Globalization And Business Cycle Comovement: Evidence From The United States

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ABSTRACT

This paper empirically evaluates the impact of globalization on the business cycle comovement of individual US states with the rest of the national economy and with the rest of world. Regressions with panel data over the period 1990-2005 provide strong evidence in support of the conventional wisdom that rising global integration over time, through either trade or foreign direct investment flows, raises a state economy's business cycle correlation with the world economy. Openness promotes greater business cycle synchronization within regional US economies than with the rest of the world. This finding reflects the impact of international borders on trade and investment flows.

Keywords: Business cycle synchronization; foreign direct investment; trade; dynamic conditional correlation; spatial dependence

1. Introduction

The rapid integration of trade and finance in the world economy in recent decades has prompted a growing body of literature that explores the impact of globalization on business cycle comovements between countries. The decline in the dispersion of economic growth among industrialized economies that has been observed in recent decades serves as anecdotal evidence in support of the view that globalization makes output movements more correlated across countries. Yet the academic literature overall offers no definitive answers to the effects of globalization.

Economic theory offers two opposite predictions on the impact of globalization. According to conventional wisdom, trade and financial linkages between two countries promote interdependence of economic activities so that economic shocks that affect one economy are more likely to be transmitted to another (McKinnon, 1963). For example, an aggregate demand shock in one country will affect its imports from another country if greater trade flows exist between the two. However, Krugman (1991) emphasizes supply-side shocks that lead to the prediction of a *negative* impact of globalization on output correlations. Accordingly, as trade flows raise interindustry specialization among countries, output comovements would decrease when business cycles are driven by industry-specific supply shocks. Obviously, reality is likely to be a blend of these two views, with the pattern of trade determining the outcome.

As the impact of foreign trade and investment flows on business cycle synchronization is theoretically ambiguous, the issue must be resolved empirically on a case-by-case basis. Evidence supporting either the convergence or divergence view, however, is equivocal. For instance, Canova and Dellas (1993), Frankel and Rose (1998), Rose and Engel (2002) and Gruben, Koo and Millis (2002) find that cyclical output movements are more correlated among industrialized countries that trade more intensively with each other. Fiess (2007) finds similar results for countries in Central America that trade intensively with the US Other than trade flows, Jansen and Stokman (2004) confirm that bilateral foreign direct investment (FDI) flows among OECD countries cause greater business cycle synchronization.

However, Kose, Prasad and Terrones (2003) explore cross-sectional data of 76 countries and find that increased trade openness entails a weak negative impact on the degree of output comovement among economies. Abeysinghe and Forbes (2005) focus on Asian countries and find evidence in support of Stockman's (1990) argument that a shock to one country affects output abroad through both trade and supply-side channels so that the behavior of international business cycles varies across different economies.

As pointed out by Frankel and Rose (1998), and Gruben, Koo and Millis (2002), conventional estimation methods using cross-country data are subject to potential bias due to problems related to endogeneity and measurement errors in variables that reflect the degree of globalization. These potential problems, broadly viewed as consequences associated with omitted variables, lead to spurious inferences on the effect of globalization on output correlation. Frankel and Rose (1998) use an instrumental variables (IV) method to account for the possibility of higher monetary coordination among large trade partners and their distances apart that may also lead to higher business cycle synchronization. Gruben, Koo and Millis (2002), however, show that Frankel and Rose's (1998) results are also biased due to their failure to account for factor mobility that may also affect output comovement.

Against the above background, this paper explores the relationship between openness and business cycle comovement using recently-published US state-level data. In contrast to country-level data, the 50 states share virtually the same language and culture, and basic economic and political institutions, including monetary policy and regulatory factors. In addition, high degrees of labor and capital mobility, and trade and financial integration exist across state economies. Yet the different regions that make up the US represent diverse economies that respond differently to nationwide economic shocks (Carlino and Sill, 1997; Karras, 2003). The extent of interactions with foreign countries, through trade or investment flows, also varies considerably across states. Heathcote and Perri (2003) show that the US economy as a whole has become less correlated with the rest of the world due to increased financial integration. It is therefore interesting to investigate whether a state's foreign trade and investment flows affect their output correlation with economies overseas. In this paper, we draw conclusions from empirical results of alternative estimators for panel data. In particular, we explore the possibility of cross-sectional or "spatial" dependence among the US states and consider an estimator that accounts for spatial correlations in panel data. The comparative results provide evidence of spatial dependence in business cycle comovements across the US.

The rest of the paper is organized as follows. The next section discusses the data and estimation methods. The third section presents empirical findings. The fourth section contains a conclusion.

2. Data and Methods

Our empirical work focuses on annual output data of 50 US states over the period 1990-2005. State output is measured by real gross state product (GSP) which is obtained from the US Bureau of Economic Analysis (BEA). We define the "rest of the world" (ROW) beyond the US by the World Bank's classification of 28 developed countries less the US, the majority of which are well integrated—economically and financially—with the US. Real GDP of the US and the aggregate real GDP data of the relevant world economy (ROW) are from the World Bank's *World Development Indicators* database.[1] All data are in expressed in 2000 US dollars.

To measure the extent of globalization, we consider two alternative metrics: (1) trade intensity, measured by the share of the sum of imports and exports (trade) in GSP; and (2) FDI intensity, measured by the ratio of value added by foreign-owned establishments over a state's GSP. Data for state exports and imports are obtained from the International Trade Administration of the US Department of Commerce, and state FDI data are obtained from the BEA.[2]

Some regressions below also control for the role of regional government policies and labor market structures in explaining variation in regional growth, and trade and investment flows. We obtain proxies for these exogenous factors using index data of Area 2 (takings and discriminatory taxation) and Area 3 (labor market freedom) from *Economic Freedom of North America* published by the Fraser Institute.[3] The two indices reflect different tax policies and labor market rigidities across states, respectively. Measured on a scale from 0 to 10, the higher the index, the higher the degree of economic freedom, as represented by lower tax burdens or lower labor market rigidities. Karabegovic and McMahon (2006) report that regional economic growth is strongly associated with these two indices.

For a given state, we explore two aspects of output comovement. The first measure is captured by the correlation of that state's output with the aggregate output of the rest of the nation (i.e., US GDP less that state's

GSP). The second measure is the correlation of the state's output with the aggregate output of ROW (aggregate GDP for all developed countries less US GDP). Given our focus on the business cycle, we first use the Hodrick-Prescott (HP) filter (with lambda equal to 100) to isolate the cyclical component from the GSP or GDP data (in log form).[4]

Next, in contrast to existing studies (e.g., Frankel and Rose, 1998; Kose, Prasad and Terrones, 2003) that investigate constant correlations over a given time interval, we take into account time variation in output correlations by applying Engle's (2002) dynamic conditional correlation (DCC) model. Among others, Lee (2006) applies this approach to trace over time the changing correlation between output growth and inflation. The DCC model is nested in a bivariate GARCH framework of a pair of output series—one for a state economy and another for another economy of interest. The covariance matrix of the conditional means of the output series assumes a parsimonious GARCH(1,1) process, which allows for volatility clustering over time. Similarly, the condition correlation coefficient is assumed to follow an ARMA(1,1) process.[5]

Figure 1 displays for each of the 50 states time-series plots of two DCC estimates—one indicates the correlation between the filtered output series of a given state and the rest of the US (solid line), and the other indicates the corresponding correlation between the filtered output series of the same state and ROW (dotted line). There is considerable disparity in the correlations across states. A few observations are noteworthy. First, except for Alabama (AL), North Carolina (NC), South Carolina (SC) and South Dakota (SD), the correlation coefficients exhibit appreciable time variation. This observation warrants the application of the DCC method instead of conventional least-squares methods that generate fixed correlation coefficients over the observation period. Second, most of the plots support the common view that state economies are more correlated with the US as a whole than with the rest of the world. Hawaii (HI) is a notable exception, perhaps due to its distance from the rest of North America. The other states that are more correlated with the rest of the world than the US are Montana and North Dakota.

The third major observation stems from some regional patterns: State economies in the East Coast (e.g., Connecticut, Pennsylvania, New York, New Jersey and New Hampshire) tend to correlate more with the national economy while those in the Plains and Rocky Mountain regions (e.g., Montana, North Dakota and Wyoming) tend to correlate less. Similarly, the extent of cyclical comovements with ROW varies widely across different states. Florida's output appears to be highly correlated with output of both the US and ROW, while Wyoming's output runs opposite to output movements of the US and ROW. Despite the observed disparity in size, the positive sign of most correlations with the US supports the finding of prior studies (e.g., Carlino and Sill, 1997; Crowley, 2001; Selover, Jensen, and Kroll, 2005) that business cycles tend to synchronize to different degrees across states or regions in the US.

Our analysis on the impact of openness on the correlation of cyclical economic activity draws on the work of Frankel and Rose (1998). More specifically, the regression model takes the form:

$$R_{it} = \alpha_i + \beta \cdot OPENNESS_{it} + \varepsilon_{it}, \qquad i = 1,\ldots, 50;\ t = 1,\ldots, T, \tag{1}$$

where R_{it} denotes the correlation of state *i*'s detrended output series with the detrended output series of the rest of the US or ROW at time *t*, *OPENNESS* is a variable measuring the degree of integration with economies outside the state, α_i and β are unknown coefficients, and ε_{it} is an error term. Equation (1) represents a panel data model that pools together time-series with cross-sectional data. The main distinction in equation (1) from Frankel and Rose's (1998) specification arises from the state-dependent intercept (α_i) that allows for unobserved heterogeneity across states. In addition, the measure of output correlation R_{it} is allowed to evolve over time.

Table 1 reports summary statistics of the data used in regression analysis. The statistics are computed for the 50 states and the crow-sectional data are means over the 1990-2005 period. As discussed above, the correlations with the rest of the US (R_{US}) as well as ROW (R_{ROW}) exhibit appreciable disparity across states. On average, the correlation with other states in the US is almost twice as high as that with ROW. Minnesota's output is on average most correlated with other regions in the US, while North Dakota is least correlated, with negative correlation coefficients over much of the sample period. Correlation with the ROW economy is overall the highest for Florida (0.67) and the lowest for Arkansas (-0.30).

The rest of Table 1 shows the summary statistics for the explanatory variables. In the case of trade intensity, Vermont ranks top (32%) while and Montana (13%) rank bottom. The mean FDI intensity among the states is 3 percent. South Carolina (8%) is the leading state, while Hawaii (0.4%) and Montana (0.4%) witness negligible output contribution from foreign-owned firms. Despite similar political and fiscal institutional structures, the two indices of economic freedom show sizable differences across states. Delaware—one of the states without a sales tax—receives the highest score (8.6) on average in the tax freedom index, while Maine receives the lowest (5.5). In the case of labor market freedom, Florida receives the highest score (8.5) while West Virginia the lowest (5.3).

3. Regression Results

In this section, we discuss regression results for the effects of globalization, as captured by equation (1). For illustrative purposes, we begin with testing the effects of the two measures of globalization by running regressions with cross-sectional data, as commonly employed in the literature. The data for each variable represents a cross-section of state data averaged over the 1990-2000 period. As such, there are 50 observations for each cross-sectional regression. The two correlation coefficients for each state are estimated using the OLS estimator over the entire sample period. The dependent variables are alternatively the states' output correlations with the rest of the US (R_{US}) and their output correlations with the ROW (R_{ROW}). The key regressor is the alternative measure of openness—trade intensity and FDI intensity. Standard errors are computed using White's (1980) method so that coefficient estimates are robust to possible heteroskedasticity. As evident in Table 2, the estimation results provide little evidence for any impact of either trade or FDI intensity on output correlations.

Next, we proceed to estimating equation (1) with panel data. There are 800 observations in each regression (50 states × 16 years = 800). As shown in Table 3, the new estimation results overall contrast sharply with results based on cross-sectional data (Table 2), reflecting the extent of efficiency gain from considering both the time-series and cross-sectional dimensions of the state data. The second column of Table 2 reports the coefficient estimates of the pooled OLS regression, which restricts the intercepts to be the same across states (e.g., $\alpha_1 = \alpha_2 = ... = \alpha_{50}$). In addition to specifying the dependent variable alternatively as the states' output correlations with all other states in the US and their output correlations with ROW, we consider the difference between the two correlations (R_{US} – R_{ROW}), henceforth termed the "correlation gap". In light of the evidence of regional patterns in correlation coefficients (recall Section 2), the regressions include a set of dummy variables each representing one of the seven regions (except Far West) classified by the BEA.[6] The covariance matrix is robust to possible heteroskedasticity and autocorrelation consistent using the methods developed by White (1980), and Newey and West (1987).

The OLS estimates indicate that output correlations with both the rest of the US and ROW are positively associated with trade intensity. In the case of FDI intensity, however, the coefficient is significant with a positive sign for explaining correlations with the rest of the US, but the variable is not statistically significant in explaining correlations with ROW. The estimation results for the correlation gap parallel those for the correlation with the rest of the US.

It is instructive to evaluate the poolability of the panel data. If the state data are not poolable, then OLS estimates that restrict coefficients to be the same across states and over time would potentially yield biased estimates. Table 4 shows the *F*-test results for individual effects and time effects in the panel data of the correlation coefficients. The test statistics for time effects are not statistically significant at conventional levels, confirming the absence of unobserved effects that vary over time but are fixed across states. In the case of individual effects, which capture unobserved state characteristics that are constant over time, the null hypothesis of no individual effects cannot be rejected for output correlations with ROW.

In light of the above diagnostic statistics particularly for correlations with ROW, we run additional regressions with a fixed-effects estimator (without the regional dummies). The fixed-effects estimator produces coefficient estimates along with a set of dummy variables, each capturing unobserved effects of a particular state. As evident in Table 2, most coefficient estimates are nevertheless similar to their OLS counterparts. The exception is the coefficient for FDI intensity in the case of the correlation with ROW. The coefficient now becomes marginally significant and it enters with a positive sign. Judging by the standard errors of estimation (SEE's), this is also the only case in which the fixed-effects estimator fits the panel data better than does the OLS estimator (with regional dummies).

We have also run regressions using the generalized method of moments (GMM) with instrumental variables. IV regression is applied to attenuate possible problems with endogeneity and measurement errors in regressors, as suggested by Frankel and Rose (1998), and Kose, Prasad and Terrones (2003). The set of instruments includes the one-period lagged value of the dependent variable, the tax freedom index, the labor freedom index, and the seven regional dummies. The far right column of Table 2 reports the *J*-statistics for testing overidentifying restrictions. All figures are statistically insignificant at conventional levels, indicating that the selected set of instruments in model estimations is relevant. In other words, the statistics support the exogeneity property of the instrumental variables with respect to output correlations.

The IV regression results confirm that both trade intensity and FDI intensity meaningfully explain the states' business cycle correlations with other regions of the US as well as with ROW. More intuitively, states with relatively more trade and foreign investment intensity tend to experience greater business cycle synchronization with the national economy as well as the world economy. In line with the findings reported in some earlier studies (e.g., Frankel and Rose, 1998; Rose and Engel, 2002), our regression results overall are consistent with the demand-driven argument for a positive relationship between openness and cross-country output correlation.

The positive association of trade and FDI intensity on cyclical output correlation between a state and the rest of the US is attributable to the presence of spillovers that are transmitted across regional economies. From this perspective, trade and FDI that affect economic activity in a region may also affect other regional economies, particularly in neighboring regions. The regression results in the case of the correlation gap between the rest of the US and with ROW (panel C) indicate that the gap between the state's output correlation with the rest of the US and with the economy abroad widens with greater trade or FDI intensity. This occurs because the impact of openness in a state tends to be stronger for its output comovement with the rest of the US than with countries abroad. In line with Clark and van Wincoop (2001), this finding reflects the effect of national borders on business cycle synchronization.

Despite the evidence supporting a positive link between openness and business cycle correlation, the regressions so far might yield spurious inferences in the presence of possible cross-sectional or spatial dependence. Estimates on the regional dummy variables, which are strongly significant, provide anecdotal evidence of such dependence in the US state data. Spatial correlation, however, may occur in a more complex manner than the extent that our regional dummies can capture. For instance, states in different regions may be subject to common shocks. According to Anselin (2001) and Driscoll and Kraay (1998), standard regression techniques that fail to account for spatial dependence will yield inconsistent estimates of standard errors. In this light, we reevaluate our empirical relationship with an estimator developed by Driscoll and Kraay (1998). The estimator yields a covariance matrix that is robust to a general form of spatial and temporal dependence.

In Table 3, we report under the heading "SCC" coefficient estimates from IV regressions along with the spatial correlated covariance (SCC) matrix. The instruments correspond to those in the previous IV estimations except omission of the seven regional dummy variables. Clearly, the coefficient estimates using the SCC method are comparable to those from the conventional IV method but their *t*-statistics are notably higher. Estimation results from the SCC estimator provide stronger evidence in support of a direct relationship between openness and business cycle correlation for the US states. The differences in the estimated standard errors, on the other hand, reflect the extent of cross-sectional dependence across US state economies.

4. Conclusion

This paper empirically evaluates the impact of globalization on the business cycle comovement of individual US states with the rest of the nation as well as with the rest of world. Regressions using panel data over the 1990-2005 period provide strong evidence in support of the conventional wisdom that deeper global integration, through either trade or foreign direct investment flows, raises a state economy's business cycle correlation with other regions of the US as well as its correlation with the world economy. Because the impact of openness on regional economies is greater for their correlation with the national economy than with the rest of the world, foreign trade and investment flows promote greater business cycle synchronization within the domestic economy. Furthermore, we have found strong evidence of cross-sectional dependence across state economies. Together, these findings bear significant policy implications, particularly in the context of policy coordination between regions and the impact of a more open US economy for monetary policy in particular.

While our conclusion in support of the demand-channel view is drawn on regional-level data that are disaggregated compared with the national-level data commonly found in the literature, some limitations remain. In particular, our work without industry-level data remains silent about the competing hypothesis that emphasizes the working of the industry-specific channel that can to some extent desynchronize business cycles across different economies. From this perspective, a promising area of future research would involve more disaggregate, industry-level data. Similarly, another potential area for research might be to compare the impact on regional economies from horizontal investment, which essentially replicates foreign firms' operations in their parent countries, and vertical investment, which shifts a particular stage of production across countries.

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Table 1: Data Summary Statistics, State Means Over 1990-2005.

	Mean	Std. Dev.	Maximum	Minimum
R_{US}	0.59	0.32	0.93	-0.28
R_{ROW}	0.32	0.23	0.68	-0.33
Trade Intensity (% GSP)	21.03	16.17	31.96	13.02
FDI Intensity (%GSP)	2.91	1.67	7.90	0.35
Economic Freedom – Tax	6.69	0.78	8.56	5.51
Economic Freedom – Labor	6.88	0.72	8.48	5.26

Table 2: Estimation Results for Cross-Sectional Data over 1990-2005.

	OLS	
	Coefficient	SEE
A. Dependent Variable: R_{US}		
1. FDI		0.28
Constant	0.58 ***	
	(6.04)	
FDI	0.61	
	(1.02)	
2. Trade		0.28
Constant	0.62 ***	
	(7.10)	
Trade	0.82	
	(0.62)	
B. Dependent Variable: R_{ROW}		
1. FDI		0.23
Constant	0.32 ***	
	(3.98)	
FDI	0.01	
	(0.02)	
2. Trade		0.23
Constant	0.39 ***	
	(5.61)	
Trade	-1.29	
	(-1.25)	

Notes: Heteroskedasticity robust *t*-statistics are in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Estimation Results for Business Cycle Correlations, Panel Data of 50 States Over 1990-2005.

	OLS		Fixed Effects		IV			SCC	
	Coefficient	SEE	Coefficient	SEE	Coefficient	SEE	$J(10)$	Coefficient	SEE
A. Dependent Variable: R_{US}									
1. FDI		0.34		0.35		0.47	2.82		0.34
Constant	0.44 ***				-0.003			0.04 ***	
	(12.33)				(-0.02)			(7.75)	
FDI	0.03 ***		0.03 ***		0.06 ***			0.21 ***	
	(5.66)		(6.07)		(3.21)			(6.41)	
2. Trade		0.36		0.36		0.39	4.55		0.38
Constant	0.49 ***				0.22			0.25 **	
	(12.02)				(1.19)			(1.98)	
Trade	0.02 ***		0.03 ***		0.05 **			0.07 ***	
	(3.40)		(4.18)		(2.37)			(6.42)	
B. Dependent Variable: R_{ROW}									
1. FDI		0.27		0.26		0.28	5.52		0.28
Constant	0.33 ***				0.25 **			0.34 ***	
	(11.23)				(1.99)			(27.09)	
FDI	-0.004		0.01 *		0.02 **			0.01 ***	
	(-0.95)		(1.88)		(2.11)			(2.62)	
2. Trade		0.27		0.27		0.30	5.17		0.3
Constant	0.41 ***				0.62 ***			0.64 ***	
	(12.12)				(4.67)			(10.14)	
Trade	0.01 **		0.01 **		0.01 ***			0.05 ***	
	(1.96)		(2.23)		(2.92)			(4.89) ***	
C. Dependent Variable: R_{US} - R_{ROW}									
1. FDI		0.34		0.34		0.35	5.79		0.35
Constant	0.11 ***				-0.08			0.15 ***	
	(2.92)				(-0.50)			(3.82)	
FDI	0.04 ***		0.05 ***		0.04 **			0.14 ***	
	(5.42)		(5.11)		(2.20)			(12.92)	
2. Trade		0.34		0.35		0.38	3.57		0.36
Constant	0.07				-0.24			0.18 ***	
	(1.44)				(-1.45)			(5.21)	
Trade	0.02 ***		0.03 ***		0.04 ***			0.07 ***	
	(4.01)		(4.57)		(3.07)			(11.14)	

Notes: OLS regressions include a set of 7 regional dummies. Estimates for the constants in fixed-effects vary across states and are omitted for brevity. IV regressions include a set of instruments: 7 regional dummies, one-period lagged dependent variable, tax freedom index and labor freedom index. Serial correlation and heteroskedasticity robust *t*-statistics are in parentheses. SCC regressions are derived from an IV estimator (without regional dummies) that is robust to cross-sectional and temporal dependence. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Test Statistics for Individual and Time Effects.

	Individual Effects		Time Effects	
	F(1)	*p*-value	*F*(1)	*p*-value
R_{US}	0.63	(0.97)	0.23	(0.96)
R_{ROW}	1.44	(0.03)	0.86	(0.52)
R_{US} - R_{ROW}	0.79	(0.84)	0.41	(0.80)

Figure 1: Correlation with the rest of the US and the Rest of the World.

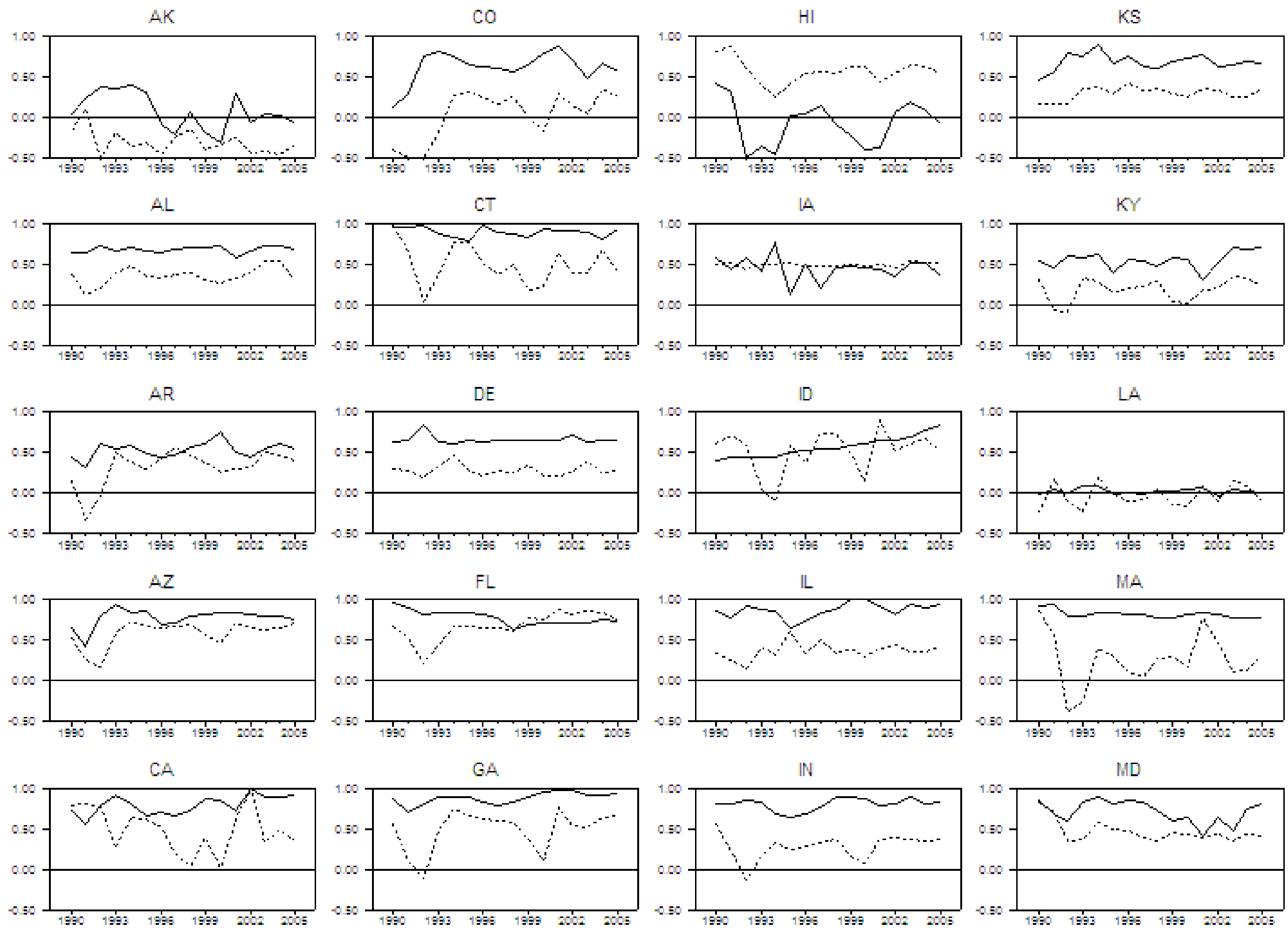
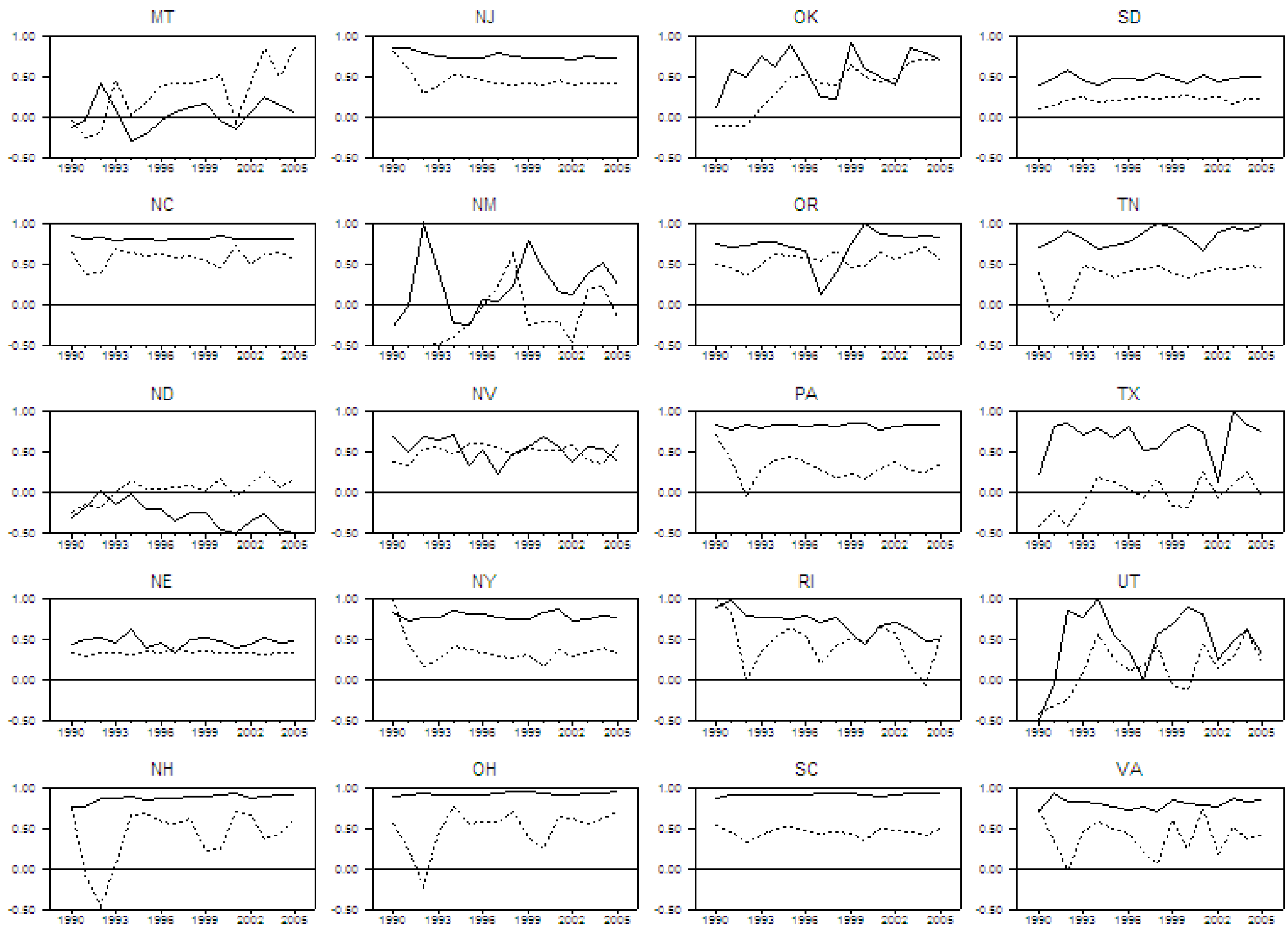


Figure 1 (Continued).



Notes: Solid lines delineate correlations between the state and the rest of US output series. Dotted lines delineate correlations between the state and the rest of the world output series.

Endnotes

[1] Instead of using simple aggregate data for ROW, we have followed Kose, Prasad and Terrones (2003) and used a dynamic factor model to extract a common factor across all countries in ROW over time. The main findings in this paper are preserved when these alternative data are used.

[2] See Wynne and Kersting (2008) for a detailed discussion of foreign investment in the US. It would be interesting to also consider investment outflows in addition to inflows, but the data are not widely available.

[3] See Karabegovic and McMahon (2006) for a detailed discussion of the indices.

[4] Instead of using the detrended data from the standard HP filter, we have replicated all empirical work presented below with first-differenced data and a multivariate HP filter (Laxton and Tetlow, 1992) that augments the univariate version of the filter with a Phillips curve relationship. Nonetheless, we have found that the qualitative results are robust to the choice of data transformation.

[5] The dynamic conditional correlation between two variables, x_t and y_t, can be simply expressed as $R_{xy,t} = \sigma^2_{xy,t} / (\sigma_{x,t}\sigma_{y,t})$ where $\sigma^2_{xy,t}$ is the time-varying covariance between the variables, and $\sigma_{x,t}$ and $\sigma_{y,t}$ are their time-varying standard deviations. In this paper, the variance and covariance terms are modeled as a GARCH(1,1) process, and $R_{xy,t}$ follows an ARMA(1,1) process. See Engle (2002) for details.

[6] The eight US regions are New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West. No dummy variable is assigned to the last region in order to avoid the singularity problem in regression.