3-1-2015

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Accepted version. *World Development*, Vol. 67 (March 2015): 186-201. DOI.

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Summary

We consider the comovement of economic volatility across multiple countries. Using spatial models with data from 187 countries over the period of 1960–2007, we find a strong spatial comovement of economic volatility. More interestingly, the effect of geographical proximity on economic volatility comovement is strongest during the period of international shocks (1973–86), but almost disappears over the globalization era (1987–2007). By way of contrast, the influence of trade relations in determining the comovement of economic volatility is significant over 1987–2007.

Key words
international business cycles, economic volatility, spatial analysis, globalization, proximity

1. Introduction

A volatile macroeconomic environment tends to create more uncertainties for consumers and producers, which in turn can cause an underinvestment in human capital and physical capital. This leads to a lower rate of economic growth. In addition, economic volatility can also have an adverse effect on a country's income distribution (Acemoglu, Bernanke, 1983, Gaggl and Steindl, 2007). Not surprisingly, business cycles have been an important focus of macroeconomic research since the Great Depression.[1] Empirical studies of business cycles/macroeconomic volatility generally examine three issues: (1) measures of business cycle volatility (Baxter and King, 1999, Blanchard and Simon, 2001, Bullard, 1998, Hodrick and Prescott, 1997); (2) determinants of business cycle volatility (Canova and De Nicolo, 2003, Holland and Scott, 1998, Shapiro); and (3) comovements of business cycle volatility across countries. The last issue has attracted increasing attention. As pointed out by Kose, Otrok, and Whiteman (2008), understanding the nature and changes of world business cycle fluctuations is of essential interest to researchers and policy makers since business cycles synchronization indicates that one country's policy can have considerable impact on the macroeconomy of other countries. At the same time, the magnitude of business cycles comovement has "important implications for international policy coordination" (p. 111).

There is a large body of empirical research on the comovement of business cycles and factors influencing the transmission of economic fluctuations across countries. Some of these studies adopt a bilateral framework and explore correlations of economic fluctuations in a country *pair* (Backus and Kehoe, 1992, Baxter and Kouparitsas, 2005, Bergman, Canova and Dellas, 1993, Clark and van Wincoop, 2001).[2] Other studies document common economic shocks and spillovers among a small number of countries, often the G-7 group or the Euro countries (Bagliano and Morana, 2010, Kose, Stock and Watson, 2005). To identify common shocks, approaches such as the dynamic factor model (Kose *et al.*, 2008) or the factor structural VAR model (Bagliano and Morana, 2010, Clark and Shin, 2000, Stock and Watson, 2005) are employed. These models estimate common trends in several time series and quantify the share of total variation of a series such as the output in a country that is attributable to common shocks in the group and to the country's domestic performance.[3]

In this paper we link the literature on the determinants of economic volatility with the literature on the transmission of volatility across countries in a *multi-country, large-scale* model.[4] We do so by including a spatial measure of other countries' economic volatility as a determinant of country *i*'s economic volatility. Spatial models consider the correlation of observations across space with an underlying assumption that "dependence is present in all directions and becomes weaker as data locations become more and more dispersed" (Cressie, 1993, p. 3).[5]

Our paper contributes to the literature in several ways. First, we consider spillovers of foreign economic volatility as a determinant of a country's economic fluctuations. In previous studies of unilateral determinants of business cycles, it is often assumed economic fluctuations of individual countries are *independent* of one another. Second, we directly quantify the comovement of economic volatility across *multiple countries.* The bilateral framework of volatility comovement literature considers the dependence of business cycles between two countries, but observations of different dyads are still considered independent of one another. This assumption does not necessarily hold either. For example, the same country can enter a large number of dyads and observations of these dyads are likely to be correlated. A major advantage of spatial analysis we use over the bilateral framework in previous studies is that we take into account economic fluctuations of all countries *simultaneously* instead of pairing up countries in a specific dyad form. Third, spatial models complement factor analysis mentioned above in the sense that these two methods answer different questions about the comovement of volatility. Factor analysis focuses on the decomposition of current economic fluctuations of an individual country and answer the question, for instance, how much economic volatility a country experiences is caused by foreign volatility and how much is caused by the country's own performance. On the other hand, spatial models investigate *changes* in economic fluctuations and quantify the impact of a *change* in neighboring countries' economic volatility on the *change* in economic volatility in our country of interest. Fourth, taking into account a general measure of spatial dependence of economic volatility in the model provides us with more reliable results—if a country's economic volatility is affected by economic volatility of other countries, omitting a measure of such a multilateral dependence might lead to biased and inconsistent estimated coefficients as well as invalid statistical inferences (Anselin, 1988).

Using data from 187 countries over 1960–2007, we find strong comovement of economic volatility across countries, *geographically and economically*. In other words, a country's economic volatility is positively associated with its geographical neighbors' and trade partners' economic volatility. Our results show that the comovement of economic volatility changes over time. The effect of geographical proximity on the comovement of economic volatility rises from 1960–72 (the Bretton Woods era) to 1973–86 (the common shock period), but almost *disappears* over the period of 1987–2007 (the period of globalization). Conversely, clustering among trade partners becomes quite evident during the globalization era of 1987–2007. The role of geographical distance in affecting comovement among countries is declining, but the importance of economic ties has increased over the past few decades. These findings are robust to different measures of economic volatility.

The comovement of economic volatility implies that nations may share the benefits of having an interdependent and more predictable economic system. They, however, also share the risks of world economic fluctuation contagions. Nevertheless, a deeper understanding of this comovement can enhance our awareness so that governments are better prepared to cope with these risks and are more cautious when implementing policies that might affect other countries adversely.

The remainder of the paper is organized as follows: we describe variables and data in Section 2 and present the general spatial lag model setup in Section 3. Empirical results for geographical-proximity and economic-proximity spatial regressions are discussed in Sections 4 Geographical proximity and spatial correlation, 5 Beyond geography: economic connectivity, respectively. Section 6 provides robustness checks, and Section 7 concludes the paper.

2. Variables and data

Our empirical model seeks to understand how the economic volatility of a country of interest is correlated with economic volatility of multiple other countries. We do so by employing a spatial lag model. Our study focuses on economic volatility comovement among geographical neighbors and trade partners as geographical proximity and economic ties are often studied in previous economics research about connections between countries (Anselin, 2010, Clark and van Wincoop, 2001). In addition, we will also look at volatility comovement among countries having a similar culture or a similar administrative structure. In this section, we present the variables in our regressions as well as our sample. The setup of a spatial lag model will be discussed in Section 3.

(a). Dependent variable

The dependent variable in our model is a measure of economic volatility. To ensure our empirical results are robust and not bound by one specific definition, we construct three different measures of economic volatility (hereafter represented by σ), commonly used in previous studies (Backus and Kehoe, 1992, Blanchard and Simon, 2001, Bullard, 1998, Fiorito and Kollintzas, 1994, Hodrick and Prescott, 1981, Hodrick and Prescott, 1997, Jaimovich and Siu, 2009, Kose, Ravn and Uhlig, 2002). These measures capture volatility in national output growth or output level, and they include: (1) output growth volatility; (2) volatility of residuals from a growth regression; and (3) the Hodrick–Prescott filtered output volatility. We focus on the measure of output growth volatility and report results based on the other two measures in the section of robustness checks.

Following Bullard, 1998, Ramey and Ramey, 1995, we calculate the standard deviation of output growth σ^{VG} as:

(1) $$\sigma_i^{VG} = \sqrt{\frac{\sum[g_{it} - (\sum g_{it}/T)]^2}{T-1}},$$

where g_{it} is the growth rate of real GDP between time $t-1$ and t in country *i* and *T* denotes the time span.

Blanchard and Simon (2001) consider an alternative measure as the unexpected fluctuations of economic growth (also called growth residuals). In constructing the volatility of growth residuals (σ^{VGR}), we estimate an AR(1) growth regression (Blanchard & Simon, 2001):

$$(2)\ g_{it} - \bar{g}_i = a_i \left(g_{it-1} - \bar{g}_i \right) + \epsilon_{it}^{\mathrm{VGR}} ,$$

where $\bar{g}_i = \sum g_{it}/T$ is the average growth rate in country *i* over *T* years, and a_i is an AR(1) parameter for country *i*. We then obtain the standard deviation of the residuals from the above growth regression as:

$$(3)\ \sigma_i^{\mathrm{VGR}} = \sqrt{\frac{\sum \left(\epsilon_{it}^{\mathrm{VGR}}\right)^2}{T-1}}.$$

The Hodrick–Prescott (HP) filter separates the trend component of a macroeconomic variable Y_t from its cyclical component. We construct the third measure of volatility by calculating the standard deviation of the cyclical component of HP filtered real GDP, with real GDP normalized as 100 in year 1995 (Buch, Doepke, & Pierdzioch, 2005). [6] Formally, after extracting the trend component of real GDP, the HP output volatility (σ^{VHP}) can be written as:

$$(4)\ \sigma_i^{\mathrm{VHP}} = \sqrt{\frac{\sum \epsilon_{it}^2}{T-1}},$$

where $\epsilon_{it} = Y_{it} - Y_{it}^{\mathrm{HP}}$ is the difference between real GDP (Y_{it}) and the HP trend (Y_{it}^{HP}) at time *t* for country *i*.

(b). Independent variable and control variables

For any country *i*, our main variable of interest on the right-hand side of the regression is a spatial lag term or a weighted average of economic fluctuations of all countries *j* $i \neq j$. The construction of this spatial lag term will be explained in Section 3. Following previous literature (Buch, Kose), we include core determinants of economic volatility as control variables in the regression, which are: the log of average real GDP per capita, average openness measured by the sum of exports and imports as a share GDP, fiscal policy volatility measured by the standard deviation of government consumption as a share of GDP, average inflation rate, exchange rate volatility measured by the standard deviation of exchange rate over the average exchange rate, average share of M2 to GDP, and money supply volatility measured by the standard deviation of M2/GDP. Regional dummies for Sub-Saharan Africa and Latin America following Barro, 1991, Barro, 1998 as well as a dummy for OPEC members are also included.

(c). Data and sample

The empirical context for our study is provided by data from 187 countries over 1960–2007. Our sample is unbalanced and the number of countries included over time is solely determined by data availability. We obtain data from the World Bank's *World Development Indicators* (WDI). Since our dependent variable is measured as the standard deviation of a series, each country will have a *single*observation of a calculated value of economic volatility over a certain period. In other words, over a period *T* our regression will be cross sectional. Consequently, all right-hand-side variables are averaged over period *T* or measured as a standard deviation of a series as described above. Kose *et al.*(2008) propose to study business cycles comovement in three distinct periods which correspond to the Bretton Woods fixed exchange rate regime (1960–72), the period of common international shocks (1973–86), and the globalization period (1987–2007). Summary statistics for control variables over 1960–2007 before they are being averaged or before the standard deviation of a series is taken are reported in Table 1 and summary statistics for variables used in cross-sectional regressions are reported in Table 2. According to Table 1, we have reliable sample coverage. The variable having the least number of observations in our sample is money supply as a share of GDP (M2/GDP) with 5,536 observations over the entire sample span, representing 63% of maximum possible observations. GDP per capita has the most observations of 7,691—about 86% of maximum possible observations.

Table 1. Descriptive statistics (1960–2007)

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Real GDP per capita (in 2005 US Dollar)	7691	9060.329	11224.23	153.165	111730.4
Fiscal policy (%)	6463	15.762	6.835	1.380	76.220
Inflation rate (%)	6766	42.40	493.632	−31.9	26762.02
Openness (%)	6607	75.286	45.626	5.310	456.650
M2/GDP (%)	5536	53.621	361.985	0.050	11048.2

Note: Fiscal policy volatility, money supply volatility, and exchange rate volatility are not included here as they do not have time variations.

Table 2. Descriptive statistics—spatial lag models

	Mean	**Std. Dev.**	**Min**	**Max**
A. The sample of 1960–2007				
Real GDP per capita (2005 US Dollar)	9020.439	10247.17	565.734	62211.2
Fiscal policy volatility (%)	3.550	2.491	0.829	15.610
Average inflation (%)	49.280	117.021	1.040	825.489
Openness (%)	81.025	46.401	17.631	412.403
Exchange rate volatility	0.777	0.756	0	6.791
Average M2/GDP (%)	54.091	117.686	9.057	1228.065
M2/GDP volatility (%)	52.641	337.518	2.252	3272.078
	No. of Obs. = 177			
B. The sample of 1960–1972				
Real GDP per capita (2005 US Dollar)	5629.217	5198.572	427.329	21654.01
Fiscal policy volatility (%)	1.687	1.607	0.202	10.593
Average inflation (%)	7.927	20.270	−0.527	184.663
Openness (%)	49.222	29.390	5.900	161.738
Exchange rate volatility	0.144	0.275	0.000	1.380
Average M2/GDP (%)	80.132	441.308	4.183	3736.269
M2/GDP volatility (%)	80.504	597.458	0.276	5021.47
	No. of Obs. = 91			
C. The sample of 1973–1986				
Real GDP per capita (2005 US Dollar)	8662.931	11039.03	586.943	79588.34
Fiscal policy volatility (%)	2.455	2.378	0.308	16.475
Average inflation (%)	25.472	92.032	−2.166	1046.881
Openness (%)	74.541	43.238	11.410	234.242
Exchange rate volatility	0.501	0.663	0	3.714
Average M2/GDP (%)	64.608	312.871	11.423	3308.615
M2/GDP volatility (%)	50.144	461.961	0.752	4850.826
	No. of Obs. = 137			
D. The sample of 1987–2007				
Real GDP per capita (2005 US Dollar)	10492.59	11153.39	497.376	55695.34
Fiscal policy volatility (%)	2.647	2.192	0.111	14.189
Average inflation (%)	64.705	206.388	−0.037	1802.865
Openness (%)	86.699	48.599	20.316	412.403
Exchange rate volatility	0.415	0.447	0	4.489
Average M2/GDP (%)	46.720	35.931	7.417	207.625
M2/GDP volatility (%)	11.166	19.171	1.786	228.162
	No. of Obs. = 176			

As shown in Table 2, the number of countries we can include in regressions rises considerably over time mainly due to two reasons. First, some countries are newly formed and therefore missing early observations. For example, 15 post-Soviet states in the 1987–2007 sample do not exist in previous subsample periods. Second, data—especially data from less developed countries—become more available over time. For example, there are 26 sub-Saharan African countries included in the 1960–72 sample, 40 included in the 1973–86 sample, and 44 included in the 1987–2007 sample. In addition, data from certain countries are not reported by the World Bank, which also limits the number of observations we possibly have in each subsample regression. For instance, the World Bank does not record data from the Germany Democratic Republic, or the East Germany. Instead, data from the Federal Republic of Germany (the West Germany) as well as later the reunited nation of Germany are reported under "Germany." In our paper, we follow previous studies and keep as many countries in our sample as data availability allows without making adjustments such as dropping certain observations or interpolation of new data points (Alper and Cakici, 2009, Barro, 1998, Fosu, 2009).[7]

Table 3 presents the correlation matrix of variables used in our cross-sectional regressions. Table 3assures us that our regressions would possibly not suffer from a severe multicollinearity problems as all correlations are below the rule of thumb threshold of 0.8 as suggested in Studenmund (2011) with the only exception of the correlation between M2/GDP and the volatility of money supply. We report in Table 4 economic volatility measures for individual countries over 1960–2007. The average value of business cycle volatility (in log) over 1960–2007 are -2.86 for growth volatility, -2.95 for the volatility of growth residuals, and 1.002 for HP output volatility. Figure 1 illustrates the output growth volatility over 1960–2007. We can see spatial clustering in economic volatility. Countries located in Africa and Middle East are most economic volatile while Western European countries, Canada, and the U.S. are least volatile. Countries in Asia and Pacific region generally experience modest economic volatility. Over the subsample time periods, it appears the volatility of output level and the volatility of economic growth are rising gradually. For instance, the HP output volatility has a mean value of -0.21 over 1960–72, 0.84 over 1973–86, and 1.06 over 1987–2007. The average growth volatility in our sample is -3.49 in 1960–1972, and -2.88 in 1973–86, before dropping to -3.1 in 1987–2007. The growth volatility over the period of 1987–2007, though smaller than that in 1973–86, is still considerably larger than the growth volatility in 1960–72. Due to data requirements for calculating our second measure σVGR, partitioning the sample into three periods reduces the number of observations considerably for each country. The degrees of freedom becomes too small to provide meaningful results. Consequently, we summarize the measure of growth residual volatility in two subsample periods of 1960–86 and 1987–2007. The mean volatility of growth residuals (in log) over the periods of 1960–86 and 1987–2007 are -2.92 and -3.21, indicating an average standard deviation of growth residuals of 0.05% and 0.04%, respectively. This measure shows that the volatility in the pre-globalization (1960–86) is somewhat higher than in the globalization era.[8]

Table 3. Correlation matrix among dependent and independent variables

	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	Volatility of output growth	1							
2	Real GDP per capita	−0.1423	1						
3	Fiscal policy volatility	0.3825	−0.1051	1					
4	Average inflation	0.2119	−0.0399	0.0602	1				
5	Openness	0.185	0.3219	0.0513	−0.0422	1			
6	Exchange rate volatility	0.1516	−0.3216	0.034	0.2088	−0.3336	1		
7	Average M2/GDP	0.0739	0.1267	−0.0361	−0.0878	0.0292	0.487	1	
8	M2/GDP volatility	0.0916	0.0313	−0.0195	−0.0254	−0.0634	0.5388	0.9663	1

Table 4. List of the 187 countries with three measures of economic volatility (1960–2007)

Country	**Code**	**VG**	**VGR**	**VHP**	**Country**	**Code**	**VG**	**VGR**	**VHP**		
Afghanistan	AFG	−1.905	−1.892	2.157	Liberia	LBR	−1.311	−1.346	4.445		
Albania	ALB	−2.771	−2.794	1.394	Libya	LBY	−2.097	−2.093	2.365		
Algeria	DZA	−2.330	−2.347	0.769	Lithuania	LTU	−2.846	−3.516	1.299		
Angola	AGO	−2.177	−2.164	2.019	Luxembourg	LUX	−3.308	−3.317	0.438		
Antigua and Barbuda	ATG	−2.925	−2.916	1.101	Macao	MAC	−2.884	−3.023	1.310		
Argentina	ARG	−3.137	−3.160	0.864	Macedonia	MKD	−3.414	−3.579	0.564		
Armenia	ARM	−3.207	−3.400	0.933	Madagascar	MDG	−2.892	−2.900	0.999		
Australia	AUS	−3.804	−3.821	−0.098	Malawi	MWI	−2.486	−2.521	1.161		
Austria	AUT	−3.817	−3.823	−0.114	Malaysia	MYS	−3.327	−3.323	0.361		
Azerbaijan	AZE	−1.738	−2.499	2.861	Maldives	MDV	−2.710	−2.703	1.609		
Bahamas	BHS	−2.633	−2.674	1.197	Mali	MLI	−2.749	−2.755	0.905		
Bahrain	BHR	−2.822	−2.851	1.019	Malta	MLT	−3.082	−3.349	0.401		
Bangladesh	BGD	−3.288	−3.315	0.328	Marshall Islands	MHL	−2.442	−2.450	1.042		
Barbados	BRB	−2.963	−2.997	1.062	Mauritania	MRT	−2.363	−2.491	1.023		
Belarus	BLR	−2.750	−3.439	1.511	Mauritius	MUS	−2.856	−2.895	0.459		
Belgium	BEL	−3.811	−3.838	−0.071	Mexico	MEX	−3.199	−3.241	0.788		
Belize	BLZ	−3.051	−3.063	0.690	Micronesia, Fed. Sts.	FSM	−2.711	−2.708	0.858		
Benin	BEN	−3.187	−3.180	0.427	Moldova	MDA	−2.467	−2.445	1.547		
Bermuda	BMU	−3.381	−3.384	0.713	Mongolia	MNG	−2.625	−2.616	1.552		
Bhutan	BTN	−2.636	−2.629	1.575	Montenegro	MNE	−1.844	−1.990	2.455		
Bolivia	BOL	−3.230	−3.231	0.310	Morocco	MAR	−2.887	−3.031	0.706		
Bosnia and Herzegovina	BIH	−1.910	−2.209	2.849	Mozambique	MOZ	−2.827	−2.842	1.226		
Botswana	BWA	−2.805	−2.850	0.642	Namibia	NAM	−3.202	−3.194	0.750		
Brazil	BRA	−3.159	−3.297	0.441	Nepal	NPL	−3.547	−3.591	−0.120		
Brunei	BRN	−2.577	−2.609	1.604	Netherlands	NLD	−3.845	−3.944	−0.032		
Bulgaria	BGR	−2.954	−3.035	0.931	New Zealand	NZL	−3.393	−3.405	0.400		
Burkina Faso	BFA	−2.754	−2.881	0.679	Nicaragua	NIC	−2.149	−2.140	2.023		
Burundi	BDI	−2.711	−2.796	0.963	Niger	NER	−2.796	−2.789	1.202		
Cambodia	KHM	−2.496	−2.717	0.922	Nigeria	NGA	−2.500	−2.585	1.671		
Cameroon	CMR	−2.948	−2.964	0.644	Norway	NOR	−3.920	−3.992	−0.007		
Canada	CAN	−3.782	−3.822	0.101	Oman	OMN	−2.444	−2.482	1.030		
Cape Verde	CPV	−2.767	−2.772	0.811	Pakistan	PAK	−3.669	−3.660	−0.140		
Central African Republic	CAF	−3.151	−3.170	0.839	Palau	PLW	−1.838	−1.876	2.795		
Chad	TCD	−2.374	−2.393	1.882	Panama	PAN	−3.023	−3.052	0.842		
Chile	CHL	−2.920	−2.930	0.550	Papua New Guinea	PNG	−2.475	−2.493	1.094		
China	CHN	−2.948	−3.380	0.749	Paraguay	PRY	−3.317	−3.355	0.427		
Colombia	COL	−3.895	−3.981	−0.160	Peru	PER	−2.911	−3.014	1.159		
Comoros	COM	−3.135	−3.144	0.375	Philippines	PHL	−3.296	−3.292	0.830		
Congo, Dem. Rep.	ZAR	−2.364	−2.375	1.726	Poland	POL	−3.041	−3.232	1.043		
Congo, Republic of	COG	−2.293	−2.300	1.247	Portugal	PRT	−3.171	−3.208	0.568		
Costa Rica	CRI	−3.344	−3.443	0.523	Puerto Rico	PRI	−3.165	−3.234	0.499		
Cote d’Ivoire	CIV	−2.892	−2.905	0.861	Qatar	QAT	−2.512	−2.503	1.853		
Croatia	HRV	−2.517	−3.357	1.576	Romania	ROM	−2.773	−3.116	1.044		
Cuba	CUB	−2.775	−2.888	1.302	Russia	RUS	−2.376	−2.541	1.586		
Cyprus	CYP	−2.452	−2.460	0.690	Rwanda	RWA	−2.027	−2.026	2.200		
Czech Republic	CZE	−2.998	−3.939	1.033	Samoa	WSM	−2.950	−3.001	1.166		

Denmark	DNK	−3.647	−3.658	0.198	Sao Tome and Principe	STP	−2.632	−2.623	1.690		
Djibouti	DJI	−2.399	−2.414	1.725	Saudi Arabia	SAU	−2.157	−2.183	1.667		
Dominica	DMA	−2.832	−2.844	0.961	Senegal	SEN	−3.213	−3.238	0.540		
Dominican Republic	DOM	−2.957	−2.972	0.981	Seychelles	SYC	−2.466	−2.469	1.335		
Ecuador	ECU	−3.173	−3.253	0.383	Sierra Leone	SLE	−2.406	−2.518	1.401		
Egypt	EGY	−2.975	−2.975	0.220	Singapore	SGP	−3.048	−3.077	0.908		
El Salvador	SLV	−3.244	−3.514	0.484	Slovak Republic	SVK	−2.708	−2.865	1.504		
Equatorial Guinea	GNQ	−1.713	−1.836	4.018	Slovenia	SVN	−3.060	−3.801	0.977		
Eritrea	ERI	−2.533	−2.839	1.260	Solomon Islands	SLB	−2.526	−2.515	1.086		
Estonia	EST	−2.451	−2.695	1.468	Somalia	SOM	−2.590	−2.580	1.688		
Ethiopia	ETH	−2.638	−2.697	1.354	South Africa	ZAF	−3.886	−4.020	−0.109		
Fiji	FJI	−2.923	−2.912	0.838	Spain	ESP	−3.459	−3.877	−0.024		
Finland	FIN	−3.324	−3.456	0.779	Sri Lanka	LKA	−3.595	−3.627	0.125		
France	FRA	−3.820	−3.957	−0.143	St. Kitts & Nevis	KNA	−3.449	−3.463	0.558		
Gabon	GAB	−2.477	−2.470	1.143	St. Lucia	LCA	−3.015	−3.024	0.887		
Gambia, The	GMB	−2.865	−2.890	1.005	St. Vincent & Grenadines	VCT	−2.747	−2.743	0.827		
Georgia	GEO	−2.347	−2.530	2.124	Sudan	SDN	−2.561	−2.599	1.526		
Germany	GER	−3.999	−4.069	0.012	Suriname	SUR	−2.505	−2.492	1.820		
Ghana	GHA	−1.926	−2.029	1.238	Swaziland	SWZ	−2.418	−2.407	0.743		
Greece	GRC	−3.241	−3.331	0.363	Sweden	SWE	−3.889	−4.010	0.068		
Grenada	GRD	−2.307	−2.334	1.607	Switzerland	CHE	−3.569	−3.698	0.332		
Guatemala	GTM	−3.662	−3.803	−0.124	Syria	SYR	−2.458	−2.508	1.048		
Guinea	GIN	−3.323	−3.321	0.250	Taiwan	TWN	−3.439	−3.554	−0.003		
Guinea-Bissau	GNB	−2.036	−2.025	1.579	Tajikistan	TJK	−1.960	−2.159	2.029		
Guyana	GUY	−2.229	−2.225	1.843	Tanzania	TZA	−3.237	−3.274	0.452		
Haiti	HTI	−3.154	−3.159	0.838	Thailand	THA	−3.251	−3.319	0.465		
Honduras	HND	−3.203	−3.196	0.596	Togo	TGO	−2.880	−2.952	1.148		
Hong Kong	HKG	−3.046	−3.150	0.418	Tonga	TON	−2.723	−2.786	1.172		
Hungary	HUN	−3.430	−3.672	0.482	Trinidad & Tobago	TTO	−2.769	−2.783	1.200		
Iceland	ISL	−2.916	−2.923	1.070	Tunisia	TUN	−3.209	−3.270	0.086		
India	IND	−3.545	−3.539	0.375	Turkey	TUR	−3.162	−3.161	0.880		
Indonesia	IDN	−3.200	−3.241	0.575	Turkmenistan	TKM	−2.173	−2.299	1.950		
Iran	IRN	−2.345	−2.394	1.336	Uganda	UGA	−2.920	−2.967	0.635		
Iraq	IRQ	−1.338	−1.333	3.167	Ukraine	UKR	−2.407	−3.452	1.240		
Ireland	IRL	−3.348	−3.471	0.398	United Arab Emirates	ARE	−1.640	−1.868	1.221		
Israel	ISR	−3.095	−3.198	0.438	United Kingdom	GBR	−3.936	−3.969	−0.004		
Italy	ITA	−3.639	−3.713	−0.037	United States	USA	−3.781	−3.796	0.087		
Jamaica	JAM	−3.252	−3.301	0.469	Uruguay	URY	−2.942	−3.031	1.123		
Japan	JPN	−3.214	−3.618	−0.027	Uzbekistan	UZB	−2.961	−3.436	0.669		
Jordan	JOR	−2.700	−2.721	0.933	Vanuatu	VUT	−2.523	−2.516	1.139		
Kazakhstan	KAZ	−2.476	−2.913	1.075	Venezuela	VEN	−2.884	−2.888	1.039		
Kenya	KEN	−3.190	−3.209	0.381	Vietnam	VNM	−3.436	−3.475	0.385		
Kiribati	KIR	−1.879	−1.885	2.552	Yemen	YEM	−2.932	−3.100	1.294		
Korea, Republic of	KOR	−3.050	−3.048	0.765	Zambia	ZMB	−2.393	−2.407	1.991		
Kuwait	KWT	−1.819	−1.807	2.069	Zimbabwe	ZWE	−2.162	−2.205	1.553		
Kyrgyzstan	KGZ	−2.451	−3.006	1.899	Mean (1960–2007)		−2.862	−2.959	1.002		
Laos	LAO	−3.230	−3.217	0.441	Mean (1960–1972)		−3.488		−0.214		
Latvia	LVA	−3.392	−3.833	0.728	Mean (1972–1986)		−2.880	−2.92[a]	0.844		
Lebanon	LBN	−1.328	−1.326	3.112	Mean (1987–2007)		−3.097	−3.214	1.056		

Lesotho	LSO	−2.644	−2.634	0.961							

Notes: VG = Volatility of Output Growth; VGR = Volatility of Growth Residuals; and VHP = Hodrick–Prescott Filtered Business Cycles. All variables are measured in log.
[a]The mean of VGR for the period of 1960–1986.

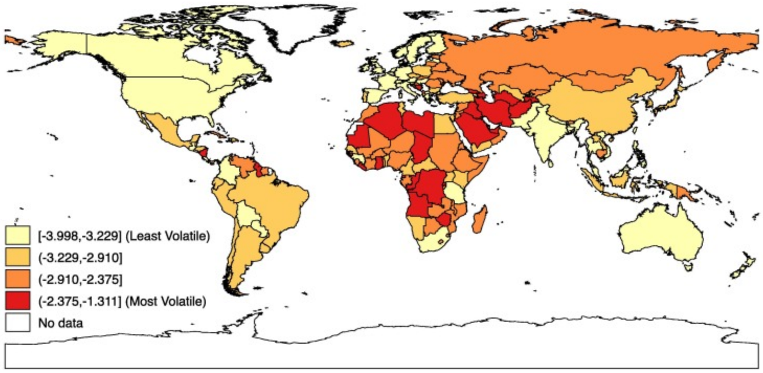

Fig. 1. Output growth business cycle volatility.

3. Spatial lag model

Spatial econometric techniques, which recognize the importance of location and distance in social and economic activities, have been widely applied in various fields such as geography and regional science. These techniques rely on the geographical location of observations to test for two spatial effects: spatial heterogeneity and spatial dependence. Spatial heterogeneity indicates coefficients as well as the functional form of a regression may vary across space while spatial dependence means that values of observations in location *i* might be correlated with values of observations in location *j* for i≠j. Since we are primarily interested in the comovement of economic volatility across space, our study looks at spatial dependence rather than spatial heterogeneity.

In this section, we briefly describe a basic model for spatial dependence—the spatial lag model.[9] A spatial lag model postulates the *feedback* among observations and it is the focus of our paper. With *N*locations, a spatial lag model suggests that the value of *Y* in location *i* is affected by values of *Y* in other locations. The general expression of a spatial lag model is as follows:

(5) $Y_i = \mathbf{x_i}\beta + \rho\mathbf{w_i}\mathbf{Y} + \eta_i,$

where Y_i is the dependent variable and xi is a vector of control variables in location *i*. The term $\mathbf{w_i}Y$ (often referred to as the spatial lag) is a weighted average of *Y* values in other locations with $\mathbf{w_i}$—the *i*th row of an $N \times N$ weight matrix $\mathbf{W}$—connecting locations in space. Locations geographically close to *i*are assigned with larger weights than locations that are far apart from *i*. The range of the coefficient on the spatial lag (i.e., *ρ*) is between -1 and +1. The sign and magnitude of *ρ* measure how values of *Y* in *other* locations affect the value of *Y* in location *i*. The larger *ρ* is (in absolute value), the stronger correlation exists across locations. If *ρ* is positive, an increase in the values of *Y* in other locations is associated with a larger value of *Y* in location *i*. If *ρ* is negative, then a larger value of *Y* in other locations is associated with a decrease in *Y* in location *i*. The stochastic error term η_i is assumed to have a normal distribution with mean of zero and variance of σ_η^2.

The first law of geography, reflecting the essence of spatial analysis, states "[e]verything is related to everything else, but near things are more related than distant things" (Tobler, 1970: 236). To represent a declining strength of spatial interaction when locations are more distant from each other, the entries of $\mathbf{W}$ are typically constructed as an inverse function of distance. Given *N* countries in a sample, $\mathbf{W}$ can be written as a $N \times N$ matrix:

(6) $\mathbf{W} = \begin{bmatrix} 0 & d_{ij}^{-1} & d_{ik}^{-1} \\ d_{ji}^{-1} & 0 & d_{jk}^{-1} \\ d_{ki}^{-1} & d_{kj}^{-1} & 0 \end{bmatrix}$,

where $d_{ij} = d_{ji}$ is the distance between capital cities of *i* and *j*. Diagonal elements of the matrix are set to zero so that no observation predicts itself. As is common in the literature, the weight matrix is also row-standardized so that elements in each row sum up to one.

The existence of spatial dependence may give rise to violations of classical assumptions, which are needed for ordinary least squares (OLS) to be the best linear unbiased estimator (BLUE). For example, the spatial lag term $\mathbf{w_i Y}$ is in fact endogenous. If $\rho \neq 0$, then OLS estimated coefficients will be biased and inconsistent (Anselin, 1988). As a result, spatial models are often estimated using alternative methods such as maximum likelihood instead of OLS.[10]

4. Geographical proximity and spatial correlation

As mentioned previously, given the nature of the dependent variable our regression is cross-sectional, which can be written as:

(7) $\sigma_i = \mathbf{z_i}\phi + \rho \mathbf{w_i}\boldsymbol{\sigma} + \eta_i$,

where σ_i is economic volatility of country *i*; the spatial lag term $\mathbf{w_i}\boldsymbol{\sigma}$ is a weighted average of economic volatility of all countries *j* for $j \neq i$; $\mathbf{z_i}$ is a $1 \times M$ vector of domestic determinants of economic volatility in country *i* as introduced in Section 2 (Buch, Kose).

Table 5 reports the spatial lag model maximum likelihood results over 1960–2007 as well as OLS results without capturing the spatial pattern of our data (model 5.1). The signs of statistically significant control variables in both groups of regressions are consistent with previous literature. For instance, inflation has a positive coefficient indicating higher inflation in general is associated with more volatility. Looking across columns, the spatial dependence of volatility of growth is evident. To be more specific, the coefficient on the spatial lag, ρ, in models 5.2–5.4 are robustly significant with a magnitude ranging between 0.49 and 0.65. The positive and significant coefficients provide support for geographical clustering in economic volatility. Since our measures of economic volatility and the spatial lag variable enter regressions in natural log, the value of ρ simply represents the relative percentage change or elasticity. For example, the result in model 5.2 indicates that if the spatially weighted average volatility of growth in other countries rises by 1%, economic volatility in the country of interest increases by 0.65%, holding other things constant.

Table 5. Spatial lag model of volatility comovement among geographical neighbors

Variables	**Model 5.1**	**Model 5.2**	**Model 5.3**	**Model 5.4**
Spatial economic volatility (ρ)		0.64711***	0.49053*	0.49081*
		[0.209]	[0.264]	[0.264]
Real GDP per capita	−0.15941***	−0.14039***	−0.10128**	−0.10977**
	[0.041]	[0.037]	[0.041]	[0.044]
Fiscal policy volatility	0.05692***	0.05446***	0.05544***	0.05561***
	[0.013]	[0.013]	[0.015]	[0.015]
Average inflation	0.00084***	0.00074***	0.00065**	0.00071**
	[0.000]	[0.000]	[0.000]	[0.000]
Openness	0.00329***	0.00326***	0.00334***	0.00322***
	[0.001]	[0.001]	[0.001]	[0.001]
Exchange rate volatility			0.08344*	0.06395
			[0.050]	[0.062]
Average M2/GDP				0.0005
				[0.001]

M2/GDP volatility				−0.00012
				[0.000]
OPEC	0.69088***	0.62564***	0.53136***	0.53933***
	[0.172]	[0.144]	[0.149]	[0.154]
Regional dummies	Yes	Yes	Yes	Yes
Constant	−2.06469***	−0.3435	−1.17464	−1.10389
	[0.362]	[0.644]	[0.818]	[0.826]
R-squared	0.3807			
Log likelihood		−94.975883	−84.949677	−84.788233
Variance ratio		0.394	0.342	0.344
Wald test of ρ = 0: chi2(1)=		9.615***	3.450*	3.458*
Likelihood ratio test of *ρ* = 0: chi2(1)=		7.201***	2.919*	2.925*
No. of Obs.	177	177	159	159

Notes: Dependent variable is volatility of output growth (in log). The spatial lag model is estimated based on the entire sample period of 1960–2007. Standard errors in brackets.
∗Significant at 10%.
∗∗Significant at 5%.
∗∗∗Significant at 1%.

To better understand how the comovement of economic volatility changes over time, we estimate the model in different subsample periods and present the results in Panel A of Table 6. Control variables in these regressions are the same as in regression 5.2 in Table 5. We also report in Table 6 the comovement of economic volatility among countries that are located within a specified distance from each other to explore how spatial correlations vary with geographical distance. In our sample, the median distance between two countries is 7,936 km (4,931 miles). The maximum distance is 19,951 kilometers (12,397 miles) between Paraguay and Taiwan. The first quartile and the third quartile cutoff distances are 4,458 km (2,770 miles) and 11,121 km (6,910 miles), respectively.

Table 6. Spatial lag model of volatility comovement among geographical neighbors based on proximity and balanced sample regression

	1960–2007	**1960–72**	**1973–86**	**1987–2007**
A. Geographical proximity[a]				
Full distance	0.64711***	0.14812	0.62485***	0.41762
	[0.209]	[0.303]	[0.203]	[0.257]
The first quartile of distance	0.44323***	−0.04993	0.37181***	0.27617
	[0.148]	[0.217]	[0.133]	[0.170]
The second quartile of distance	0.50618***	−0.00708	0.49041***	0.32342
	[0.194]	[0.267]	[0.173]	[0.220]
The third quartile of distance	0.60656***	0.09344	0.59763***	0.41792*
	[0.202]	[0.293]	[0.191]	[0.234]
B. Balanced sample regressions[b]				
Spatial economic volatility (ρ)	0.49155**	0.14812	0.45398**	0.37293
	[0.209]	[0.303]	[0.218]	[0.241]
Real GDP per capita	−0.21004***	−0.33240***	−0.20335***	−0.17074***
	[0.040]	[0.062]	[0.046]	[0.052]
Fiscal policy volatility	0.05396***	0.09148***	0.07502***	0.08001**
	[0.018]	[0.031]	[0.023]	[0.040]
Average inflation	0.00059*	0.00084	−0.00019	0.00025
	[0.000]	[0.002]	[0.000]	[0.000]
Openness	0.00312***	0.00505***	0.00308**	0.00247**
	[0.001]	[0.002]	[0.001]	[0.001]
OPEC	0.59038***	0.46031**	0.39983**	0.21557

	[0.164]	[0.230]	[0.191]	[0.233]
Regional dummies	Yes	Yes	Yes	Yes
Constant	−0.19574	−0.48594	−0.33438	−1.00562
	[0.545]	[1.023]	[0.594]	[0.780]
Log likelihood	−24.532	−54.56	−38.506	−56.461
No. of Obs.	91	91	91	91

Notes: Dependent variable is volatility of output growth (in log).

[a]In Panel A, the second quartile (median) of distance among countries is 7,935.88 km. The first and third quartiles across countries are 4,457.72 km and 11,120.99 km, respectively. The maximum distance between two countries in the sample (Paraguay and Taiwan) is 19,951.2 km Other control variables are average real GDP per capita (in log), average inflation rate, fiscal policy volatility, trade openness, and regional dummies (Sub-Saharan Africa and Latin America and Caribbean).

[b]Regressions in panel B are based on a sample of 91 countries which are available in the subsample period of 1960–72. Standard errors in brackets.

∗Significant at 10%.

∗∗significant at 5%.

∗∗∗Significant at 1%.

The spatial dependence of economic volatility among countries that are within a 4,458-km radius (first-quartile distance regression) is first estimated. Then we allow countries within a 7,936-km radius to affect each other spatially (second-quartile distance regression). This is followed by an estimation of spatial dependence among countries within a 11,121-km radius (third-quartile distance regression). The weight matrix in each distance quartile regression is constructed by setting an entry to zero if the distance between countries *i* and *j* is greater than a threshold distance stated above. For example, the weight matrix in the first-quartile distance regression is:

$$\mathbf{W}^{\mathbf{Q1}} = \begin{bmatrix} 0 & w(d_{ij}) & w(d_{ik}) \\ w(d_{ji}) & 0 & w(d_{jk}) \\ w(d_{ki}) & w(d_{kj}) & 0 \end{bmatrix},$$

where $w(d_{ij})$ is zero if $d_{ij} > 4{,}458\text{km}$, and $w(d_{ij}) = 1/d_{ij}$ otherwise. Stated differently, any country *j*within the first quartile distance radius of country *i* would be included in the weight matrix. If country *j* is apart from country *i* by more than the first quartile distance, then entry $w(d_{ij})$ is set to zero. We apply the same technique to construct the second- and the third-quartile distance weight matrices for our estimations.

Panel A of Table 6 includes results of 16 spatial lag regressions with different distance radii (by row) and sample periods (by column). For the purpose of brevity, we restrict the reported results to the coefficient on the spatial lag term, with full results provided in Table 10 in the appendix.

There are two notable points from Panel A of Table 6. First, the spatial effect is increasing as we allow countries farther apart to affect each other, but at a decreasing rate. This is consistent with the expectation that the strongest spatial dependence, if any, should occur among countries that are located closest to each other. For example, the 1973–86 regression indicates that the spatial lag coefficient changes from 0.372 to 0.49, a 0.118-point increase, when we move from the first-quartile distance regression to the second-quartile distance regression. The spatial lag coefficient only increases by 0.107 from the second-quartile to the third-quartile distance regression and by 0.027 from the third-quartile to the full distance regression. Allowing countries that are within a 7,936-km radius rather than a 4,458-km radius to affect each other increases the magnitude of spatial dependence by approximately 31.7%. Including countries that are within a 11,121-km radius rather than just a 7,936-km radius increases the magnitude of spatial dependence by only 21.8%. Finally, allowing all countries in our sample to affect each other increases the strength of spatial dependence by merely 4.5%, compared to that based on countries that are within a 11,121-km radius.

Second, interesting differences between full sample (Table 5) and subsample results (Table 6) emerge. Geographical clustering of economic volatility appears to *peak* over the period of international shocks (1973–86). In addition, we do not observe a significant comovement of economic volatility during the Bretton Woods era and the *decline* in economic volatility comovement among neighbors over the period of 1987–2007 is evident in all regressions. For example, the second-quartile distance volatility regressions show that ρ is -0.007 in 1960–72, which is not statistically different from zero. It increases to 0.49, significant at the 1% level in 1973–86 and then drops to 0.323 (not significant) in 1987–2007. These results suggest that with a 1% increase in the output volatility of neighboring countries (within a 7,935.88-km radius), the output volatility in our country of interest rises by 0.49% in 1973–86, while over the period of 1960–72 and 1987–2007, a significant comovement of growth volatility does not exist across neighboring countries.

Furthermore, we note that our sample is unbalanced and the number of countries available over time is rising. One tends to ask about its implications for our results regarding the comovement of economic volatility. The answer depends on whether the countries that are missing over a certain period are more volatile or less volatile than other countries. If the missing countries are more (less) volatile, then the model tends to overestimate (underestimate) the strength of comovement of economic volatility among economies. For example, currently we have 137 countries in the 1973–86 sample, 91 of which are also in the 1960–72 sample and 46 of which are new either because they were newly established over 1973–86 or because their data are not available in the previous subsample period. Counterfactually, if we had all 137 countries over 1960–72 and the additional 46 countries on average experienced a higher economic volatility than the other 91 countries, then the estimated coefficient on our spatial lag term in the 1960–72 subsample regression would have been smaller than shown in the full distance regression. However, the actual economic volatility of these 46 countries over 1960–72 is unobservable, because they did not exist or no data from these countries are available. In this case, to see whether our results are robust, we run spatial regressions based on a balanced sample including 91 countries, from which we have data over the entire sample span and report the results in Panel B of Table 6. The results based on this balanced panel show that the comovement of economic volatility of geographical neighbors peaks over 1973–86 (0.454 and significant at the 5% level) while it is not significant over 1960–72 and 1987–2007, which are qualitatively similar to those based on the unbalanced panel.[11] In short, Table 6 results indicate that the role of geographical proximity in influencing the spatial dependence across countries increases in the period of international shocks compared to the Bretton Woods era, but *declines* rapidly during the past two decades. In other words, distance matters in pre-globalization periods, but its importance decreases drastically in the era of globalization.

5. Beyond geography: economic connectivity

Spatial models have routinely used geographical distance to measure "connectivity". However, in the era of globalization, it is also meaningful to consider the connectivity among countries based on their "economic distance." Due to technology improvement and increasing ease in communication, the impact of geographical distance on the connectivity of countries is arguably declining. This may explain why in regressions over the period of 1987–2007 in Table 6, the coefficient on our distance-weighted spatial lag term tends to be insignificant. Indeed, countries can be geographically far apart while sharing a strong economic bond and in turn experience a strong comovement of their business cycles (Baxter and Kouparitsas, 2005, Clark and van Wincoop, 2001). For example, the U.S. and Japan may share a more similar pattern of economic volatility than the U.S. and Mali due to the strength of their bilateral economic relationship although Mali is geographically closer to the U.S. Beck, Gleditsch, and Beardsley (2006, p. 27) also argue that "most applications [of spatial econometrics] are still based on geographic notions of distance …[I]t is often more fruitful to consider political economy notions of distance, such as relative trade or common dyad membership."

To focus on economic distance, we modify the weight matrix in the spatial lag estimation by replacing geographical distance with bilateral trade (Beck *et al.*, 2006). As argued by Clark and van Wincoop, 2001, Frankel and Rose, 1998, imports and exports often serve as channels for economic transmission and countries are "economically closer" if they conduct a large volume of trade with each other. In constructing the weight matrix for economic distance, we scale bilateral trade by importing and exporting countries' GDP. These weights are also similar to weights based on trade flows in Claeys, Kelejian, which use spatial modeling to explore the contagion of foreign exchange crisis and spillovers in financial markets, respectively.[12] In particular, a typical entry in the weight matrix $\mathbf{W}$, capturing the bilateral trade between country *i* and country *j*, is:

$$(8)\ trd_{ij} = \frac{\sum_{t=1}^{T}\left(\frac{X_{ijt}+M_{ijt}}{Y_{it}+Y_{jt}}\right)}{T},$$

where X_{ijt} is the value of exports from country *i* to country *j* in year $t; M_{ijt}$ is the value of imports in country *i* from country $j; Y_{it}$ and Y_{jt} denote real GDP in country *i* and country *j* in year *t*, respectively. Since country *i*'s imports from country *j* is country *j*'s exports to country *i*, it follows that $trd_{ij} = trd_{ji}$. Data on bilateral trade are from Rose (2005). [13]

Table 7 reports results from the economic-distance based spatial lag model.[14] On average, we see that a country's economic fluctuations are positively associated with the extent of economic fluctuations among its trading partners over 1960–2007, with ρ significant at the 1% level. But again substantial variation exists across subsamples. The coefficient on the spatial lag term is positive, but insignificant over 1960–72. Conversely, after 1972, the coefficient on the spatial lag becomes positive and significant. It appears that the importance of trade in connecting countries has been rising after the collapse of the Bretton Woods system. Both the magnitude and the level of significance of ρ in regressions over 1987–2007 tend to improve from Table 6, Table 7. In Panel A of Table 6, the full distance volatility regression shows that the coefficient on the spatial lag is 0.42, and not statistically significant. In Table 7, the coefficient is 0.5 and significant at the 1% level. This indicates that if the trade-weighted average growth volatility in other countries increases by 1%, the growth volatility in the country of interest rises by 0.5% over the time period of 1987–2007.

Table 7. Spatial lag model based on economic distance

	1960–2007	**1960–72**	**1973–86**	**1987–2007**
Spatial economic volatility (ρ)	0.59018***	0.01347	0.53624***	0.49980***
	[0.112]	[0.240]	[0.143]	[0.119]
No. of Obs.	172	88	132	170

Notes: Dependent variable is volatility of output growth (in log). Spatial weight matrix is constructed based on the bilateral trade level between countries i and j. Other control variables are average real GDP per capita (in log), average inflation rate, fiscal policy volatility, trade openness, OPEC dummy, and regional dummies (Sub-Saharan Africa and Latin America and Caribbean). Standard errors in brackets.
*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

In summary, Table 6, Table 7 together suggest that geographical proximity and economic proximity *both* matter. However, the importance of geographical clustering is *declining* while the importance of economic connectivity is *increasing*. Prior to 1972, international trade did not serve as an important channel for economic volatility spillovers. Spatial dependence is more evident based on a trade relationship than based on geographical proximity over 1987–2007. The dynamics of spatial dependence in Table 7 may be caused by the fact that during the period of 1960–72, the number of trade partners a country had as well as the volume of trade among partners were not as large as in the period of international shocks and the globalization period. For instance, the average imports plus exports as a share of GDP in OECD countries in 1960–72 was 23%, and the world average share of trade to GDP in the same time period was 25%. This share in OECD countries rose to 34% in 1973–86 and 40% over the period of 1987–2007. Similarly, the world average share of trade to GDP also increased after the Bretton Woods system to 36% in 1973–1986 and 44% in 1987–2007.

6. Robustness checks

(a). CAGE distance and GNI

In this subsection, we conduct robustness checks by introducing the CAGE distance between countries in our model, providing results based on HP output volatility and volatility of growth residuals, and adopting measures of economic volatility calculated based on gross national income (GNI). The CAGE distance framework is proposed by Ghemawat (2007), which includes four aspects of remoteness between countries, namely cultural, administrative, geographical, and economic distances. We obtain the cultural distance (measured based on language, religion, and diaspora) and administrative distance (measured based on trade blocs, currency, colonizer, corruption, political stability, and legal origin) measures between countries from *CAGE Comparator* on Ghemawat's website, and then use them to reconstruct the weight matrix, respectively. [15] We report results with spatial volatility based on cultural and administrative distances in Panel A of Table 8, results with HP output volatility and volatility of growth residuals in Panel B, and results based on the growth volatility measure calculated using GNI instead of GDP in Panel C. [16] Panel A shows that cultural distance is not an important factor affecting the comovement of economic volatility compared to geographical distance or economic distance, as the coefficient on the spatial lag term is not significant at conventional levels over different subsample periods. Results based on administrative distance–weight matrix indicate that countries with a shorter administrative distance tend to have a stronger comovement of economic volatility over the subsample period of 1987–2007. In terms of Panel B results, it seems that the coefficient on the spatial lag term is not estimated precisely in the HP output volatility regression in Panel B. The growth residual volatility regression results do support comovement of geographical neighbors over 1960–2007 as well as over 1960–86, which do not change qualitatively from our results reported in Table 6. In addition, we also estimate geographical-proximity based regressions over two subsample periods, 1960–86 and 1987–2007 and report the results in Table 11 in the appendix. The output growth volatility and HP output volatility results all indicate a strong comovement of economic volatility over 1960–1986, but not over 1987–2007. In Panel C, results from output growth volatility based on GNI are qualitatively similar to Table 6 results as well.

Table 8. Robustness checks—cultural and administrative distance matrices and alternative measures of volatility

***A. The CAGE distance*[a]**								
	Cultural distance				**Administrative distance**			
	1960–2007	**1960–72**	**1973–86**	**1987–2007**	**1960–2007**	**1960–72**	**1973–86**	**1987–2007**
Spatial economic volatility (ρ)	0.1069	−3.79439	−0.34155	0.23426	0.71190***	−1.56414*	−1.16566	0.60330*
	[0.754]	[2.840]	[0.908]	[0.655]	[0.273]	[0.923]	[0.963]	[0.363]
No. of Obs.	152	83	116	151	152	83	116	151
B. Alternative measures of volatility[b]								
	HP-filtered output volatility				Growth residual volatility			
	1960–2007	1960–1972	1973–1986	1987–2007	1960–2007	1960–1986		1987–2007
Spatial economic volatility (ρ)	0.16446	0.06086	0.38305	0.00333	0.71197***	0.61827***		0.40104
	[0.311]	[0.331]	[0.267]	[0.321]	[0.181]	[0.201]		[0.247]
No. of Obs.	177	91	137	176	177	137		176
C. Output growth volatility based on GNI[b]								
	1960–2007	1960–1972	1973–1986	1987–2007				
Spatial economic volatility (ρ)	0.52034**	−0.09573	0.45119*	0.37969				
	[0.261]	[0.353]	[0.274]	[0.284]				
Observations	127	72	90	127				

Notes: Dependent variable is volatility of output growth (in log). Standard errors in brackets. Control variables are average real GDP per capita (in log), average inflation rate, fiscal policy volatility, trade openness, OPEC dummy, and regional dummies. Standard errors in brackets.

[a]In panel A, spatial weight matrices are constructed based on the cultural distance and administrative distance between countries i and j, respectively (Ghemawat, 2007).

[b]Spatial weight matrix is constructed based on the geographical distance between countries i and j in panel B. Other control variables are average real GDP per capita (in log), average inflation rate, fiscal policy volatility, trade openness, and regional dummies.

∗Significant at 10%.

∗∗Significant at 5%.

∗∗∗Significant at 1%.

(b). Additional robustness checks: spatial error model

Next, we refer to the spatial error model for additional evidence of comovement of business cycles following the empirical specification of Ramey and Ramey (1995). They investigate the effect of fluctuations of economic growth on the rate of growth itself. Their specifications serve as a natural setting for a spatial error model since they take *error terms* in an economic growth regression to represent business cycle volatility.

A spatial error model explores how the errors/shocks are correlated across locations. We write our spatial error model as:

(9) $g_{it} = \mathbf{x_{it}}\beta + \epsilon_{it}$,

(10) $\epsilon_{it} = \lambda \mathbf{w_{it}} \epsilon + v_{it}$,

where g_{it} is the annual growth rate of real GDP per capita for country *i* in year *t*; $\mathbf{x_{it}}$ is a vector of growth determinants; ϵ_{it} is the error term for country *i* in year *t*, which is used as a proxy for business cycle volatility. For country i,$\mathbf{w_{it}}$ ϵ is a weighted average of business cycle volatility in all other countries. Eqns. (9), (10) indicate that business cycle volatility in country *i* (ϵ_{it}) is correlated with business cycle volatility of other countries (ϵ).[17]

The list of $\mathbf{x_{it}}$ variables comes from Barro, 1991, Levine and Renelt, 1992, Ramey and Ramey, 1995, including investment share of GDP per capita, population growth rate, initial level of human capital, the log value of initial per capita GDP, the log of GDP at time $t-1$ and $t-2$, a time trend, a square term of the time trend, and regional dummy variables. [18]

The even-numbered regressions in Table 9 report the maximum-likelihood results of the spatial error model and the odd-numbered regressions present OLS results without considering the spatial dependence of error terms. Note that dependent variables in spatial lag and spatial error models are different. In the spatial lag model presented in previous sections, the dependent variable is a measure of volatility (σ_i), while the dependent variable in our spatial error model here is economic growth (g_{it})git. Consequently, we cannot directly compare the quantitative results from these two models. [19]

Table 9. Spatial error model of international economic volatility

Variables	**1960–2007**	**1960–2007**	**1960–72**	**1960–72**	**1973–86**	**1973–86**	**1987–2007**	**1987–2007**
	Model 9.1	**Model 9.2**	**Model 9.3**	**Model 9.4**	**Model 9.5**	**Model 9.6**	**Model 9.7**	**Model 9.8**
Spatial economic volatility (λ)		0.31440***		0.02802		0.36706***		0.13443**
		[0.036]		[0.099]		[0.063]		[0.065]
Average investment share of GDP	0.08302***	0.07984***	0.16849***	0.16814***	0.07056**	0.06898***	0.05526**	0.05236**
	[0.018]	[0.015]	[0.043]	[0.027]	[0.032]	[0.026]	[0.023]	[0.021]
Average population growth rate	−41.42556**	−40.67635**	−5.48557	−5.4088	−26.75128	−24.95604	−69.92068**	−69.38418***
	[16.217]	[16.195]	[25.908]	[26.382]	[28.534]	[28.087]	[31.139]	[22.740]
Initial per capita GDP	0.25751***	0.29022**	0.28662	0.28556	0.44991**	0.46668*	−0.09266	−0.06173
	[0.099]	[0.137]	[0.231]	[0.299]	[0.178]	[0.247]	[0.178]	[0.207]
Initial human capital	−1.33291***	−1.40504***	−5.39572***	−5.41929***	0.16729	−0.0158	0.91677	0.92014
	[0.307]	[0.242]	[1.940]	[1.478]	[1.163]	[1.033]	[1.521]	[0.574]
Per capita GDP_{-1}	4.08695	3.83631**	−18.93149*	−18.93662***	9.19299*	10.29607***	8.31237	8.16036***
	[4.946]	[1.587]	[10.966]	[3.205]	[5.358]	[2.636]	[5.661]	[2.063]

Per capita GDP$_{-2}$	−3.74151	−3.40795**	23.08630**	23.11845***	−10.50586*	−11.38411***	−9.68782*	−9.51998***
	[4.971]	[1.615]	[11.643]	[3.512]	[5.400]	[2.820]	[5.785]	[2.134]
Trend	−0.24129***	−0.23957***	−0.29281	−0.29624	−0.44334**	−0.45594	−0.08029	−0.08021
	[0.035]	[0.046]	[0.407]	[0.468]	[0.204]	[0.297]	[0.086]	[0.113]
Trend squared	0.00405***	0.00400***	0.01827	0.01842	0.0178	0.01824	0.00891***	0.00887*
	[0.001]	[0.001]	[0.024]	[0.027]	[0.012]	[0.019]	[0.003]	[0.005]
Sub-Saharan Africa	−0.86569**	−0.77567**	−0.68635	−0.69745	−1.53628**	−1.50694**	−1.39443**	−1.32357***
	[0.347]	[0.328]	[0.774]	[0.606]	[0.679]	[0.637]	[0.607]	[0.502]
Latin America and Caribbean	−0.46393**	−0.40584	−0.92732*	−0.92986*	−0.96056**	−0.93499*	−1.04597**	−0.99553**
	[0.231]	[0.276]	[0.483]	[0.524]	[0.450]	[0.552]	[0.419]	[0.412]
OPEC dummy	−0.15816	−0.10517	1.80221*	1.80358*	−2.27280**	−2.15077**	−0.13677	−0.15774
	[0.537]	[0.461]	[1.081]	[0.999]	[1.089]	[0.938]	[0.728]	[0.673]
Constant	11.81243***	11.69624***	10.92076***	10.91594***	12.47874***	12.14217***	6.09795**	5.93113***
	[1.787]	[1.594]	[4.072]	[3.379]	[2.713]	[2.698]	[2.702]	[2.279]
R-Squared	0.0613		0.1342		0.069		0.0466	
Log likelihood		−12233.189		−2742.3784		−4669.0359		−7140.4771
Variance ratio		0.059		0.134		0.071		0.045
Wald test of λ=0: chi2(1)=		74.221***		0.08		33.569***		4.255**
Likelihood ratio test of *λ* = 0: chi2(1)=		69.847***		0.079		31.06***		4.175**
Observations	3,915	3,915	870	870	1,414	1,414	2,162	2,162

Note: Standard errors in brackets.
∗Significant at 10%.
∗∗Significant at 5%.
∗∗∗Significant at 1%.

Spatial error model results are qualitatively similar to the spatial lag model results: the spatial effect is strong in general, but quite different across three subsample periods. [20] We observe positive and significant spillovers over both 1973–86 and 1987–2007, suggesting a shock in neighboring countries tends to affect the stochastic disturbance in the country of interest. However, the coefficient on the spatial error term is not statistically significant in the Bretton Woods era (1960–72). This indicates a much weaker comovement among countries in 1960–72 than in later time periods. In addition, the spatial dependence during the international shocks period appears to be stronger than that in the period of globalization—a 1% increase in positive spatial error is accompanied by a larger percentage increase in growth of country *i* over 1973–86 than over 1987–2007 (0.37 *vs.* 0.13). Signs of coefficients on control variables in general agree with Ramey and Ramey (1995) and the growth literature. For example, the investment share of GDP is found to have a positive effect on growth while population growth rate tends to have a negative and significant coefficient. Coefficients on control variables are also relatively unaffected by the addition of the spatial measure despite the statistical significance of the spatial term. Spatial models are our preferred specifications, but this is "reassuring evidence of the validity of previous empirical studies" (Blonigen *et al.*, 2007, p. 1314).

7. Conclusions

We study the economic volatility comovement across countries. In contrast to previous research, we go beyond the often-adopted bilateral framework and allow for spatial dependence of economic fluctuations across multiple countries. Using data from 187 countries over the period of 1960–2007, spatial lag model results show that the distance-weighted value of economic volatility in neighboring countries positively affects the magnitude of economic volatility in the country of interest. There also exists strong dependence of economic volatility among trade partners. These results are robust to different specifications and alternative measures of economic volatility.

More importantly, we observe a change in the pattern of comovements. The influence of geographical distance on the comovement of economic volatility increases from the Bretton Woods era (1960–72) to the period of international shocks (1973–86), while it declines afterward (1987–2007). During the globalization era (1987–2007), economic distance matters more than geographical distance. Over the period of 1987–2007, countries located close to each other may not necessarily share similar patterns of economic volatility. Countries that have a closer economic tie (measured by a trade relationship) are more likely to exhibit a distinct comovement in their economic fluctuations.

Our findings are important for policy makers since they provide a basis for understanding the formation and contagion of business cycle volatility. Volatility experienced in one country inevitably spills over to its geographical neighbors or trade partners. Although it is impossible to completely end the risks of contagion among countries, better policies—such as fiscally sustainable policies—can help to reduce transmission vulnerabilities. This is especially important for less developed countries since they experience much larger adverse contagion effects in the long run than in developed countries. Sustainable fiscal policies alone are not the only tactic policy makers possess in reducing contagion risk. Individual nations should also continue to strengthen their macroeconomic frameworks (e.g., monetary system), promote a transition to more diverse production structures, and reduce structural rigidities in labor markets. International organizations can also contribute to a more stable global economy by taking further steps to encourage transparency of regulations and policies and enhance international monitoring of country compliance with certain standards essential to the global economic development.

Our study has several limitations. The sample of this paper is cross-sectional due to the nature of our dependent variable. As a result, we are unable to include country dummies to control for potential time-invariant country-level unobserved heterogeneity. Although we focus on subsample results to capture the dynamics of comovement of economic volatility, a time dummy cannot be included in each regression again due to a cross-sectional sample over each subsample period. Future research may use different measures of economic volatility that allow for time variation in the regression to estimate how results change over time. In addition, another interesting topic for future research could be, for example, to compare the difference in economic volatility comovement among countries based on their administrative distance and geographical proximity.

Acknowledgements

We are grateful to three anonymous referees and the editor for providing invaluable comments to improve our paper. We would like to thank Bruce Blonigen, Brian Brush, Elizabeth Cheung, David Clark, Joseph Daniels, Jeremy Gilmore, Eran Guse, Mohammad Hajizadeh, James Reade, Rajesh Singh, and the participants at the Canadian Economics Association Meeting 2012 for their helpful comments and suggestions. This research is supported by the Miles Research Grant from the College of Business Administration, Marquette University, and the Marquette University Regular Research Grant.

Appendix A.

A.1. Appendix tables

Table 10, Table 11, Table 12, Table 13.

Table 10. Geographic proximity of international economic volatility

	Full distance				**The first quartile of distance**			
	1960–2007	**1960–72**	**1973–86**	**1987–2007**	**1960–2007**	**1960–72**	**1973–86**	**1987–2007**
Spatial economic volatility (ρ)	0.64711***	0.14812	0.62485***	0.41762	0.44323***	−0.04993	0.37181***	0.27617
	[0.209]	[0.303]	[0.203]	[0.257]	[0.148]	[0.217]	[0.133]	[0.170]
Real GDP per capita	−0.14039***	−0.33240***	−0.07377*	−0.17684***	-0.13397***	−0.34124***	−0.07383*	−0.17410***
	[0.037]	[0.062]	[0.044]	[0.044]	[0.038]	[0.061]	[0.044]	[0.044]
Fiscal policy volatility	0.05446***	0.09148***	0.09784***	0.11084***	0.05259***	0.09384***	0.09285***	0.10969***
	[0.013]	[0.031]	[0.017]	[0.020]	[0.013]	[0.031]	[0.017]	[0.020]
Average inflation	0.00074***	0.00084	−0.00012	0.00042**	0.00077***	0.00086	−0.00012	0.00043**
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
Openness	0.00326***	0.00505***	0.00250***	0.00316***	0.00324***	0.00490***	0.00246***	0.00317***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
OPEC	0.62564***	0.46031**	0.62535***	0.25361	0.61546***	0.46705**	0.63623***	0.24688
	[0.144]	[0.230]	[0.177]	[0.179]	[0.144]	[0.230]	[0.177]	[0.179]
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.3435	−0.48594	−1.00431	−0.85662	−0.97695**	−1.06781	−1.73762***	−1.31662**
	[0.644]	[1.023]	[0.692]	[0.851]	[0.488]	[0.815]	[0.536]	[0.612]
No. of Obs.	177	91	137	176	177	91	137	176
	The second quartile of distance				The third quartile of distance			
	1960–2007	1960–72	1973–86	1987–2007	1960–2007	1960–72	1973–86	1987–2007
Spatial economic volatility (ρ)	0.50618***	−0.00708	0.49041***	0.32342	0.60656***	0.09344	0.59763***	0.41792*
	[0.194]	[0.267]	[0.173]	[0.220]	[0.202]	[0.293]	[0.191]	[0.234]
Real GDP per capita	−0.14304***	−0.33901***	−0.07909*	−0.17907***	−0.13968***	−0.33492***	−0.07437*	−0.17611***
	[0.038]	[0.061]	[0.044]	[0.044]	[0.037]	[0.062]	[0.044]	[0.044]

Fiscal policy volatility	0.05541***	0.09341***	0.09735***	0.11177***	0.05497***	0.09174***	0.09803***	0.11074***
	[0.013]	[0.031]	[0.017]	[0.020]	[0.013]	[0.031]	[0.017]	[0.020]
Average inflation	0.00076***	0.00089	−0.00014	0.00042**	0.00075***	0.00084	−0.00014	0.00042**
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
Openness	0.00322***	0.00495***	0.00250***	0.00314***	0.00322***	0.00502***	0.00247***	0.00313***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
OPEC	0.63268***	0.46578**	0.64124***	0.25382	0.62467***	0.46125**	0.62846***	0.24977
	[0.145]	[0.230]	[0.177]	[0.179]	[0.144]	[0.230]	[0.176]	[0.179]
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.73291	−0.94199	−1.36000**	−1.13333	−0.46597	−0.64272	−1.07436	−0.85871
	[0.608]	[0.949]	[0.631]	[0.755]	[0.626]	[1.007]	[0.666]	[0.788]
No. of Obs.	177	91	137	176	177	91	137	176

Notes: Standard errors in brackets.
∗significant at 10%.
∗∗significant at 5%.
∗∗∗Significant at 1%.

Table 11. Spatial regressions with two subsample periods

	Output growth volatility			**Growth residual volatility**			**HP-filtered output volatility**		
	1960–2007	**1960–86**	**1987–2007**	**1960–2007**	**1960–86**	**1987–2007**	**1960–2007**	**1960–86**	**1987–2007**
Spatial economic volatility (ρ)	0.64711***	0.63334***	0.41762	0.71197***	0.61827***	0.40104	0.16446	0.46252*	0.00333
	[0.209]	[0.197]	[0.257]	[0.181]	[0.201]	[0.247]	[0.311]	[0.253]	[0.321]
Real GDP per capita	−0.14039***	−0.11647***	−0.17684***	−0.15063***	−0.11263***	−0.18362***	−0.16306***	−0.02196	−0.16365***
	[0.037]	[0.041]	[0.044]	[0.038]	[0.043]	[0.044]	[0.056]	[0.055]	[0.053]
Fiscal policy volatility	0.05446***	0.08872***	0.11084***	0.05466***	0.08800***	0.10429***	0.07880***	0.11229***	0.12020***
	[0.013]	[0.014]	[0.020]	[0.014]	[0.015]	[0.020]	[0.020]	[0.019]	[0.024]
Average inflation	0.00074***	0.00054	0.00042**	0.00038	0.00075	0.00033*	0.00143***	0.00023	0.00032
	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.001]	[0.000]
Openness	0.00326***	0.00309***	0.00316***	0.00318***	0.00345***	0.00341***	0.00419***	0.00189	0.00348***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
OPEC	0.62564***	0.82859***	0.25361	0.71383***	0.81961***	0.38937**	0.56011***	0.63846***	0.26025

	[0.144]	[0.163]	[0.179]	[0.145]	[0.169]	[0.178]	[0.215]	[0.218]	[0.215]
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.3435	−0.68245	−0.85662	−0.09698	−0.8143	−0.96943	1.49564**	−0.23824	1.79649***
	[0.644]	[0.652]	[0.851]	[0.595]	[0.675]	[0.850]	[0.609]	[0.487]	[0.605]
Log likelihood	−94.975	−68.159	−131.56	−97.038	−72.853	−130.705	−165.23	−108.107	−163.21
No. of Obs.	177	137	176	177	137	176	177	137	176

Notes: Standard errors in brackets.
∗Significant at 10%.
∗∗Significant at 5%.
∗∗∗Significant at 1%.

Table 12. Correlation matrix among three measures of economic volatility

A. The 1960–2007 sample	**VG**	**VGR**	**VHP**
VG	1		
VGR	0.9460	1	
VHP	0.8816	0.8235	1
n=177			
B. The 1960–72 sample	VG	VHP	
VG	1		
VHP	0.7092	1	
n=91			
C. The 1973–86 sample	VG	VHP	
VG	1		
VHP	0.8035	1	
n=137			
D. The 1960–86 sample	VG	VGR	VHP
VG	1		
VGR	0.9867	1	
VHP	0.753	0.7614	1
n=137			
E. The 1987–2007 sample	VG	VGR	VHP
VG	1		
VGR	0.9615	1	
VHP	0.9403	0.9214	1
n=176			

Notes: VG = volatility of output growth; VGR = volatility of growth residuals; and VHP = Hodrick–Prescott filtered output volatility. All variables are measured in log.

Table 13. Correlation matrix of economic volatility measures among three sample periods

	1960–72	**1973–86**	**1987–2007**
A. Output growth rate			
1960–72	1		
1973–86	0.1133	1	
1987–2007	0.081	0.1983	1
n = 163			

B. Volatility of output growth (VG)			
1960–72	1		
1973–86	0.2737	1	
1987–2007	−0.0090	0.5044	1
n = 163			
C. Volatility of growth residuals (VGR)			
1960–72	1		
1973–86	0.5082	1	
n = 163			
D. Hodrick–Prescott filtered output volatility (VHP)			
1960–72	1		
1973–86	0.6785	1	
1987–2007	0.3931	0.6420	1
n = 163			

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Note

[1]Keynes (1936) argues business cycles are a function of exogenous shocks in aggregate demand. Others attribute changes in money supply growth as the dominant source (Friedman & Schwartz, 1963). More recent research emphasizes the importance of technological shocks (Kydland & Prescott, 1982), expectation errors (Lucas, 1973, Lucas, 1977), and various forms of staggered price adjustment (Mankiw, 1985, Taylor, 1979, Taylor, 1980).

[2]Baxter and Kouparitsas, 2005 identify robust factors which drive the comovement of business cycles between countries and conclude that bilateral trade is a significant determinant of business cycles comovement. “Border effects” have also been stressed in cross-country studies. Clark and van Wincoop (2001) compare within-country and cross-country correlations of business cycles based on data from nine U.S. census regions and EU countries. They find that correlations of business cycles between EU country pairs are smaller than those between paired regions in the U.S. due to the effect of European national borders.

[3]It is worth mentioning that a major difference exists between these two methods: the dynamic factor model identifies the share of common and domestic shocks, but the factor structural VAR can also quantify the share of total variance of a series that is from spillovers of idiosyncratic foreign shocks. Kose *et al.* (2008) study the comovement of business cycles in G-7 countries using the dynamic factor model and argue there is a higher degree of business cycles synchronization among G-7 countries during the period of 1987–2007 than in the Bretton Woods period. Stock and Watson (2005), employing a structural factor VAR model, conclude that the increase in synchronization of business cycles among G-7 is not evident over the period of 1960–2002. However, the correlation of economic fluctuations within the continental Europe G-7 and within the English-speaking G-7 is rising significantly. Bagliano and Morana (2010), in a large-scale factor-structural VAR framework, hold that the spillover of foreign idiosyncratic disturbances is not as important as common global shocks in explaining international macroeconomic comovements.

[4]The terms "business cycle volatility," "macroeconomic volatility," "economic volatility," and "economic fluctuations" are used interchangeably in the text.

[5]To the best of our knowledge, there is a small literature on cross-country spillovers in explaining economic growth, which adopts spatial analysis (Artis, Conley and Ligon, 2002, Ertur and Koch, 2007). Spatial analysis has also been used in studies of foreign direct investment, although the literature still remains scant (see Blonigen, Coughlin and Segev, 2000).

[6]Ravn and Uhlig (2002) show the smoothing parameter for the HP filter is determined by the frequency of the time series. The authors suggest that a smoothing parameter of 6.25 is recommended for annual data. While the Hodrick–Prescott filter can be considered a high-pass filter (i.e., detrending the data to uncover high-frequency components of a series), an alternative approach has been advocated by Baxter and King (1999). They use a band-pass filter to remove both low- and high-frequency components in a series. Baxter and King (1999) argue that the band-pass filter corresponds well to the NBER definition of business cycles. It is a filter that "passes through components of the time series with periodic fluctuations between six and 32 quarters, while removing components at higher and lower frequencies" (Baxter & King, 1999, p. 575). We also estimate spatial lag regressions with the Baxter-King output volatility. For the case of annual data, the band-pass (2,8) filter is used to extract the cyclical component of the data (Bergman, Buch). The correlation between Baxter-King output volatility and the Hodrick–Prescott output volatility is 0.98, and the regression results are similar. We report the Hodrick–Prescott results. The Baxter–King results are available upon request.

[7]Similar to samples in many macroeconomic studies focusing on a large number of countries, our sample is unbalanced with different number of cross sectional units over time (Barro, 1998, Alper and Cakici, 2009, Fosu, 2009). U.S., Canada, and West European countries in general are present in all three subsamples and the number of less developed countries included does rise as data availability improves and as new countries form. The proportions of countries presented across regions are similar in different sample periods. Sub-Saharan Africa (SSA) countries (26 countries) accounted for 28% of the countries in our 1960–72 sample and 27% on average in later subsamples. Similarly, countries located in Latin America and Caribbean (LAC) account for 24% of our sample in the 1960–72 sample and 22% on average in later subsamples. We also find that about 22% of countries over 1960–72 and 23% on average over later periods are from North America and Europe and Central Asia (NA and ECA). Since the distributions of countries across regions are similar over different subsamples, no single region is overrepresented in our samples. Hence, we believe the small number of countries in our first subsample relative to other subsamples is unlikely to cause any bias in our estimations.

[8]The correlation matrices for the three measures of economic volatility are described in Table 12, Table 13 in the appendix.

[9]Interested readers are referred to Anselin, 1988, Anselin, 2010, Anselin for a thorough discussion of the development of different spatial models and technical details.

[10]There are alternative methods to estimate spatial models such as adopting spatially exogenous variables in an instrumental variable estimation for a spatial lag model and dynamic panel methods for both spatial error and spatial lag models. See Kapoor, Lee and Yu, 2010.

[11]Alternatively we estimate regressions of later sample periods (i.e., 1973–86 and 1987–2007) including a dummy variable, which takes the value of one for those countries that are in the 1960–72 subsample. This would help to capture any unobserved differences between countries available in earlier periods and countries only available after. Results with this new dummy variable are qualitatively similar to those we present in our paper.

[12]Claeys *et al.*, 2012 and Kelejian *et al.*, 2006 use an instrumental variables estimation method to estimate their spatial models.

[13]The bilateral trade data in Rose, 2005 cover the period of 1948–2000. We use data over 1960–2000 construct the weight matrices. In particular, the average bilateral trade values during 1987–2000 are used to construct the weight matrix for the 1987–2007 subsample regressions.

[14]To save space, we report the coefficient on the spatial lag term. Other coefficients are available upon request.

[15]The cultural (administrative as well) distance (d_{ij}), obtained from www.ghemawat.com, is already scaled in a way so that it is comparable to the geographical distance between two countries. Similar to Eqn. (6), the entries in the weight matrix are constructed as an inverse of cultural (or administrative) distance, $1/d_{ij}$. See Ghemawat (2007) for the detailed description of the CAGE distance framework.

[16]GNI data are obtained from *World Development Indicators* reported by the World Bank.

[17]As the growth model (Eqns. (9), (10)) is estimated across countries over time, we modify the spatial weight matrix W as a block diagonal matrix with a dimension of $NT \times NT$, where each block capturing a single year's observations (Blonigen *et al.*, 2007). Specifically, with *T* time periods, we have the following weight matrix:

$$W=\begin{pmatrix} W_1 & 0 & 0 & 0 \\ 0 & W_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & W_T \end{pmatrix}, \qquad (11)$$

where $W_t=\begin{pmatrix} 0 & w_{tdij} & w_{tdik} \\ w_{tdji} & 0 & w_{tdjk} \\ w_{tdki} & w_{tdkj} & 0 \end{pmatrix}$, where $w_{tdij}=d_{ij}^{-1}$ for $1 \leqslant t \leqslant T$. Each block matrix W_t is an $N \times N$ symmetric matrix, with *N* corresponding to the number of countries in our sample. Since distances between capital cities are time-invariant, it follows that $W_1=W_2=\ldots=W_T$.

[18]Being consistent with Ramey and Ramey (1995), data for variables in the spatial error model are collected from PennWorld Table 6.3. Human capital is measured by the average years of secondary education in male population over the age of 25 and comes from the Barro-Lee Education Attainment data set 2010 (Barro, 1991, Barro and Lee, 1993, Barro and Lee, 2010). We also replace the average investment share of GDP and the average population growth rate with the initial values and the results do not change substantially. The results can be obtained upon request.

[19]Panel A of Table 13 in the appendix presents the correlation matrix of output growth rate. We find that the correlation of output growth rate between 1960–72 (Bretton Wood regime) and 1973–86 (common international shocks) is 0.11 and that between common international shocks and globalization era (1987–2007) is 0.20.

[20]There are 87 countries in our sample which have GDP per capita dating back to 1960. Given that initial GDP per capita is one of the control variables in the cross-sectional regressions, the number of observations for model 6.3 is 870.