}}_t \equiv \mathbf{W}\boldsymbol{\sigma}_t$ and $\bar{\mathbf{u}}_t \equiv \mathbf{W}\mathbf{u}_t$, the model can also be written as

$$\boldsymbol{\sigma}_t = \alpha_t + \beta_t \mathbf{y}_{0,t} + \lambda_t \bar{\boldsymbol{\sigma}}_t + \mathbf{u}_t \text{, with} \tag{3a}$$

$$\mathbf{u}_t = \rho_t \bar{\mathbf{u}}_t + \boldsymbol{\varepsilon}_t . \tag{3b}$$

The elements of the so-called ‘spatial lag’ of the dependent variable $\bar{\boldsymbol{\sigma}}_t = (\bar{\sigma}_{i,t})$ can be interpreted as weighted averages of other countries’ volatility, since $\bar{\sigma}_{i,t} = \sum_{j=1}^{N} w_{ij}\sigma_{j,t}$. An

that many economies were about the return to their pre-war growth path in the early 1950s and that growth (and volatility) in the early 1950s was still driven by adjustments to potential output.

analogous interpretation holds for the spatial lag of the disturbances ($\bar{\mathbf{u}}_t$). In economic terms, the spatial regressive structure implies that shocks induce multilateral spillover effects.

As it is standard in the spatial econometrics literature, the $N \times N$ weights matrix **W** has zero main-diagonal elements **W** (ruling out self-influence) and is row-normalized (such that each row sums to 1) to ensure well-behaved asymptotics. In particular, we assume that spillovers from country *j* to country *i*, reflected in element w_{ij}, are decreasing in distance between countries *i* and *j* ($Dist_{ij}$) according to the function $e^{-\delta Dist_{ij}}$. Hence, the elements of the (unnormalized) weights matrix $\mathbf{W}^0$ are defined as:

$$w_{ij}^0 = \exp(-\delta Dist_{ij}), \text{ for } i \neq j \text{ and zero otherwise.} \quad (4)$$

Distance is measured in 1000 kilometers, and the distance decay parameter is set to $\delta = 2.5$. This implies that the half-life distance of shocks amounts to some 280 kilometres; three quarters of a shock have faded away after 550 kilometers, and after some 1000 kilometers, the spillover effects of local shocks are reduced to 10 percent. Data on bilateral distances is taken from the CEPII database.

The final weights matrix **W** is obtained by row-normalizing the weights matrix defined by (4), such that **W** reflects the structure and strength of linkages between country *i* and *j* in relative terms, i.e, relative to all linkages of country *i*. With row-normalized matrices, model (3) implies that – in case of $\lambda = 0$ – a uniform shock to ε leads to an increase in volatility by $1/(1-\rho)$; similarly, for $\lambda \neq 0$, the implied effect amounts to $1/[(1-\rho)(1-\lambda)]$. Notice that model stability requires that $|\lambda| < 1$ and $|\rho| < 1$.

III. Output Volatility of the World Economy

Before turning to the estimation results, we briefly summarize the evolution of output volatility over the period 1960-2006 (Figure 1). We consider averages over all 135 countries of our sample (referred to as 'world') and three subsamples: the G-7 countries, 20 OECD countries, and the USA. Notice that each observation refers to the period over the last 10 years.

< Figure 1 >

On average over the sample period, global output volatility amounted to 3.4 percent. Starting from a level of 2.5 percent in the mid 1950s, volatility increased steadily and peaked in the period from the mid-1970s to the mid-1980s at a level of 4.8 percent, following the disruptions in the world economy through the two major oil price shocks in 1973 and 1979, resulting in a period of high inflation. In addition, a high level of discretionary fiscal and monetary policy, a period of turmoil in international financial markets, and the breakdown of the Bretton Woods system contributed to the increased instability in the first half of the 1980s.

Since then output volatility has declined down to some 3 percent in the period from 1996-2006.[2] As evident from Figure 1, the 'great moderation' in US output volatility, which was halved since 1985 was less pronounced at a global scale, where volatility decreased by one third only. The reduction in output volatility of OECD countries is of a comparable magnitude, but materialized with a delay. Whether these reductions in volatility were due to improvements in institutional quality, inventory management, macroeconomic policy or simply good luck (smaller and less synchronized shocks) is still subject to debate, though

[2] Obviously, there has been a surge since 2007 in course of the pronounced recent financial and economic crises, causing sizeable reductions in GDP in many countries.

there is evidence that the reduction in the magnitude of common shocks has been the main reason (see Stock and Watson, 2005).

It is also worth emphasizing that – while for the subgroups of developed countries considered, whose output volatility today is significantly lower than it had been in 1950s – this is not true for the world economy. On average over all countries, output volatility in recent years (slightly above 3 percent) is comparable to the levels experienced in the 1960s.

IV. The Evolution of Cross-Country Interdependence, 1965-2006

In the following we provide some descriptive analysis and specification tests, before turning to more rigorous econometric estimates.

1. Prima-facie Evidence

As simplest measures of cross-country interdependence, we calculate – for 10-year moving time windows over the period 1965 to 2006 – the correlation (r_t) between output volatility $\boldsymbol{\sigma}_t$ and distance weighted averages of other countries' output volatility $\bar{\boldsymbol{\sigma}}_t$, as well as the partial correlation ($r_{p,t}$), controlling for the initial level of GDP per capita ($y_{0,t}$). We next consider the least squares estimate $\hat{\lambda}_{LS,t}$ from equation (2a), which should be regarded as purely descriptive, however, since the spatial lag $\bar{\boldsymbol{\sigma}}_t$ is endogenous. The three measures used so far relate to equation (2a) only, ignoring the possible cross-sectional dependence in the disturbance term as given equation by (2b).

As more comprehensive and systematic measures, allowing cross-country interdependence to appear through $\bar{\boldsymbol{\sigma}}_t$ in (2a) or $\bar{\mathbf{u}}_t$ in (2b) or both, we consider Lagrange multiplier (*LM*) specification tests of model (2) suggested by Anselin et al. (1996). In particular, we calculate i) the LM test of the null hypothesis that $\lambda = 0$ and $\rho = 0$ (LM_t), ii) the LM test that $\lambda = 0$, assuming that $\rho = 0$ ($LM_{\lambda,t}$), and iii) the LM test that $\rho = 0$, assuming that $\lambda = 0$ ($LM_{\rho,t}$).

Figure 2 shows six panels, tracing the evolution of the aforementioned measures over the period 1965 to 2006. To reduce sampling variation, we also show the Hodrik-Prescott filtered series (as dashed line). Note that that LM test statistics are χ^2-distributed with two degress of freedom (LM_t) and one degree of freedom ($LM_{\lambda,t}$, $LM_{\rho,t}$), such that the critical values at the 5 percent level amount to 6 and 3.84, respectively.

< Figure 2 >

For all measures of cross-country interdependence of output volatility, the pattern is fairly similar. Interdependence was very low and typically insignificant in the 1950s and early 1960s, but increased continuously over time to peak in the late 1970s and early 1980s. Afterwards interdependence declined somewhat but remained at relatively high levels over the recent decade and shows a slight upward trend again in the most recent periods. Notice that, since the model is estimated for each time period, the average level of output volatility is controlled for by the constant. Overall, results suggest that interdependence has become statistically and economically significant in the early 1980s and remained so since then.

These results hold up under alternative specifications: in fact we obtained qualitatively very similar results, when i) using the standard deviation of output growth instead of the regression-based volatility measures as defined above, and ii) varying the distance decay parameter δ in (4) between 1 and 5. The evidence so far is suggestive but should be regarded as descriptive. In the following we provide a more rigorous econometric analysis.

2. Estimation Results for Spatial Regressive Model

Before turning to the estimation of model (2), we determine its proper specification, i.e., whether cross-country interdependence should be modelled through the spatial lag of the dependent variable ($\overline{\boldsymbol{\sigma}}$), the spatial lag of the error term ($\overline{\mathbf{u}}$), or both. We follow the specification search strategy suggested by Anselin et al. (1996), which is based on a set of five LM tests. In addition to the LM considered above, they also provide 'robust' LM tests of the null hypothesis that $\lambda = 0$ (or $\rho = 0$), leaving the 'other' spatial regressive parameter ρ (or λ) unrestricted under the null hypothesis. The robust tests are referred to as LM_{λ}^{*} and LM_{ρ}^{*} respectively. Results for all five types of LM tests are typically indicative of the proper specification.

In the present paper, results are largely inconclusive. While all three LM tests illustrated in Figure 1 are significant at the five percent level for almost all periods since 1975, the robust LM test for the spatial lag and error model turned out insignificant for essentially the whole time period, each of them thus pointing to the relevance of the 'other' source of interdependence, i.e., to the spatial lag or the spatial error model. In light of the results for all five LM tests, we conclude i) that there is significant cross-sectional dependence either through the spatial lag or the spatial error (but not both simultaneously), and ii) that hence both the spatial lag model and the spatial error model are a legitimate choice for the empirical specification. This result is not too surprising, given the parsimonious specification of model (2) with a single explanatory variable.[3]

[3] Without explanatory variables (apart from the constant) model (2), which includes both a spatial lag in the dependent variable and the error term, would be unidentified.

For both economic and econometric reasons we opt for the spatial error model, i.e., the model given by (2a) and (2b) with λ_t set to zero. From an economic perspective, the spatial error model better fits the goal of the present paper to model and estimate the transmission of volatility in the sense of shocks that are unrelated to changes in the level of development or institutional quality (which is upward trending for most countries and thus has a dampening effect of output volatility over time).

From an econometric perspective, using a spatial lag model (2a) would require using (spatial lags of y_0 as) instruments for $\bar{\boldsymbol{\sigma}}_t$ (given the absence of other convincing instruments). The corresponding two-stages least squares (2SLS) estimates of λ_t turned out implausible, with huge variation in the coefficients between single time periods, many of them outside the admissible parameter space (given by the interval (–1,+1) with a row-normalized weights matrix **W** as used here). The alternative route – using maximum likelihood (ML) estimation – has the drawback that produces inconsistent parameters estimates under heteroskedasticity of unkown form (Lee, 2004).

Hence, we opt for a spatial error model and estimate the spatial regressive parameter ρ_t using the general moments (GM) approach by Kelejian and Prucha (2010), which is robust to heteroskedasticity of arbitrary form in the error term $\boldsymbol{\varepsilon}$. They suggest using a three-step estimation procedure: First, the main equation is estimated to obtain consistent estimates of the disturbances. Second, a GM approach is used to estimate the spatial regressive parameter (ρ) of the disturbance process (and the variance-covariance matrix of $\mathbf{u}$). Third, the main equation is re-estimated by feasible generalized least squares. For inference, they provide the joint asymptotic distribution of the estimates of all model parameters, which is robust to heteroskedasticity of unknown form in $\boldsymbol{\varepsilon}$.

< Table 1 >

Table 1 shows the estimates of the spatial error model for alternative time periods, starting from the period 1955-1965 up to the most recent period 1996-2006. In the main equation, the initial level of income shows the expected negative sign but is rarely significant with p-values slightly above 10 percent. The spatial regressive parameter of the disturbance process is both statistically and economically significant as of the 1970s; using its estimate for the most recent period considered, the results suggest that a uniform increase output volatility in all countries roughly doubles through spillover effects and the associated repercussions.

< Figure 3 >

To provide a more comprehensive picture, Figure 3 shows the estimates for all 10-year time periods in the period from 1965 to 2006. Overall the descriptive results of the previous section are confirmed. We find a substantial increase in cross-country interdependence over time, which has peaked in the 1970s, then decreased somewhat over the 1980s but went up to statistically significant and at high levels since the 1990s again.

These results provide another angle to interpret the results by Stock and Watson (2005). They suggest that the reduced size of common shocks has contributed most to the great moderation of business cycles in the G-7 countries. In light of the present results, it is apparent that such a reduction of shocks implies a magnified reduction in volatility through a stabilization multiplier effect (which of course works into the opposite direction when the size of common shocks were to increase again, as it has been the case during the recent financial and economic crisis). At a more general level, this has an important and highly intuitive policy implication: Stabilization policy, e.g. through imposing fiscal rules to reduce volatility enhancing use of discretionary fiscal policy (Fatas and Mihov, 2004), is way more effective in a group of countries, when it is done in a coordinated way (or even at a supranational level). This should be borne in mind when (re)designing fiscal policy rules in a group of highly integrated countries such as the stability and growth pact in the European Union.

V. The Channels of Cross-Country Interdependence: Trade versus Financial Linkages

Till now we have focussed on the evolution of cross-country interdependence over time, using a time-invariant weights matrix based on geographical distance. In the following, we provide an assessment of alternative channels of interdependence (for the most recent time period 1996-2006), using weights matrices that are based on measures of economic rather than geographical distance.

1. Empirical Framework

Assume for now that there are two known weights matrices $\mathbf{W}_T$ and $\mathbf{W}_F$ associated with trade and financial openness, respectively. Their exact definition and construction will be outlined below. In order to assess the relevance of these two channels of interdependence, we specify a second order spatial regressive error model:

$$\boldsymbol{\sigma} = \alpha + \beta \mathbf{y}_0 + \mathbf{u}, \text{ with} \tag{5a}$$

$$\mathbf{u} = \rho_T \mathbf{W}_T \mathbf{u} + \rho_F \mathbf{W}_F \mathbf{u} + \boldsymbol{\varepsilon}, \tag{5b}$$

where the matrices $\mathbf{W}_T$ ($\mathbf{W}_F$) and the parameters ρ_T (ρ_F) reflect the structure and strength of cross-country interdependence related to trade openness and financial openness respectively. For estimation of model (5), we rely on Badinger and Egger (2010) who extend the GM estimation approach for first order spatial regressive models by Kelejian and Prucha (2010) to the case of higher order spatial regressive models.[4]

2. Construction of Weights Matrices

A straightforward approach would be to included bilateral measures of trade and financial openness as elements of the matrices $\mathbf{W}_T$ and $\mathbf{W}_F$. Unfortunately, this is not feasible for two reasons: First, weights matrices based on economic rather than geographic distance are likely to be endogenous, invalidating estimation and inference in spatial error models. Second, bilateral data, in particular those relating to financial openness, are available only for a small subset of our sample of 135 countries.

We thus suggest a new method to construct bilateral values from aggregate data, which also provides a means to addressing endogeneity concerns. Thereby we construct weights matrices using predicted values from bilateral gravity models. Without data on the dependent variable (such as measures of bilateral financial openness) the model parameters cannot be estimated directly. The basic idea is to combine observed aggregate, country-specific data (such as financial openness) with observed explanatory variables in the bilateral gravity model (such as distance and country size). The parameters of the gravity model can then be 'estimated' indirectly such that the correlation between the aggregate predicted values (obtained as sum of the bilateral predicted values) with the observed aggregate data is maximized. By restricting

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[4] Badinger and Egger (2010) consider estimation of the general model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \sum_{r=1}^{R} \mathbf{W}_r \mathbf{y} + \mathbf{u}$ with $\mathbf{u} = \sum_{s=1}^{S} \mathbf{W}_s \mathbf{u} + \boldsymbol{\varepsilon}$, where R and S denote the spatial regressive order of the model and where $\boldsymbol{\varepsilon}$ is allowed to exhibit heteroskedasticity of unknown form. In the present context we thus have a special case with $R = 0$ and $S = 2$.

the gravity to include exogenous variables only, this also provides a way to avoid endogeneity concerns, an idea introduced by Frankel and Romer (1999) in a slightly different context as 'geographical gravity equation'.[5] The technical details of the approach are outlined in appendix B.

In particular, we use a simplified version of the geographical gravity model in Frankel and Romer (1999) that takes the following form:

$$\ln w_{ij}^{0} = \gamma_0 + \gamma_1 \ln Dist_{ij} + \gamma_2 \ln Pop_i + \gamma_3 \ln Pop_j + \gamma_4 \ln Area_i + \gamma_5 \ln Area_j + \varpi_{ij}, \qquad (6)$$

where w_{ij}^{0} is the unobserved measure of bilateral (trade or financial) openness, whose predicts will be used to set up the (unnormalized) weights matrices.[6] The specification in (6) is motivated by the fact that the gravity model works well not only for trade, but also for FDI and portfolio investment (and thus also financial openness) and that geography plays a significant role in determining the spatial allocation of financial flows (Sarisoy Guerin, 2006).[7] Data sources for the explanatory variables are as above.

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[5] Frankel and Romer (1999) consider a cross-country regression of per capita income on trade and suggest using as instrument for trade the country-specific sums of bilateral predicted values from a gravity model that includes geographical variables only. Hence, the difference to the present study is that their ultimate model of interest uses aggregate, country-specific rather than bilateral data and that their use of predicted values is not motivated (only) by the lack of data but the endogeneity of trade.

[6] Other geographical variables such as common border and landlocked dummies were omitted for the sake of parsimony. While these variables typically turn out significant in gravity models they also show relatively little variation and thus hardly improve the predictive power of the model. As a consequence, their omission does not affect our main results.

[7] Results by Sarisoy Guerin (2006) cannot be used directly since her sample, comprising at most 200 bilateral observations, is not representative for our large cross-section of 135 countries; moreover, her

We use the following aggregate, country-specific variables to generate corresponding bilateral (predicted) values: trade openness in terms of imports plus exports, FDI assets and liabilities, portfolio equity assets and liabilities, (portfolio and other investment) debt assets and liabilities, and finally total assets and liabilities, all of them expressed as a share of GDP. Trade openness is taken from the Penn World Tables 6.2. Measures of financial openness are from the dataset by Lane and Milesi-Feretti (2007).

< Table 2 >

Table 2 provides estimation results of the gravity model (6) for the aforementioned openness measures. Since, trade is available at a bilateral level for a reasonably large subsample of our 135 countries, results for model (6) using actual bilateral data on trade openness are reported in column (1a) for comparison.[8] The coefficients are as expected: trade is decreasing in distance and area and increasing in country *j*'s size in terms of population. The coefficients in columnn (1a) are then used as starting values for the indirect estimation procedure for model (6), which is defined in equation (B2) in appendix B and solved numerically by a grid search strategy.[9] Since the explanatory variables in the parsimonious model (6) are available for most countries, the aggregate predicted values are calculated by summing the bilateral predicted values not only over the 135 sample countries, but over a total of 195 countries, which better matches the definition of the actual data at the aggregate level.

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model uses inflows as dependent variable, whereas we are more interested in overall openness measures, including both in- and outflows (relative to county size).

[8] Data on bilateral trade are from the IFS direction of trade statistics were kindly provided by Badinger (2008). The sample, on which the results in column (1a) are based, comprises 7574 non-zero bilateral observations and refers to the year 1996.

[9] For each parameter, we consider intervals of ± 0.5 around the starting values, which corresponds to some 13 to 23-fold of the coefficients standard errors in the directly estimated gravity model.

The indirect gravity estimates in Table 2 are based on data for the year 2001, matching the sample mid-point of the cross-section models considered below. Column (1b) reports the indirect estimates using aggregate data on openness. Most coefficients, in particular that relating to geographical distance, are quite close to that from the 'direct' estimation. The correlation of the bilateral predicted values from the models in column (1) and (2) amounts to 0.919, the correlation of the implied aggregate values to 0.424.

Columns (2a) to (2d) show the corresponding indirect estimates for the financial openness measures. Overall results are close to that of the gravity model for trade. This is in line with results by Sarisoy Guerin (2006) in her comparative study on the performance of the gravity model for trade, FDI, and portfolio investment (for a sample of at most 200 bilateral flows). She finds that the estimated coefficients, in particular those for distance, are virtually identical for trade and FDI, whereas distance plays a smaller role for portfolio investment, which matches the results of the indirect estimates in Table 2. On the one hand this is a reassuring result. On the other hand, the similarity of the pattern for the alternative openness measures suggests that it will be difficult to identify their effects separately. In fact, the correlation between the aggregate (bilateral) predicted values is above 0.880 (0.950) across the board. This is not too surprising: Aizenman and Noy (2009), using causality tests and variance decompositions, show that trade and financial openness are intricately intertwined, with two-way feedbacks between both openness dimensions, making it difficult (if not impossible) for a country to increase trade openness while holding financial openness constant.

The estimates of the parameters $\gamma_0,...,\gamma_5$ in model (6) are then used to generate predicted values for the bilateral openness measures in levels according to

$$\tilde{w}_{ij}^0 = \exp(\tilde{\ln} w_{ij}^0)\text{, with} \tag{7}$$

$$\tilde{\ln} w_{ij}^0 = \tilde{\gamma}_0 + \tilde{\gamma}_1 \ln Dist_{ij} + \tilde{\gamma}_2 \ln Pop_i + \tilde{\gamma}_3 \ln Pop_j + \tilde{\gamma}_4 \ln Area_i + \tilde{\gamma}_5 \ln Area_j .$$

The elements $\tilde{w}_{ij}^{0}$ are then used to set up the (unnormalized) weights matrices. The final weights matrices for trade ($\mathbf{W}_T$), FDI ($\mathbf{W}_{FDI}$), portfolio ($\mathbf{W}_P$), debt ($\mathbf{W}_D$) and total financial openness ($\mathbf{W}_F$) are then obtained after row-normalization. Notice that the use of row-normalized matrices makes the choice of the constant $\tilde{\gamma}_0$ irrelevant, which enters the prediction in levels in a multiplicative way such that it cancels out by row-normalization.[10]

3. Estimation Results for Second Order Spatial Regressive Model

In a first step, we check the reliability of our approach to constructing weights matrices from aggregate data. The first two columns in Table 3 compare the estimates of the spatial error model, using the trade based weights matrix, which is constructed from the direct gravity estimates using bilateral trade data (see column (1a) in Table 2) with those using the weights matrix based on the indirect gravity estimates from aggregate data (column (1b) in Table 2). The spatial regressive coefficients of the two models turn out virtually identical, suggesting that weights matrices based on the indirect estimation approach yield results comparable to those obtained from estimates based on actual bilateral data. We next turn to the estimation of the second order spatial regressive model given by (5) for alternative combinations of weights matrices, constructed from the indirect gravity estimates in columns (1b)-(2d) in Table 2.

< Table 3 >

[10] A similar argument applies to the fact that the conditional expectation of w_{ij} is equal to $\exp(\tilde{\ln} w_{ij})$ times $E[\exp(\varpi_{ij})]$ (see Frankel and Romer, 1999, p. 384). Under normality $E[\exp(\varpi_{ij})] = \exp[(\sigma^2_{ik,jl}/2)]$, where $\sigma^2_{ik,jl}$ is the variance of $\omega_{ik,jl}$. Since ω is modelled as homoskedastic, this correction factor is the same for all observations and can be dropped without consequences for the results regarding the final row-normalized weights matrix.

Comparing the point estimates of the spatial regressive parameters across the different specifications from column (2)-(8) suggests that financial openness is a stronger transmission channel than trade openness, and that – within different subcategories of financial openness – debt linkages appear to be more important than (FDI or portfolio related) equity linkages. However, these results should not be overstressed. As expected, the high correlation of the elements of the weights matrices, resulting from the two-way linkages between trade and financial openness (Aizenman and Noy, 2009), prevents us from identifying their effects in a statistically significant way: In none of the models we can reject the null hypothesis that the two spatial regressive parameters are identical. Overall, we thus conclude that both trade and financial linkages are important transmission channels volatility spillovers, and that there is no statistical significant evidence for a dominance of either of the two channels.

Hence, we proceed with a restricted model, imposing equality of the two spatial regressive parameters associated with the weights matrices for trade openness and total financial openness. In particular, we use $(\mathbf{W}_T + \mathbf{W}_F)/2$ as single weights matrix, where the division by two ensures that the rows sum to one and that the coefficients are directly comparable with the estimates using a single weights matrix. Results for this preferred specification are given in the last column (9) of Table 3. The spatial regressive parameter turns out statistically significant and larger than that in the model using the distance based weights matrix (compare the last column of Table 1). The likely reason for this discrepancy in magnitude is that the weights matrix based on geographic distance only reflects the extent and structure of cross-country linkages less precisely than the weights matrices based on economic distance (in terms of trade and financial openness), causing an attenuation bias that results in a smaller estimate of the spatial regressive parameter. In economic terms, the estimates of our preferred model suggest that common shocks have a magnified impact and quadruplicate as a result of spillover effects and the associated repercussions, which are transmitted to an equal extent through trade and financial linkages.

The finding that both trade and financial linkages turn out as equally important transmission channels also provides an explanation for the evolution of cross-country interdependence over time as illustrated in Figures 2 and 3. One could argue that the increase in trade openness in the early post-war period has increased countries' vulnerability to foreign shocks, but that economic agents have become more alert to this phenomenon during the period of high volatility in the 1970s (see Figure 1) and have developed and adopted strategies to adjust to and insure better against trade-related spillovers from foreign shocks, leading to a decrease in the strength of cross-country interdependence. With the strong increase in financial openness starting in the mid-1980s, which outpaced the moderate increase in trade openness in the recent two decades (Lane and Milesi-Feretti, 1997), however, a new transmission channel of international spillovers has emerged, which is more complex, less transparent and less-well understood than the trade channel, resurrecting countries' vulnerability of foreign shocks again and increasing cross-country interdependence to the highest level in the post-war period.[11]

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[11] This argument is also supported by results of a time series regression of the estimated interdependence parameter on measures of trade and financial openness. As in the cross-section, the time series of the two openness measures are highly correlated (0.88) such that their effect cannot be disentangled. Regressing the estimate of ρ in Figure 3 on a joint openness measure, calculated as sum of trade and financial openness, over the period 1965 to 2006 suggests that an increase in openness by 10 percentage points increase the spatial regressive parameter by 0.007 (with a t-value of 2.384).

VI. Conclusions

This paper provides evidence that the world has become singificantly smaller in terms of economic distance over the last decades. The impact of local shocks was rather local in the early post-war period, but has increased substantially up to the mid 1980s as a results of increases in trade and financial openness, and remained at a high level since then.

As the recent financial and economic crisis has shown, common shocks rapidly spread over the globe and have a magnified impact. According to our results, a global shock quadruplicates by propagating through the world economic system. Trade and financial linkages turn out as equally important in transmitting volatility spillovers.

Results of the present paper also suggest some extensions for future research. It would be of interest to consider spillovers in terms of monetary instability and financial stress and their most relevant transmission channels, as well as the interaction between real instability and monetary instability. More generally, the method suggested for constructing bilateral data from country-specific aggregate data, which are available for many potentially interesting transmission channels, enables the estimation of various kinds of economics models involving alternative channels of multilateral interdependence.

References

Aizenman, J. and Noy, I. (2009). Endogenous financial and trade openness. *Review of Development Economics*, 13(2), 175-189.

Anselin, L., Bera, A.K., Florax, R. and Yoon, M.J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, 26, 77-104.

Badinger, H. and Egger, P. (2010). Estimation of higher-order spatial autoregressive cross-section models with heteroskedastic disturbances. *Papers in Regional Science*, 90(1), 2011, 213-236.

Cairncross, F. (1997). *The Death of Distance*. Cambridge: Harvard Business School Press.

Fatas, A. and Mihov, I. (2003). The case for restricting fiscal policy discretion. *Quarterly Journal of Economics*, 4, 1419-1448.

Frankel, J.A. and Romer, D. (1999). Does trade cause growth? *American Economic Review*, 89(3), 279-399.

Jacks, D.S., C.M. Meissner, and D. Novy (2009). Trade booms, trade busts, and trade costs. *NBER Working Paper*, No. 15267.

Kelejian, H.H. and Prucha, I.R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, forthcoming.

Lane, P.R. and Milesi-Ferretti, G,M. (2007). The external wealth of nations mark II. *Journal of International Economics*, 73, 223-250.

Leamer, E.E. and Levinsohn, J. (1995). International trade theory: the evidence. In Grossman, G.M. and Rogoff, K. (eds.). *Handbook of International Economics*, Vol. III. New York: Elsevier; chapter 6.

Maddison (2010). Historical statistics, 1-2006AD. www.ggdc.net/Maddison.

Sarisoy Guerin, S. (2006). The role of geography in financial and economic integration: a comparative analysis of foreign direct investment, trade and portfolio investment flows. *World Economy*, 29(2), 189-209.

Stock, M. and Watson, J. (2005). Understanding changes in international business cycle dynamics. *Journal of the European Economic Association*, 3(5), 968–1006.

Appendices

Appendix A. Data Description

Our final sample comprises 135 countries, for which the main variables are available over the whole period 1955 to 2006. Table A1 provides a list of the countries used. Data on real GDP (in Geary Khamis PPPs) and population are taken from Maddison (2010, www.ggdc.net/Maddison). Data on area and bilateral distances are from the CEPII database (www-cepii.fr). Measures of financial openness are calculated from the updated and extended version of the External Wealth of Nations Mark II database developed by Lane and Milesi-Ferretti (2007).

< Table A1 >

Appendix B. Indirect Estimation of Gravity Models from Aggregate Data

In the following we suggest a method to construct weights matrices involving bilateral relationships from aggregate data. This approach should be useful in a variety of applications considering multilateral interdependence, when there is no bilateral data on particular channels of interdependence, but when aggregate data is available and when there is a theoretically motivated bilateral model with a set of observed explanatory variables (that may be assumed to be exogenous in the respective context).

Consider the bilateral model

$$l_{ij} = f(\mathbf{x}_{ij}, \boldsymbol{\beta}) + \varpi_{it}, \tag{B1}$$

where l_{ij} is the unobserved value of the dependent variable reflecting some bilateral linkage (e.g., financial openness) between countries *i* and *j*, and $\mathbf{x}_{ij}$ is a $1 \times K$ vector of (bilateral or country-specific) observed explanatory variables. Since actual data for l_{ij} are not available, the parameter vector $\boldsymbol{\beta}$ in model (B1) cannot be estimated directly by standard methods, e.g. by least squares ($\hat{\boldsymbol{\beta}}$).

Now suppose that aggregate data on the variable *l* is available for each country *i*, given by $l_i = \sum_{j=1}^{N_i} l_{ij}$ (e.g., country *i*'s total financial openness), where N_i is the number of country *i*'s partner countries. Then, a reasonable approach to approximate bilateral (predicted) values on the variable *l* is to choose the 'estimate' of $\boldsymbol{\beta}$ such that the correlation between the aggregate predicted value (obtained as sum from the bilateral predicted values) and the actual value of the aggregate variable is maximized, i.e.,

$$\tilde{\boldsymbol{\beta}} = \arg\max_{\underline{\boldsymbol{\beta}}} Corr[\mathbf{l}, \underline{\mathbf{l}}(\underline{\boldsymbol{\beta}})], \tag{B2}$$

where $\mathbf{l} = (l_i)$ is a vector with observations of the aggregate, country-specific values of the variable *l*, and $\underline{\mathbf{l}}(\underline{\boldsymbol{\beta}}) = [\underline{l}_i(\underline{\boldsymbol{\beta}})]$ is vector with the predicted counterpart (for the parameter values $\underline{\boldsymbol{\beta}}$) with elements $\underline{l}_i(\underline{\boldsymbol{\beta}}) = \sum_{j=1}^{N_i} \underline{l}_{ij}(\underline{\boldsymbol{\beta}})$.

In general, the (least squares) estimate $\hat{\boldsymbol{\beta}}$ from (B1) and the indirect estimate $\tilde{\boldsymbol{\beta}}$ from (B2) are not equivalent., i.e., it does not necessarily hold that the least squares estimate $\hat{\boldsymbol{\beta}}$ in model (B1), which maximizes the (squared) correlation between the bilateral values l_{ij} and $\hat{l}_{ij}$, also maximizes the correlation of the aggregate actual and predicted values (and vice versa).

However, we argue that it is reasonable to assume that the predicted values implied by the estimator in (B2) are a reasonable approximation of those implied by the direct estimate from model (B1). This will indeed be confirmed in the present paper in section V, subsections 2 and 3, for trade, where a reasonable subsample of bilateral observations is available.

Notice that the correlation between the aggregate predicted and actual values is invariant to overall level shifts, such the choice of the constant in is arbitrary in the first place, i.e., only the slope parameters are 'identified' by (B2). However, when model (B1) is linear in parameters, the overall intercept (or country-specific intercepts) can be recovered, exploiting the algebraic properties of linear least squares by using the aggregate values of the dependent variable, the means of the explanatory variables and the slope coefficients.[12] (In the present paper this is not required, however, since the constant is eliminated by the use of row-normalized weights matrices.)

[12] Denote the vector of slope coefficients by $\boldsymbol{\beta}^*$ and the constant by β_0. Assuming there is a single overall constant, we have $\tilde{\beta}_0 = \bar{l} - \bar{\mathbf{x}}\tilde{\boldsymbol{\beta}}^*$, where $\bar{l}$ and $\bar{\mathbf{x}}$ are averages over all bilateral observations. Obviously, the overall mean of the bilateral values $\bar{l}$ can be calculated from the observed aggregate values l_i. Assuming there are country-specific constants, we have $\tilde{\beta}_{0,i} = \bar{l}_i - \bar{\mathbf{x}}_i\tilde{\boldsymbol{\beta}}^*$, where $\bar{l}_i$ and $\bar{\mathbf{x}}_i$ are observed country-specific averages.

Table 1. *Estimates of spatial error model for alternative time periods*

	1965	1970	1975	1980	1985	1990	1995	2000	2006
constant	-3.709***	-3.106***	-3.144***	-2.69***	-2.97***	-3.31***	-2.853***	-2.218***	-2.908***
	(0.520)	(0.837)	(0.806)	(0.706)	(0.572)	(0.478)	(0.469)	(0.47)	(0.538)
y_0	-0.001	-0.076	-0.044	-0.086	-0.046	-0.02	-0.074	-0.156***	-0.101
	(0.065)	(0.106)	(0.1)	(0.087)	(0.07)	(0.058)	(0.057)	(0.057)	(0.064)
mean [1)]	-3.713	-3.666	-3.479	-3.347	-3.366	-3.482	-3.445	-3.466	-3.731
sd [2)]	0.823	0.879	0.841	0.778	0.979	0.913	0.665	0.741	0.717
Disturbance process									
ρ	-0.160	0.233**	0.306***	0.388***	0.353**	0.165***	0.288***	0.210*	0.447***
	(0.122)	(0.109)	(0.102)	(0.079)	(0.140)	(0.052)	(0.102)	(0.126)	(0.124)
LM_ρ	0.822	0.747	4.782**	9.032***	15.759***	10.134***	8.147***	1.800	11.3***
LM_ρ^*	0.113	0.666	0.884	0.421	0.369	1.223	1.933	4.882**	0.051
LM_λ	0.825	0.899	5.164**	9.797***	16.193***	10.417***	7.693***	1.043	11.332***
LM_λ^*	0.116	0.818	1.266	1.185	0.802	1.506	1.479	4.125**	0.083
LM	0.938	1.565	6.048**	10.218***	16.561***	11.64***	9.626***	5.925*	11.384***
σ_u	0.823	0.873	0.838	0.767	0.975	0.912	0.663	0.727	0.704
σ_ε	0.818	0.869	0.815	0.727	0.934	0.891	0.639	0.718	0.662

Notes: Dependent variable is the log of σ_y. Main equation is estimated by feasible generalized least squares, using the transformation matrix $(\mathbf{I}-\hat{\rho}\mathbf{W})$. Spatial regressive parameter (ρ) is estimated by GM (Kelejian and Prucha, 2010), based on least squares residuals. Standard errors in parentheses are robust against heteroskedasticity in ε. [1)] Mean of dependent variable. [2)] Standard deviation of dependent variable.

Table 2. *Gravity 'estimates' for alternative openness measures*

	(1a)	(1b)	(2a)	(2b)	(2c)	(2d)
	Trade[1)]	Trade	FDI	Portfolio	Debt	Total
$\ln DIST_{ij}$	-1.222	-1.342	-1.342	-1.162	-1.442	-1.342
$\ln Area_i$	-0.114	-0.726	-0.734	-0.602	-0.734	-0.734
$\ln Area_j$	-0.386	-0.134	-0.586	-0.198	-0.062	-0.122
$\ln Pop_i$	0.0170	0.249	0.417	0.537	-0.007	0.121
$\ln Pop_j$	1.268	1.064	1.300	0.812	0.648	0.648
Correlation[2)]	0.324	0.650	0.610	0.356	0.629	0.657

Notes: [1)] Column (1a) reports estimates of model (6) using bilateral trade data. Columns (1b)-(2d) report indirect estimates based on aggregate data, using the estimator defined in (B2) (see Appendix B). [2)] Correlation between actual and predicted values of the respective aggregate (country-specific) openness measure.

Table 3. *Estimates of first and second order spatial error model using weights matrices based on economic distance*, *1996-2006*

	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbf{W}_1$	Trade[1)]	Trade	Trade	Trade	Trade	Trade	FDI	FDI	Portfolio	Trade
$\mathbf{W}_2$	-	-	FDI	Portfolio	Debt	Total	Portfolio	Debt	Debt	Total
constant	-2.938***	-2.984***	-2.867***	-2.895***	-2.999***	-2.966***	-2.891***	-2.903***	-2.902***	-2.934***
	(0.525)	(0.527)	(0.519)	(0.601)	(0.613)	(0.603)	(0.474)	(0.564)	(0.573)	(0.571)
y_0	-0.092	-0.097*	-0.095	-0.097	-0.099*	-0.098	-0.101*	-0.098	-0.098	-0.098
	(0.057)	(0.058)	(0.058)	(0.059)	(0.06)	(0.06)	(0.055)	(0.061)	(0.062)	(0.060)
Disturbance process										
ρ_1	0.704*	0.679**	0.135	0.167	0.471	0.416	0.010	0.010	0.010	0.751**
	(0.372)	(0.321)	(0.455)	(0.445)	(0.346)	(0.288)	(0.370)	(0.265)	(0.711)	(0.322)
ρ_2	-	-	0.516***	0.639***	0.338	0.384	0.456	0.696*	0.714	$\rho_1 = \rho_2$
			(0.16)	(0.182)	(0.416)	(0.351)	(0.674)	(0.409)	(0.632)	
H_0: $\rho_1 = \rho_2$ [2)]			(0.523)	(0.41)	(0.854)	(0.954)	(0.667)	(0.294)	(0.595)	
σ_u	0.704	0.704	0.704	0.704	0.704	0.704	0.704	0.704	0.704	0.704
σ_ε	0.692	0.688	0.688	0.687	0.683	0.684	0.692	0.677	0.677	0.683

Notes: See Table 2. [1)] Based on weights matrix implied by gravity estimates of in column (1a) of Table 2. [2)] p-value of Wald test that $\rho_1 = \rho_2$. Spatial regressive parameters in second order models estimated using by GM (Badinger and Egger, 2010).

Table A1. *List of countries*

Albania	Guatemala	Panama
Algeria	Guinea	Paraguay
Angola	Guinea Bissau	Peru
Argentina	Haïti	Philippines
Australia	Honduras	Poland
Austria	Hong Kong	Portugal
Bahrain	Hungary	Puerto Rico
Bangladesh	India	Qatar
Belgium	Indonesia	Romania
Benin	Iran	Russian Federation
Bolivia	Iraq	Rwanda
Botswana	Ireland	São Tomé and Principe
Brazil	Israel	Saudi Arabia
Bulgaria	Italy	Senegal
Burkina Faso	Jamaica	Seychelles
Burma	Japan	Sierra Leone
Burundi	Jordan	Singapore
Cambodia	Kenya	Somalia
Cameroon	Kuwait	South Africa
Canada	Laos	South Korea
Cape Verde	Lebanon	Spain
Central African Republic	Lesotho	Sri Lanka
Chad	Liberia	Sudan
Chile	Libya	Swaziland
China	Madagascar	Sweden
Colombia	Malawi	Switzerland
Comoro Islands	Malaysia	Syria
Congo 'Brazzaville'	Mali	Taiwan
Costa Rica	Mauritania	Tanzania
Côte d'Ivoire	Mauritius	Thailand
Cuba	Mexico	Togo
Denmark	Mongolia	Trinidad and Tobago
Djibouti	Morocco	Tunisia
Dominican Republic	Mozambique	Turkey
Ecuador	Namibia	Uganda
Egypt	Nepal	United Arab Emirates
El Salvador	Netherlands	United Kingdom
Equatorial Guinea	New Zealand	United States
Finland	Nicaragua	Uruguay
France	Niger	Venezuela
Gabon	Nigeria	Vietnam
Gambia	North Korea	Yemen
Germany	Norway	Zaire
Ghana	Oman	Zambia
Greece	Pakistan	Zimbabwe

Figure 1. *Output volatility of the world economy and selected subgroups, 1955-2006 (in percent)*

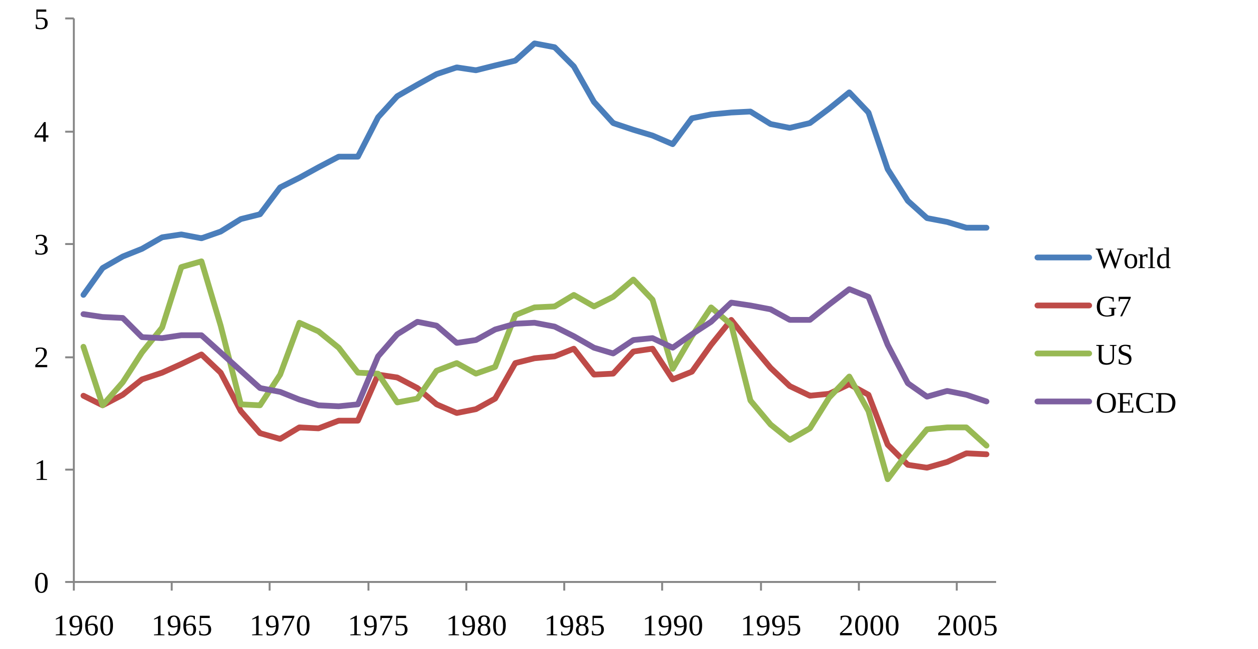

Figure 2. *Descriptive measures of cross-country interdependence, 1955-2006*

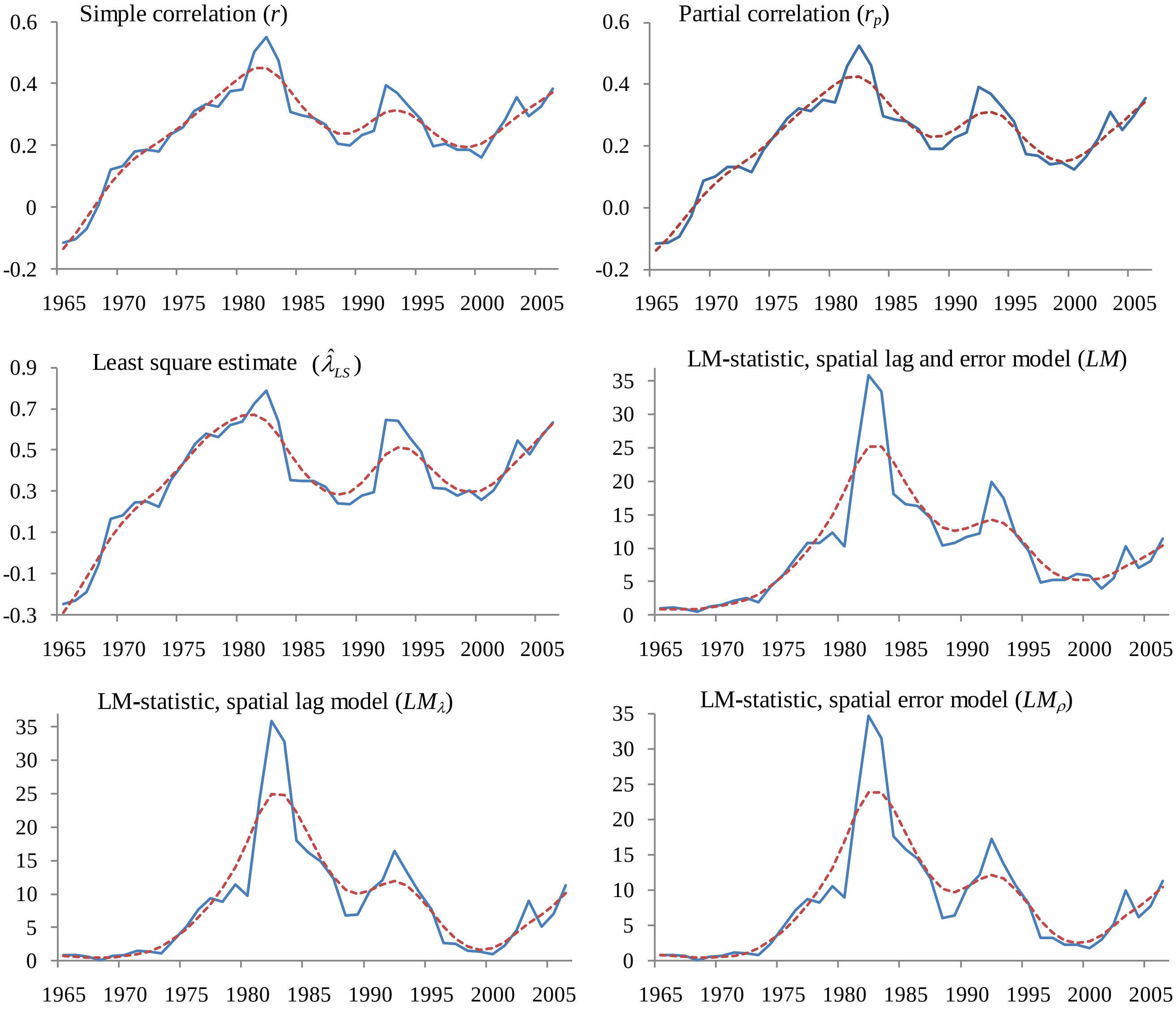

Figure 3. *GM estimates of spatial regressive parameter ρ, 1965-2006*