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What Ties Us Together? Explaining Synchronized GDP Volatility

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Abstract:
Amid heightened policy uncertainty, understanding the drivers of global macroeconomic instability becomes increasingly critical. This paper studies the determinants of output volatility synchronization using data for 42 economies worldwide. We construct a bilateral time-varying index of volatility synchronization and infer its drivers using Bayesian model averaging, complemented by weighted average least squares (WALS) and least absolute shrinkage and selection operator (LASSO) regression. We find that differences in total factor productivity, interest rate, and fiscal policy volatility robustly explain cross-country synchronization, with nuances between developed and developing countries. Overall, the results highlight the role of technological divergence and macroeconomic policy uncertainty in shaping the international co-movement of output volatility.

JEL Classifications: C23, E32, F44

Keywords: Macroeconomic volatility synchronization, Bayesian model averaging, total factor productivity, interest rate volatility, output volatility

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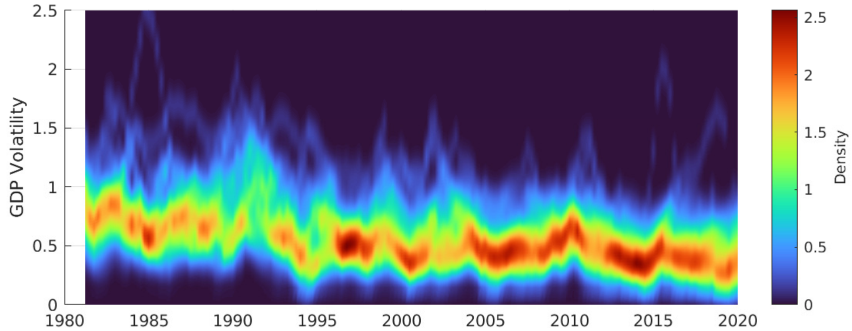
1 Introduction

Does macroeconomic volatility move together across countries? If so, what determines the degree of that co-movement? These questions have become increasingly pressing as economic integration has deepened, with emerging countries' business cycles becoming more synchronized with the rest of the world (Ductor and Leiva-Leon, 2016) and as global shocks (for example, the 2008 Global Financial Crisis, the COVID-19 pandemic, and the 2022 commodity price surge) have demonstrated how quickly volatility can propagate across borders. Since the Great Moderation— a period beginning in the 1980s characterized by a structural reduction in the size of U.S. macroeconomic fluctuations (Kim and Nelson, 1999)— interest in understanding the drivers of macroeconomic volatility has been growing. (Peña, 2005). It can be particularly harmful when most countries simultaneously experience elevated output volatility, potentially undermining the insurance value of international financial markets, overwhelming the capacity of multilateral institutions to provide effective support, and hitting the poorest households hardest, precisely when cross-border support is most constrained—among other negative consequences. Despite a large literature on the determinants of volatility levels and on business cycle synchronization, there is a significant gap in the empirical literature on the determinants of synchronized macroeconomic volatility.

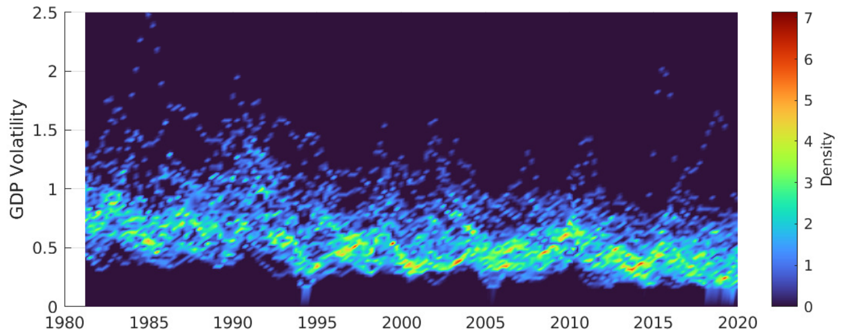
Output volatility levels have been widely studied since Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) documented the Great Moderation. This phenomenon has been researched across most advanced economies (Davis and Kahn, 2008; Aalbers, 2016), and a substantial literature identifies its main determinants, including trade openness (Bejan, 2006; Giovanni and Levchenko, 2009; Ductor and Leiva-León, 2022), government size (Fatás and Mihov, 2001; Furceri, 2007), financial integration (Kose et al., 2003), total factor productivity (TFP) (Ductor and Leiva-León, 2022), exchange rate regimes (Bleaney and Fielding, 2002; Grydaki and Fountas, 2009), and monetary policy uncertainty (Mumtaz and Zanetti, 2013). Our empirical framework builds on the determinants identified in this literature but with a focus on their second-order, rather than their first-order, moment. In particular, we consider differences in volatility of trade openness, fiscal policy, financial openness, TFP, exchange rates, terms of trade, and interest rates as potential drivers of cross-country output volatility synchronization. These variables capture both real and financial channels through which shocks may propagate differently across economies, leading to divergence or convergence in volatility dynamics.

This paper also relates to the literature that analyzes the synchronization of business cycles, defined as the co-movement of output levels across countries, and finds that trade integration, financial linkages, and industrial structure are the primary drivers of output co-movement (Frankel and Rose, 1998; Imbs, 2004). Ductor and Leiva-Leon (2016) document a substantial increase in global business cycle synchronization since the 2000s, driven by the integration of emerging markets into the global economy. Importantly, business cycle synchronization differs from output volatility synchronization: Two countries may experience coinciding expansions and contractions while exhibiting very different volatility profiles around those cycles, implying high business cycle synchronization accompanied by low volatility co-movement.

Figure 1: Distribution of Cross-country GDP Volatility over Time



A. Bandwidth of Kernel = 0.1



B. Bandwidth of Kernel = 0.01

Note. The figure plots the density of cross-country volatility over time based on different bandwidths. The y-axis indicates the level of volatility, the x-axis indicates time periods expressed in quarters, and the colored area represents the mass of the corresponding density.

Source. Cross-country GDP volatility data are sourced from Ductor and Leiva-León (2022) and available on the author's webpage.

List of countries. Developed: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom, and United States. Developing: Argentina, Brazil, Chile, China, India, Indonesia, Kazakhstan, Mexico, Peru, Philippines, Russia, Thailand, Turkey, and Venezuela.

Volatility synchronization captures the global co-movement of uncertainty and macroeconomic instability. In Figure 1, we illustrate the evolution of this co-movement using time-varying GDP growth volatility for 42 developed and developing economies, as estimated by Ductor and Leiva-León (2022). For each period, the figure presents kernel density estimates of volatility levels across countries for two distinct bandwidth parameters. Greater density concentration indicates periods of heightened synchronization, whereas dispersed distributions indicate divergent volatility patterns. Figure 1 depicts substantial temporal changes in the degree of global volatility synchronization. These shifts in synchronization lead us to examine the driving factors of cross-country output volatility co-movement.

This paper makes three contributions to the literature. First, we construct a time-varying output volatility synchronization index for 42 countries across four world regions (that is, North America, South America, Europe, and Asia-Oceania), covering both advanced and developing economies over the 1981–2019 period. Second, we identify the robust determinants of this synchronization index using a Bayesian model averaging (BMA) approach that explicitly addresses model uncertainty by averaging over all possible combinations of candidate regressors, weighting each model by its posterior probability. This approach is appropriate in our setting, since there is no strong prior regarding which of the potential determinants identified in the literature should be included in our empirical model for volatility synchronization. Third, we examine how the determinants of synchronization differ between advanced and developing economies to understand the importance of the different channels of synchronization in countries with different levels of development.

Our main findings are as follows. Total factor productivity shocks emerge as the most robust determinant of output volatility synchronization across all methodologies—BMA, least absolute shrinkage and selection operator (LASSO) regression, and weighted average least squares (WALS). Larger absolute differences in TFP volatility between country pairs are strongly and consistently associated with lower output volatility synchronization across subsamples, with the exception of developed economies. This evidence suggests that similarities in productive capacity, technological adoption, and structural transformation are highly associated with more synchronized output volatility (1) globally, (2) among developing countries, and (3) between developed and developing countries.

By contrast, volatility in macroeconomic policies (monetary and fiscal) is a robust factor associated with volatility synchronization both globally and exclusively among developed countries. While fiscal volatility and interest rate volatility appear robust in the full sample and among advanced economies, they do not play a significant role in explaining synchronization across developing countries. This asymmetry suggests that the level of development is a critical conditioning factor for the channels through which volatility shocks propagate internationally. In economies with lower levels of development, structural factors such as technological advancement represent the primary transmission channels. Conversely, for advanced economies, volatility shocks propagate predominantly through cyclical factors. Trade openness is a less robust determinant, appearing to be significant only from a global perspective rather than within specific subsamples. This pattern is consistent with the mixed evidence in the literature regarding the relationship between trade integration and macroeconomic volatility, which suggests that effects vary based on economic structure (for example, Bejan (2006); Cavallo et al. (2008); Giovanni and Levchenko (2009); Karras (2006)). Finally, exchange rate volatility, terms of trade volatility, and financial openness volatility do not emerge as robust determinants in any subsample.

Our findings make three primary contributions to the literatures on optimum currency areas (OCAs), policy coordination, and development economics. First, we show that the divergence of TFP shocks is the dominant driver of volatility synchronization, suggesting that structural convergence in productive capacity and technology adoption is a fundamental precondition for international macroeconomic stability. Second, we find that macroeconomic policy volatility (monetary and fiscal) is a robust determinant exclusively among advanced economies. This result implies that the benefits of financial deepening and the convergence of monetary frameworks—such as within monetary unions—are contingent upon the level of economic development. Finally, our results challenge traditional OCA theory, which emphasizes nominal exchange rate regimes as the primary filter for macroeconomic shocks (for example, Bleaney and Fielding (2002); Grydaki and Fountas (2009)). Instead, we provide evidence that in financially integrated economies, the international propagation of policy uncertainty (e.g., Fernández-Villaverde et al., 2011; Mumtaz and Theodoridis, 2017) accounts for synchronized volatility patterns better than do exchange rate movements alone.

The paper proceeds as follows. Section 2 describes the data, the construction of the synchronization index, and the employed methodology. Section 3 presents the main empirical results. Section 4 concludes.

2 Empirical Framework

This section describes the data, the construction of the output volatility synchronization index, and the econometric framework used to identify its robust determinants.

2.1 Data

We use quarterly real GDP growth rates for 42 countries, measured in constant 2010 U.S. dollars and sourced from Datastream. The sample spans from the first quarter of 1981 (1981:Q1) through the fourth quarter of 2019 (2019:Q4), covering 39 years of data.[1] The 42 countries represent four regions: North America, South America, Europe, and a combined Asia-Oceania group. To analyze heterogeneous effects, we further categorize the sample into two subgroups: 28 advanced economies and 14 developing countries. The full list of countries is provided in the note to Figure 1.

A common approach to measuring time-varying volatility relies on the rolling-window standard deviation of GDP growth. However, such an approach is highly sensitive to the choice of window duration and may confound the timing of the relationship between synchronization and its potential determinants. Instead, we measure country-level *output volatility* using time-varying estimates derived from the hierarchical second-order moments factor model of Ductor and Leiva-León (2022). This model estimates the volatility of country-specific GDP fluctuations by accounting for global, regional, and idiosyncratic components within a hierarchical structure, yielding a theoretically grounded and model-consistent measure of underlying volatility.[2]

Because the potential determinants of volatility synchronization are available at only an annual frequency, we convert the quarterly volatility estimates into annual measures by averaging the

[1] We deliberately exclude the post-pandemic period to avoid distorting long-term historical relationships with the atypical nature of the pandemic shock.

[2] The factor model decomposes the log-volatility of country i, located in region k, $F_{i_k,t}$, into global, g_t, regional, $h_{k,t}$, and idiosyncratic, $\chi_{i_k,t}$, components using corresponding loadings, that is, $F_{i_k,t} = \gamma_{i_k} g_t + \lambda_{i_k} h_{k,t} + \chi_{i_k,t}$. Both global and regional factors are assumed to evolve endogenously according to vector autoregression of order one. The model is estimated using Bayesian methods; for further details on the estimation procedure, see Ductor and Leiva-León (2022).

quarterly values. These annual volatility series then serve as the primary input for our synchronization index.

2.2 Output Volatility Synchronization

To measure the co-movement of volatility across country pairs over time, we construct a time-varying bilateral synchronization index following Cerqueira and Martins (2009). Unlike purely cross-sectional measures, the panel dimension of this index allows us to capture temporal shifts in synchronization, which is essential for identifying the determinants of volatility co-movement in a dynamic setting. The index for country pair (i, j) at year t is defined as

$$\rho_{ij,t} = 1 - \frac{1}{2}\left(\frac{d_{j,t} - \bar{d}_j}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(d_{j,t} - \bar{d}_j)^2}} - \frac{d_{i,t} - \bar{d}_i}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(d_{i,t} - \bar{d}_i)^2}}\right)^2, \tag{1}$$

where $\rho_{ij,t} \in (-\infty, 1]$ represents the synchronization index, and $d_{i,t}$ and $d_{j,t}$ denote the annual output volatilities for countries i and j, respectively. The index equals one when the two countries' volatility series move perfectly in tandem relative to their historical means and decreases as their deviations from those means diverge.

Importantly, the time-invariant correlation between $d_{i,t}$ and $d_{j,t}$, denoted as ρ_{ij}, is equivalent to the sample average of this synchronization index: $\rho_{ij} = \frac{1}{T}\sum_{t=1}^{T}\rho_{ij,t}$. In this sense, the index serves as a localized measure of the correlation between the volatility of country i and country j at each point in time.

Our explanatory variables include seven potential determinants: Total factor productivity volatility, fiscal policy volatility, interest rate volatility, trade openness volatility, exchange rate volatility, financial openness volatility, and terms of trade volatility. Each variable is first constructed at the country-year level following the transformations described in Table 1. It is then defined at the country-pair level as the absolute difference between the values of the two countries in the pair at period t so that larger values indicate greater dissimilarity between the two economies along that dimension.

We estimate the following pairwise panel regression:

$$\rho_{ij,t} = X_{ij,t}^{k}\beta^{k} + \eta_{ij} + \mu_t + V_{ij,t}, \tag{2}$$

where $\rho_{ij,t}$ is the output volatility synchronization index defined in equation (1); $X_{ij,t}^{k}$ is the set of potential explanatory variables described earlier; η_{ij} is a pairwise country fixed effect that captures all time-invariant factors specific to each country pair, such as geographical distance, common language, or historical ties; μ_t is a year fixed effect that absorbs common shocks affecting all country pairs in a given year, such as global recessions or financial crises; and $V_{ij,t}$ is the idiosyncratic error term.

A key challenge in estimating equation (2) is model uncertainty: The literature provides no consensus on which subset of the seven candidate variables constitutes the true model, and standard variable-selection methods, such as stepwise regression, are inappropriate in this context because they generate pre-testing bias (Magnus and Wang, 2014). We therefore follow Ductor and Leiva-León (2022) by adopting a Bayesian model averaging approach, which addresses model uncertainty by estimating all $2^7 = 128$ possible combinations of regressors and constructing a weighted average over all models, in which the weight assigned to each model is its posterior model probability—the probability that the model is the true data-generating process given the data.

The key output of the BMA is the posterior inclusion probability (PIP) for each variable, defined as the sum of the posterior model probabilities across all models that include that variable. The PIP represents the probability that a given variable belongs to the true model. Following the standard rule of thumb in the literature, we classify a variable as a robust determinant of output volatility synchronization if its PIP exceeds 0.80.

We assess the robustness of the BMA results using two complementary approaches. First, we employ weighted average least squares, a model-averaging estimator that takes a middle ground between Bayesian and frequentist methods (Magnus and Wang, 2014). Under WALS, a variable is considered robust if the absolute value of its t-statistic exceeds four. Second, we estimate a least absolute shrinkage and selection operator (LASSO) regression, a shrinkage-based variable-selection method that penalizes model complexity by shrinking coefficients toward zero and setting those of irrelevant variables exactly to zero. The LASSO provides a data-driven benchmark for variable selection that does not rely on prior distributions.

3 Results

In this section, we present the results of the BMA approach for the determinants of output volatility synchronization. Table 2 reports the results from the dynamic BMA specification, which includes one lag of the dependent variable alongside pairwise country fixed effects and year fixed effects. For each subsample, we report the posterior inclusion probability (PIP), the posterior mean coefficient, and the standard error. A variable is considered a robust determinant of output volatility synchronization if its PIP exceeds 0.80.

In the full sample, four variables emerge as robust determinants, all with PIPs equal to one: dissimilarities in fiscal policy volatility (posterior mean = -0.03), in TFP volatility (posterior mean = -0.30), in interest rate volatility (posterior mean = -0.09), and in trade openness volatility (posterior mean = -0.20). All four variables have negative posterior mean coefficients, indicating that greater dissimilarity between country pairs along each of these dimensions is associated with lower output volatility synchronization. Dissimilarities in exchange rate volatility, in terms of trade volatility, and in financial openness volatility have PIPs of 0.01, providing no evidence of a robust association with synchronization.

The subsample results reveal heterogeneity in the relative importance of these determinants. In the advanced-economy subsample, dissimilarities in fiscal policy volatility (PIP = 1.00, posterior mean = -0.08) and interest rate volatility (PIP = 1.00, posterior mean = -0.10) remain robustly significant, while differences in TFP volatility and in trade openness volatility lose significance entirely. This pattern suggests that among advanced economies (which share productive structures that are more similar than those of developing economies), divergences in macroeconomic policy uncertainty are the only robust factors associated with output volatility synchronization. The developing-country subsample presents a sharply different picture: Only TFP volatility is robustly significant (PIP = 1.00, posterior mean = -0.89), with a posterior mean more than twice as large in absolute value as in the full sample, while dissimilarities in macroeconomic policy volatilities have PIPs close to zero. In the mixed subsample, TFP volatility (PIP = 1.00, posterior mean = -0.39), interest rate volatility (PIP = 1.00, posterior mean = -0.07), and trade openness volatility (PIP = 0.92, posterior mean = -0.19) appear robust factors.

Tables 3 and 4 report the WALS and LASSO results, respectively. Both methods produce results that are highly consistent with the BMA findings. The WALS results confirm the four robust variables identified by the BMA in the full sample: TFP volatility ($t = -8.10$), interest rate volatility ($t = -14.25$), fiscal policy volatility ($t = -4.84$), and trade openness volatility ($t = -4.35$). In the developed subsample, fiscal policy volatility ($t = -8.48$) and interest rate volatility ($t = -17.26$) are robustly significant, while TFP falls well below the threshold ($t = -2.09$), and trade openness volatility is negligible ($t = 0.87$). In the developing subsample, TFP is the only robust variable ($t = -5.34$), with all policy variables well below the threshold.

The LASSO corroborates these findings. In the full sample, the LASSO selects TFP (post-OLS coefficient = -0.390), interest rate volatility (post-OLS = -0.085), and the lagged dependent variable (post-OLS = 0.712). Fiscal policy volatility is not selected in the full sample, though it is selected in the developed-country subsample (post-OLS = -0.070) alongside interest rate volatility (post-OLS = -0.094). In the developing-country subsample, only the lag synchronization is selected (post-OLS = 0.646). In the mixed subsample, TFP (post-OLS = -0.408) and interest rate volatility (post-OLS = -0.071) are selected alongside the lag.

Overall, the three methods show that TFP is among the most robust determinant of output volatility synchronization, except for advanced economies. Higher (lower) absolute differences in TFP volatility between country pairs are strongly and consistently associated with lower (higher) output volatility synchronization. TFP volatility is the main factor correlated with volatility synchronization precisely in those economies in which productive structures diverge most and in which financial and fiscal transmission channels are weakest. TFP captures the efficiency with which productive inputs are deployed across sectors of the economy (Comin, 2010). When two countries differ substantially in their pace and pattern of technological progress, their production structures diverge, generating different sectoral compositions and different sensitivities to common global shocks. A country undergoing rapid productivity-driven structural transformation will have an output cycle driven increasingly by domestic supply-side factors rather than shared external demand, decoupling its volatility dynamics from those of economies at a different stage of development. The particularly large coefficient in the developing-country subsample reflects the greater weight that real-sector forces carry relative to financial and policy channels, consistent with Malik and Temple (2009).

In advanced economies, fiscal policy uncertainty and monetary policy uncertainty are the key factors associated with synchronization in output volatility. Fiscal policy volatility and interest rate volatility are jointly robust in the full sample and in advanced economies under the three methods—BMA, WALS, and LASSO—but lose significance entirely in the developing-country subsample. This heterogeneity points to a common underlying cause: the weakness of policy transmission channels in lower-income economies. In advanced economies, government expenditure represents a large share of GDP, automatic stabilizers are well developed, and monetary policy operates through deep credit markets. When two advanced economies differ substantially in the volatility of their fiscal stances or monetary policy frameworks, their output cycles respond differently to common shocks, reducing volatility co-movement. In developing countries, by contrast, lending rates are often weakly linked to policy rates, credit markets are shallow, fiscal institutions are less effective, and firms rely heavily on internal finance, so neither fiscal nor monetary policy uncertainty translates robustly into output volatility dynamics. This channel has direct implications for monetary unions; for advanced-economy groupings such as the euro area, convergence of both monetary and fiscal policy across member countries may be as important as nominal exchange rate fixity for achieving macroeconomic volatility synchronization.

Trade openness volatility is also robust in the full sample under BMA (PIP = 1.00, posterior mean = -0.20) and WALS ($t = -4.35$) and in the mixed sample. However, it is not selected by the LASSO in the full sample and is not robust in either the developed- or developing-country subsamples individually, suggesting that the full-sample effect is driven by cross-group heterogeneity (the contrast in trade integration between advanced and developing economies) rather than variation within each group. The mixed evidence across methods is consistent with the broader literature, in which the trade-volatility relationship proves sensitive to sample composition and trade structure (Bejan, 2006; Giovanni and Levchenko, 2009; Ductor and Leiva-León, 2022).

From a policy perspective, the prominence of TFP divergence implies that structural convergence in productive capacity and technology adoption is a precondition for output volatility synchronization. For advanced-economy monetary unions, the joint significance of fiscal and monetary policy uncertainty suggests that completing financial and fiscal integration, the Capital Markets Union and convergence of fiscal frameworks in the euro area, is as important for synchronization as exchange rate stabilization.

4 Conclusion

This paper studies the determinants of output volatility synchronization from a global perspective. While the literature examines the drivers of volatility levels in individual countries and studies the synchronization of business cycles, the determinants of volatility synchronization remain largely unexplored. We fill this gap by constructing a time-varying bilateral synchronization index for 42 advanced and developing economies over the 1981–2019 period, based on the country-level volatility estimates of Ductor and Leiva-León (2022), and identifying its robust determinants using Bayesian model averaging complemented by WALS and LASSO as robustness checks.

Our main findings reveal a striking heterogeneity across country groups. In the full sample, four variables emerge as robust determinants of output volatility synchronization: total factor productivity volatility, interest rate volatility, fiscal policy volatility, and trade openness volatility, all with posterior inclusion probabilities of one. Greater similarity between country pairs along each of these dimensions is associated with higher output volatility synchronization. However, the relative importance of these determinants differs between advanced and developing economies. Among developing countries, TFP is the only robust determinant, with a posterior mean of -0.89 (nearly three times the full-sample coefficient) pointing to real-economy divergence in productive capacity and structural transformation as the dominant force driving volatility synchronization. Among advanced economies, by contrast, TFP loses significance entirely; instead, the divergence in monetary and fiscal policy uncertainty (interest rate volatility and government consumption share volatility) drives output volatility synchronization, consistent with the important roles of financial markets and fiscal institutions in these economies.

These findings have several implications. They suggest that structural convergence in productive capacity and technology adoption is a precondition for macroeconomic synchronization, particularly for regional integration arrangements in the developing world. For advanced-economy monetary unions, the joint significance of monetary and fiscal policy uncertainty implies that convergence of policy frameworks is as important as exchange rate stabilization for achieving synchronization. The results also suggest that actions aimed at reducing cross-country differences in technological development and macroeconomic policy stability could contribute to greater international macroeconomic volatility synchronization.

References

Aalbers, M. B. (2016): "The great moderation, the great excess and the global housing crisis," in *The financialization of housing*, Routledge, 64–80.

Alizadeh, S., M. W. Brandt, and F. X. Diebold (2002): "Range-based estimation of stochastic volatility models," *the Journal of Finance*, 57, 1047–1091.

Bejan, M. (2006): "Trade openness and output volatility," *Available at SSRN 965824*.

Bleaney, M. and D. Fielding (2002): "Exchange rate regimes, inflation and output volatility in developing countries," *Journal of development economics*, 68, 233–245.

Cavallo, E. A., J. De Gregorio, and N. V. Loayza (2008): "Output volatility and openness to trade: A reassessment [with comments]," *Economia*, 9, 105–152.

Cerqueira, P. A. and R. Martins (2009): "Measuring the determinants of business cycle synchronization using a panel approach," *Economics Letters*, 102, 106–108.

Comin, D. (2010): "Total factor productivity," in *Economic growth*, Springer, 260–263.

Davis, S. J. and J. A. Kahn (2008): "Interpreting the great moderation: Changes in the volatility of economic activity at the macro and micro levels," *Journal of Economic perspectives*, 22, 155–180.

Ductor, L. and D. Leiva-Leon (2016): "Dynamics of global business cycle interdependence," *Journal of International Economics*, 102, 110–127.

Ductor, L. and D. Leiva-León (2022): "Fluctuations in global output volatility," *Journal of International Money and Finance*, 120, 102533.

Fatás, A. and I. Mihov (2001): "Government size and automatic stabilizers: international and intranational evidence," *Journal of international economics*, 55, 3–28.

Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramirez, and M. Uribe (2011): "Risk matters: The real effects of volatility shocks," *American Economic Review*, 101, 2530–2561.

Frankel, J. A. and A. K. Rose (1998): "The endogenity of the optimum currency area criteria," *The economic journal*, 108, 1009–1025.

Furceri, D. (2007): "Is government expenditure volatility harmful for growth? A cross-country analysis," *Fiscal studies*, 28, 103–120.

Giovanni, J. d. and A. A. Levchenko (2009): "Trade openness and volatility," *The review of Economics and Statistics*, 91, 558–585.

Grydaki, M. and S. Fountas (2009): "Exchange rate volatility and output volatility: a theoretical approach," *Review of International Economics*, 17, 552–569.

Imbs, J. (2004): "Trade, finance, specialization, and synchronization," *Review of economics and statistics*, 86, 723–734.

Karras, G. (2006): "Trade openness, economic size, and macroeconomic volatility: Theory and empirical evidence," *Journal of Economic Integration*, 254–272.

Kim, C.-J. and C. R. Nelson (1999): "Has the US economy become more stable? A Bayesian approach based on a Markov-switching model of the business cycle," *Review of Economics and Statistics*, 81, 608–616.

Kose, M. A., E. S. Prasad, and M. E. Terrones (2003): "Financial integration and macroeconomic volatility," *IMF Staff papers*, 50, 119–142.

Lane, P. R. and G. M. Milesi-Ferretti (2007): "The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004," *Journal of international Economics*, 73, 223–250.

Magnus, J. R. and W. Wang (2014): "Concept-Based Bayesian Model Averaging and Growth Empirics," *Oxford Bulletin of Economics and Statistics*, 76, 874–897.

Malik, A. and J. R. Temple (2009): "The geography of output volatility," *Journal of Development Economics*, 90, 163–178.

McConnell, M. and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed since the Early 1980's?" *American Economic Review*, 90, 1464–1476).

Mumtaz, H. and K. Theodoridis (2017): "Common and country specific economic uncertainty," *Journal of International Economics*, 105, 205–216.

Mumtaz, H. and F. Zanetti (2013): "The impact of the volatility of monetary policy shocks," *Journal of Money, Credit and Banking*, 45, 535–558.

Peña, C. (2005): "Volatilidad macroeconómica e inversión privada. Venezuela, 1968-2002," *Revista venezolana de análisis de coyuntura*, 11, 185–202.

Table 1: Potential Explanatory Factors of Output Volatility Synchronization

Variable	Transformation	Source	Description
Trade openness volatility	$\sigma(T)_{it} = \left(\frac{T_{it}-T_{it-1}}{T_{it-1}}\right)^2$	WDI	Square of the growth rate of trade openness, where $T_{it} = \frac{E_{it}+I_{it}}{GDP_{it}}$, E_{it} is total exports, I_{it} total imports, and GDP_{it} nominal GDP in country i in year t
Financial openness volatility	$\sigma(F)_{it} = \left(\frac{F_{it}-F_{it-1}}{F_{it-1}}\right)^2$	WDI	Square of the growth rate of financial openness, where $F_{it} = \frac{A_{it}+L_{it}}{GDP_{it}}$, A_{it} is total assets to GDP and L_{it} is liquid liabilities to GDP in country i
Terms of trade volatility	$\sigma(tot)_{it} = (log(tot_{it}) - log(tot_{it-1}))^2$	PWT 11.0	Square of the first differences in log of tot_{it} from $t-1$ to t
Exchange rate volatility	$\sigma(xr)_{it} = (log(xr_{it}) - log(xr_{it-1}))^2$	PWT 11.0	Exchange rate defined as national currency units per U.S. dollar. Volatility defined as the square of the first differences in log from $t-1$ to t
Fiscal policy volatility	$\sigma(gov)_{it} = (log(gov_{it}) - log(gov_{it-1}))^2$	PWT 11.0	Square of the first differences in log of government consumption share from $t-1$ to t
Interest rate volatility	$\sigma(int)_{it} = \left(\frac{int_{it}-int_{it-1}}{int_{it-1}}\right)^2$	PWT 11.0	Square of the growth rate of the real internal rate of return
TFP volatility	$\sigma(TFP)_{it} = \left(\frac{TFP_{it}-TFP_{it-1}}{TFP_{it-1}}\right)^2$	PWT 11.0	Square of the growth rate of TFP. TFP is the variable *ctfp* in PWT

Note. As a measure of financial globalization, we use a financial openness indicator based on Lane and Milesi-Ferretti (2007). Terms of trade is defined as $tot_{it} = \frac{PE_{it}}{PI_{it}}$, the ratio between the price level of exports and imports in country i in year t. The square of the growth rate is a standard proxy for volatility (Alizadeh et al., 2002). Both measures of volatility, $\sigma(tot)$ and $\sigma(xr)$, test the importance of supply shocks in explaining changes in output volatility synchronization over time. To account for the potential effect of fiscal policy on volatility synchronization, we use the share of government consumption, as in Fatás and Mihov (2001). TFP is computed using output-side real GDP, capital stock, labor input, and the share of labor income of employees and self-employed workers in GDP. WDI: World Development Indicators; PWT: Penn World Table.

Developed Countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom, and United States.
Developing Countries: Argentina, Brazil, Chile, China, India, Indonesia, Kazakhstan, Mexico, Peru, Philippines, Russia, Thailand, Turkey, and Venezuela.

Table 2: BMA Results

	All Countries			Developed			Developing			Mixed		
	PIP	Coef.	S.E.	PIP	Coef.	S.E.	PIP	Coef.	S.E.	PIP	Coef.	S.E.
Fiscal policy volatility	1.00	-0.03	0.01	1.00	-0.08	0.01	0.02	0.00	0.00	0.01	-0.00	0.00
TFP volatility	1.00	-0.30	0.04	0.03	-0.00	0.00	1.00	-0.89	0.14	1.00	-0.39	0.06
Exchange rate volatility	0.01	-0.00	0.00	0.01	-0.00	0.00	0.06	-0.00	0.02	0.02	-0.00	0.00
Terms of trade volatility	0.01	-0.00	0.00	0.01	0.00	0.00	0.02	-0.00	0.01	0.08	-0.00	0.01
Financial openness volatility	0.01	0.00	0.00	0.01	-0.00	0.00	0.03	-0.00	0.00	0.01	-0.00	0.00
Interest rate volatility	1.00	-0.09	0.01	1.00	-0.10	0.01	0.02	-0.00	0.00	1.00	-0.07	0.01
Trade openness volatility	1.00	-0.20	0.04	0.02	0.00	0.00	0.03	-0.00	0.02	0.92	-0.19	0.08
Synchronization index (lag)	1.00	0.71	0.00	1.00	0.75	0.01	1.00	0.64	0.02	1.00	0.68	0.01

Note: This table presents Bayesian model averaging (BMA) results for the full sample, developed countries, developing countries, and mixed countries. Results for all the countries are estimated in a dynamic panel, with one lag of output volatility as regressors. PIP denotes posterior inclusion probability. Year fixed effects and pair-country fixed effects are included but not reported.

Table 3: WALS Regression Results

	Full Sample			Developed			Developing			Mixed		
	Coef.	S.E.	T-stat	Coef.	S.E.	T-stat	Coef.	S.E.	T-stat	Coef.	S.E.	T-stat
Fiscal policy volatility	-0.028	0.006	-4.840	-0.065	0.008	-8.482	0.009	0.020	0.449	-0.005	0.008	-0.592
TFP volatility	-0.301	0.037	-8.103	-0.017	0.008	-2.085	-0.715	0.134	-5.341	-0.379	0.059	-6.372
Exchange rate volatility	-0.009	0.009	-1.053	0.007	0.035	0.200	-0.078	0.042	-1.868	-0.018	0.013	-1.383
Terms of trade volatility	-0.021	0.015	-1.417	0.006	0.006	0.916	-0.014	0.059	-0.239	-0.053	0.023	-2.302
Financial openness volatility	0.000	0.004	0.081	-0.003	0.006	-0.429	-0.012	0.015	-0.820	-0.001	0.006	-0.262
Interest rate volatility	-0.090	0.006	-14.248	-0.100	0.006	-17.259	-0.008	0.021	-0.406	-0.065	0.010	-6.602
Trade openness volatility	-0.161	0.037	-4.349	0.006	0.007	0.865	-0.041	0.105	-0.392	-0.155	0.054	-2.880
Synchronization index (lag)	0.705	0.005	153.601	0.743	0.006	117.173	0.615	0.016	38.483	0.668	0.007	92.788

Note: The full sample includes all country pairs. Developed includes pairs in which both countries are developed. Developing includes pairs in which both countries are developing. Mixed includes pairs with one developed and one developing country. As a rule of thumb, variables with $|t\text{-statistic}| > 4$ are considered robust predictors.

Table 4: LASSO Selected Variables

	Full Sample		Developed Sample		Developing Sample		Mixed Sample	
	Lasso	Post-est OLS	Lasso	Post-est OLS	Lasso	Post-est OLS	Lasso	Post-est OLS
TFP volatility	-0.192	-0.390					-0.135	-0.408
Interest rate volatility	-0.029	-0.085	-0.031	-0.094			-0.013	-0.071
Fiscal policy volatility			-0.018	-0.070				
Synchronization index (lag)	0.680	0.712	0.709	0.752	0.592	0.646	0.643	0.680

Note: Year and country fixed effects are included but not reported. Standard errors are clustered at the pair-country level.