Finance and Synchronization☆

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Abstract

It is well known that the bulk of international financial flows across countries are driven by common shocks. In response to these common shocks, we find that capital tends to flow systematically between the same types of countries, while the discrepancy between GDP growth rates widens. Thus, in the data synchronization falls when financial linkages rise, but only so in response to common shocks. In contrast, financial linkages tend to increase the synchronization of business cycles in response to purely country-specific shocks.

Keywords: Financial linkages, Business cycles synchronization, Contagion, Common Shocks, Idiosyncratic Shocks.

JEL Codes: E32, F15, F36, G21, G28.

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1 Introduction

Understanding how disturbances propagate across countries is of first-order importance. Openness in general is often singled out as a plausible and significant propagation channel. Historically openness to goods trade came first, and there is robust evidence that trade partners display correlated business cycles.[1] The global consequences of the 2007-2008 recession have contributed to shifting the focus on the importance of financial linkages. While it was always important to assess how financial integration affects the international synchronization of business cycles, the question has become of paramount importance since 2008, for policy-makers and researchers alike.

Theory is an imperfect guide. In a two-country real business cycles model with country-specific productivity shocks, capital flows to wherever returns are higher, so greater financial linkages lower the international synchronization of business cycles. But in a similar two-country model, augmented with credit or collateral constraints, a country-specific shock (not necessarily to productivity) that makes the constraint bind at home is contagious abroad as domestic agents recall foreign assets to meet the constraint.[2] So greater financial linkages can increase synchronization. The predictions of theory as regards the consequences of financial integration on international contagion are inconclusive. The common feature of these models is that they analyze the consequences of purely idiosyncratic, country-specific shocks. They are silent about the relation between financial integration and synchronization in the face of common shocks.

It is well known that the bulk of the volatility in GDP across countries can be

[1]Among many others, see Frankel and Rose (1998) or Baxter and Kouparitsas (2005).

[2]See Backus, Kehoe, and Kydland (1992) for the workhorse model of international real business cycles. Devereux and Yetman (2010), Kalemli-Ozcan, Papaioannou, and Perri (2013), or Allen and Gale (2000) offer different versions of the latter mechanism, where constraints are at bank or firm level.

explained by common shocks. In a series of influential papers, Kose, Otrok, and Whiteman (2003), Ayhan Kose, Otrok, and Whiteman (2008), Crucini, Kose, and Otrok (2011), or Hirata, Kose, and Otrok (2013) identify the contribution of common shocks (global or regional) to individual countries' business cycles. A key result is that shocks common to two or more countries constitute the main driver of business cycles in both the developed and developing worlds. The details of the decompositions depend on the sample of countries and time coverage; but common shocks rarely explain less than half of GDP growth volatility, and often more than 75 percent.[3]

This paper documents the same pattern in international financial linkages. It shows that over the past few decades, 80 to 90 percent of the volatility in (gross) international capital flows can be explained by as few as two common shocks. This is not a new result: for instance, Forbes and Warnock (2012) document that global shocks are an essential driver of gross capital flows, and provide an extensive review of the empirical literature that reached similar conclusions. International positions change over time, but in response to common shocks they typically do so between the same types of countries and with constant elasticities. Therefore, for each country pair there exist two elasticities: one that captures the effects of common shocks on bilateral capital flows, and another that captures the effects of common shocks on the differential in GDP growth rates. This has important consequences.

Empirically, Kalemli-Ozcan, Papaioannou, and Peydro (2013) (KPP henceforth) show that an increase in financial integration causes a fall in business cycle synchronization in 18 OECD countries. They conclude the data support the view that

[3]The possibility that common shocks have heterogeneous loadings is an old tradition in empirical macroeconomics. Forni and Reichlin (1998) identify sector-level effects of aggregate shocks in the US. Bernanke, Boivin, and Eliasz (2005) augment standard Vector Auto-Regressions with unobserved factors to identify their potentially heterogeneous consequences on economic activity. Mumtaz, Simonelli, and Surico (2011) extend the approach to an international context. Peersman and Smets (2005) identify heterogeneous effects of monetary shocks at sector level. Kilian (2008) shows the consequences of exogenous oil shocks are heterogeneous across G7 countries.

financial flows are efficient in their quest for high returns, which exacerbates the cycle asymmetry created by a country-specific productivity shock. This paper argues the finding arises in response to common shocks. Both GDP growth differentials and capital flows tend to respond to common shocks. We show that capital tends to flow from countries with inelastic GDP to countries with elastic GDP in response to a positive common shock, and vice versa for negative shocks. Therefore, finance and synchronization are negatively correlated because in the data, capital tends to flow between the same types of country pairs in response to common shocks, with always similar consequences on GDP growth differentials. As in KPP, capital flows between countries that tend to have different GDP growth rates. But in the data, this tends to happen always between the same economies, as it reflects permanent responses to common shocks, rather than an efficient quest for idiosyncratic high returns.

A direct implication is that on average countries with elastic GDP should be net recipients of international capital in years of global boom, but net contributors in years of global recession. The paper documents such a correlation in OECD data. In years of positive common shocks, net capital holdings increase in countries with elastic GDP (Denmark, the US, Switzerland), and fall in countries with inelastic GDP (Japan, Australia, Portugal). The opposite tends to occur in years of negative common shocks.

In contrast there is no systematic time pattern in the response of international investment to purely country-specific shocks: source and destination countries change randomly over time, depending on the realization of the shocks. Interestingly, increases in financial linkages tend to be associated with *more* synchronized business cycles in response to country-specific shocks. This stands in contrast with common shocks, and suggests financial links foster the contagious propagation of *country-specific* shocks across borders. In theory, the result supports the existence of (endogenously binding) constraints: In response to country-specific shocks, financial flows serve to alleviate collateral or balance sheet constraints, rather than to take advantage of attractive differentials between returns across countries.

The decomposition of GDP growth rates and international capital flows into common and idiosyncratic components is of the essence for the question at hand. Evidently, the mere inclusion of year effects in a panel regression only identifies shocks that are common and homogeneous in the cross-section. Similarly, the inclusion of trends with heterogeneous slopes identifies a specific kind of common shock, with effects that grow linearly over time. To identify common shocks with country-specific effects, this paper follows the simplest possible approach: factors are given by the principal components that are common to at least two countries, and the loadings for each factor are country-specific. In the main text, the loadings are also assumed constant. Section 4 repeats the main analysis estimating a simple factor model that allows for time-varying loadings using Bayesian techniques. The two decompositions we propose have the advantage of simplicity and an established place in the literature. There are of course many alternatives, which we leave for further work. But we provide a general intuition for the results of the paper, that is not conditioned on one specific way to isolate common shocks.

The rest of the paper is structured as followed. Section 2 presents the conventional estimation of the effects of finance on synchronization. Common shocks are discussed in terms of their theoretical impact on the correlation between finance and synchronization. Section 3 introduces the data, and discusses the relevance of common vs. idiosyncratic shocks in GDP and in financial data. The decomposition is then used to discuss the effects of finance on synchronization. Section 4 discusses some extensions. Section 5 concludes.

2 Finance and Synchronization: Why Common Shocks Matter

This Section first discusses the consequences of common shocks on business cycle synchronization, and then turns to the consequences of common shocks on the estimated effect of finance on synchronization.

2.1 Synchronization

It has become standard to measure the synchronization between two economies i and j on the basis of the absolute differential in GDP growth $\mathcal{S}_{ij,t}$ given by:

$$\mathcal{S}_{ij,t} = -\left|y_{i,t} - y_{j,t}\right|, \tag{1}$$

where $y_{i,t}$ and $y_{j,t}$ are the growth rates of GDP in country i and j at time t. The measure presents two key advantages: first it is readily observable at yearly frequency. Second, unlike the Pearson correlation coefficient, it is invariant to the volatility of the underlying shock, see Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005). The variable increases with the degree of synchronization, with negative values close to zero between synchronized countries. It is now used widely, by Giannone, Lenza, and Reichlin (2010), Kalemli-Ozcan, Papaioannou, and Perri (2013), Kalemli-Ozcan, Papaioannou, and Peydro (2013), or IMF (2013) among others.

Morgan, Rime, and Strahan (2004), Kalemli-Ozcan, Papaioannou, and Perri (2013), or Kalemli-Ozcan, Papaioannou, and Peydro (2013) introduce an alternative that controls for common shocks, given by:

$$\mathcal{S}^2_{ij,t} = -\left|\epsilon_{i,t} - \epsilon_{j,t}\right|,$$

where $\epsilon_{i,t}$ is a residual of a panel growth regression:

$$y_{i,t} = \alpha_i + \gamma_t + \epsilon_{i,t}.$$

As is clear, $\mathcal{S}^2_{ij,t}$ controls for shocks that are common across the panel of GDP growth rates, but that are constrained to have homogeneous effects across countries.

This paper argues the existence of common shocks with country-specific effects alters the interpretation of $\mathcal{S}_{ij,t}$ (or $\mathcal{S}^2_{ij,t}$). To see this, assume the true model for GDP growth involves a vector of common shocks $\mathcal{F}^y_t$ with heterogeneous country loadings, i.e.:

$$y_{i,t} = a^y_i + b^y_i \mathcal{F}^y_t + \varepsilon^y_{i,t}. \tag{2}$$

where a^y_i is the average growth of GDP in country i, $\varepsilon^y_{i,t}$ denotes the response of GDP growth to an idiosyncratic shock, and b^y_i is the vector of country i's loading on a $f \times 1$ vector of common (to at least two countries) factors $\mathcal{F}^y_t$. By definition, the synchronization measure in equation (1) can be re-written as:

$$\mathcal{S}_{ij,t} = -\left| a^y_i - a^y_j + \left(b^y_i - b^y_j\right) \mathcal{F}^y_t + \varepsilon^y_{i,t} - \varepsilon^y_{j,t} \right|.$$

The equilibrium response of synchronization to idiosyncratic shocks is given by:

$$\mathcal{S}^{\varepsilon}_{ij,t} = -\left| \varepsilon^y_{i,t} - \varepsilon^y_{j,t} \right|, \tag{3}$$

which differs from $\mathcal{S}_{ij,t}$ because of the equilibrium response of GDP in both countries to the common shocks summarized in $\mathcal{F}^y_t$. Denote the guilty term by:

$$\mathcal{S}^{\mathcal{F}}_{ij,t} = -\left| \left(b^y_i - b^y_j\right) \mathcal{F}^y_t \right|. \tag{4}$$

By definition, $\mathcal{S}^{\mathcal{F}}_{ij,t}$ varies with both dimensions of the panel, and so has the potential to affect the behavior of $\mathcal{S}_{ij,t}$ meaningfully, even in a regression controlling for country-pair fixed and for year effects. Inasmuch as it only controls for common shocks with a single loading, $\mathcal{S}^{2}_{ij,t}$ suffers from the same potential issue.

Figure 1 reports the behavior of the synchronization measure $\mathcal{S}_{ij,t}$ (solid line) in the cross-section of 18 advanced economies from 1980 to 2012, together with its decomposition $\mathcal{S}^{\mathcal{F}}_{ij,t}$ (dotted line) and $\mathcal{S}^{\varepsilon}_{ij,t}$ (dashed line).

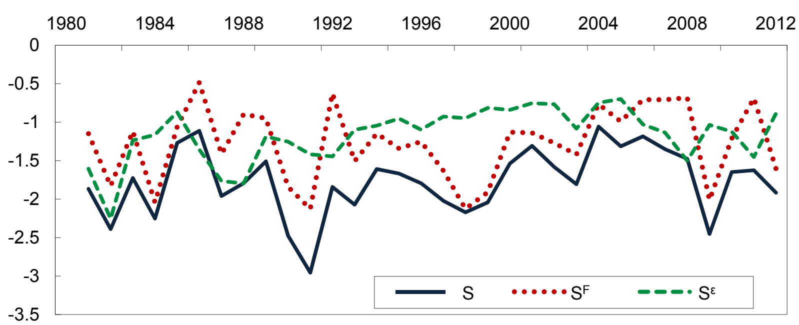

Figure 1 The Evolution Of Synchronization (And Of Its Idiosyncratic And Common Components). The solid line plots the evolution over time of the average value of $\mathcal{S}_{ij,t}$ for the 1980-2012 period. The average is computed across 153 country pairs (our sample spans 18 countries) for each year. The chart also reports the cross-sectional averages of the idiosyncratic component (dashed line) and the common component (dotted line) of $\mathcal{S}_{ij,t}$. $\mathcal{F}_t$ has been proxied by the first 3 principal components on the full panel of GDP growth rates. The averages are computed across 153 country pairs for each year over the 1980-2012 period.

The recessions of 1991 and 2008 are associated with large fall in measured business cycle synchronization. This somewhat counter-intuitive result happens because of heterogeneous country-specific responses to common shocks. Even though most countries were moving in the same direction (for instance during the global recession of 2008-09) $\mathcal{S}_{ij,t}$ fell, as the pace of the contraction in GDP was heterogeneous across countries. For instance, US annual GDP growth went from about -0.3 in 2008 to about -2.8 percent in 2009, whereas UK GDP growth went from -0.3 to -4.3 percent. Even though both growth rates fell with the Great Recession, $\mathcal{S}_{ij,t}$ fell from 0 to -1.5, and thus implied that the UK and the US became less synchronized.

The plots of $\mathcal{S}^{\mathcal{F}}_{ij,t}$ and $\mathcal{S}^{\varepsilon}_{ij,t}$ in Figure 1 confirm this conjecture, showing that the decline in $\mathcal{S}_{ij,t}$ observed during the 1991 or 2008 recessions is clearly associated with common shocks, as $\mathcal{S}^{\mathcal{F}}_{ij,t}$ drops substantially in both cases. In contrast, $\mathcal{S}^{\varepsilon}_{ij,t}$ increases in 2008, and does not fall in 1991. This suggests the measure $\mathcal{S}_{ij,t}$ conflates two mechanisms: the international propagation of idiosyncratic shocks, $\mathcal{S}^{\varepsilon}_{ij,t}$, and the international equilibrium response to common shocks, $\mathcal{S}^{\mathcal{F}}_{ij,t}$. The former is a measure of co-movement across countries; the latter is a measure of the dispersion in GDP growth rates in response to common shocks. This complicates the estimated effect of financial integration on synchronization.

2.2 The Effects of Finance on Synchronization

The conventional panel regression that investigates the impact of financial integration on synchronization is due to KPP. It writes:

$$\mathcal{S}_{ij,t} = \alpha_{ij} + \gamma_t + \beta \cdot K_{ij,t} + \delta \cdot Z_{ij,t} + \eta_{ij,t}, \tag{5}$$

where $K_{ij,t}$ measures bilateral financial linkages between i and j, and $Z_{ij,t}$ denotes a vector of controls, for instance bilateral goods trade. The year effects γ_t account for global shocks that affect the whole cross-section homogeneously. The country-pair specific effect α_{ij} ensures β is estimated over time, in deviations from country-pair averages. This is important, for it constitutes a substantial improvement relative to earlier estimations, typically obtained in cross-section. See for instance Frankel and Rose (1998), Doyle and Faust (2005), Imbs (2006) or Baxter and Kouparitsas (2005), among many others. While estimates of β are positive and significant in cross-section regressions, KPP show they switch signs and become significantly negative within country-pairs. Since the theory that underpins equation (5) models the propagation of shocks over time, the estimation should include country-pair fixed effects. The resulting negative estimates of β are suggestive that financial integration exacerbates the asymmetry caused by country-specific shocks. This is the interpretation espoused by KPP.

This paper argues the existence of common shocks in equation (5) can affect the estimates of β. The previous section argues common shocks are mechanically embedded in $\mathcal{S}_{ij,t}$, provided they have country-specific effects. Consider now the possibility that common shocks also affect bilateral capital linkages. This is a well charted area. For instance Forbes and Warnock (2012) document that a key driving force of gross capital flows are changes in global risk. Rey (2013) argues capital linkages worldwide obey "global factors". Bruno and Shin (2014) document that changes in the VIX affect the cyclicality in capital flows worldwide. For simplicity, we posit a straightforward relation between capital cross-holdings and (common or idiosyncratic) shocks, i.e.:

$$K_{ij,t} = a_{ij}^K + b_{ij}^K \mathcal{F}_t^K + \varepsilon_{ij,t}^K.$$

This specification allows for permanent differences in capital cross-holdings, a_{ij}^K, for idiosyncratic shocks to bilateral capital $\varepsilon_{ij,t}^K$, and for a vector of common shocks $\mathcal{F}_t^K$. Common shocks can have heterogeneous consequences across country pairs, captured by b_{ij}^K. The specification is general, in that it can account for global cycles in financial integration, or for a potential trend in $K_{ij,t}$. If financial flows are procyclical as in Rey (2013) or Broner, Didier, Erce, and Schmukler (2013), we should have $b_{ij}^K \geq 0$. If $K_{ij,t}$ displays an upward trend, $\mathcal{F}_t^K$ takes positive and rising values in t.

In order to bring into focus the role of common shocks, consider a version of equation (5) where the dependent variable, $\mathcal{S}^{\mathcal{F}}_{ij,t}$, is conditioned on common shocks only. The equation becomes:

$$- \left| b_i^y - b_j^y \right| \cdot \left| \mathcal{F}_t^y \right| = \alpha_{ij} + \gamma_t + \beta^{\mathcal{F}} \cdot \left[a_{ij}^K + b_{ij}^K \mathcal{F}_t^K + \varepsilon_{ij,t}^K \right] + \delta \cdot Z_{ij,t} + \eta_{ij,t}^{\mathcal{F}}. \quad (6)$$

where we used the fact that:

$$\mathcal{S}^{\mathcal{F}}_{ij,t} = - \left| \left(b_i^y - b_j^y \right) \mathcal{F}_t^y \right| = - \left| b_i^y - b_j^y \right| \cdot \left| \mathcal{F}_t^y \right| .$$

Clearly, the sign of $\beta^{\mathcal{F}}$ is given by:

$$Cov \left[- \left| b_i^y - b_j^y \right| \cdot \left| \mathcal{F}_t^y \right| , b_{ij}^K \mathcal{F}_t^K \right] = - \left| b_i^y - b_j^y \right| \cdot b_{ij}^K \; Cov \left[\left| \mathcal{F}_t^y \right| , \mathcal{F}_t^K \right] . \quad (7)$$

where $Cov[\cdot]$ denotes the covariance operator. According to equation (7), a negative estimate of $\beta^{\mathcal{F}}$ requires, for example, a positive correlation between $|b_i^y - b_j^y|$ and b_{ij}^K and a positive covariance between $|\mathcal{F}_t^y|$ and $\mathcal{F}_t^K$.

In what follows, we show that $|b_i^y - b_j^y|$ and b_{ij}^K display a positive correlation in OECD data, i.e. capital and GDP happen to be responsive to common shocks in the same countries. Countries with elastic GDP are also the systematic destination of capital flows during global (or regional) booms, but their source in global (or regional) recessions. We also show that $|\mathcal{F}_t^y|$ and $\mathcal{F}_t^K$ correlate positively, which in turn implies that $\mathcal{F}_t^y$ and $\mathcal{F}_t^K$ do not correlate perfectly.[4] In our data, $Cov[|\mathcal{F}_t^y|, \mathcal{F}_t^K]$ ranges from 0.20 to 0.50.

We emphasize these results are driven by *permanent* features of GDP growth and of capital flows, that prevail systematically in response to common shocks. They

[4]If $\mathcal{F}_t^y$ and $\mathcal{F}_t^K$ were perfectly correlated, then $cov[|\mathcal{F}_t^y|, \mathcal{F}_t^K]$ would be zero.

reflect the fact that permanent differences exist across countries in terms of how GDP growth and capital flows respond to common shocks. But they are silent on the response of financial flows to country-specific developments, and its consequence on synchronization.

The issues just discussed are absent when the measure of synchronization is focused on idiosyncratic shocks. By definition, idiosyncratic shocks do not display any permanent cross-sectional pattern, and therefore $\mathcal{S}^{\varepsilon}_{ij,t} = -\left|\varepsilon^{y}_{i,t} - \varepsilon^{y}_{j,t}\right|$ cannot correlate systematically with b^{K}_{ij}.

3 Results

This Section first introduces the various data sources, that have now become standard in this literature. It then moves to a description of the paper's key results.

3.1 Data

Annual data on GDP at constant prices are collected from the OECD National Accounts. GDP is measured using the expenditure approach, and deflated with each country's GDP deflator. Bilateral financial linkages are obtained from the "International Locational Banking Statistics" released by the Bank of International Settlements (BIS). The data collect information on international financial claims and liabilities of banks resident in a BIS reporting country, vis-a-vis counterparty countries. The data are in USD, and deflated using the US GDP deflator. These data are focused on bank linkages, and therefore of somewhat limited scope. But few alternatives exist that measure bilateral financial linkages over time for other classes of assets. The only option are the surveys collected by the International Monetary Fund as part of the Coordinated Portfolio Investment Survey, which collect information on all classes of financial assets. But the time coverage is limited to the 2000's, and is very sparse for the earlier years.

Data coverage is best for reporting countries, which include most developed economies. It is much more incomplete for counterparty countries that include many developing economies, where a lot of data points are missing. The practice, followed for instance by KPP, has been to combine information about claims and liabilities in both directions. For instance, information on liabilities due by counterparty country j towards country i is completed by data on claims held by reporting country i in country j. In addition, given the recent globalization in financial flows, the data are normalized, by population or GDP. In particular, consider two measures for $K_{ij,t}$:

$$K_{ij,t}^{pop} = \frac{1}{4}\left[\ln\left(\frac{A_{ij,t}}{P_{i,t}+P_{j,t}}\right) + \ln\left(\frac{L_{ij,t}}{P_{i,t}+P_{j,t}}\right) + \ln\left(\frac{A_{ji,t}}{P_{i,t}+P_{j,t}}\right) + \ln\left(\frac{L_{ji,t}}{P_{i,t}+P_{j,t}}\right)\right],$$

and:

$$K_{ij,t}^{gdp} = \frac{1}{4}\left[\ln\left(\frac{A_{ij,t}}{Y_{i,t}+Y_{j,t}}\right) + \ln\left(\frac{L_{ij,t}}{Y_{i,t}+Y_{j,t}}\right) + \ln\left(\frac{A_{ji,t}}{Y_{i,t}+Y_{j,t}}\right) + \ln\left(\frac{L_{ji,t}}{Y_{i,t}+Y_{j,t}}\right)\right],$$

where $A_{ij,t}$ ($L_{ij,t}$) denotes the claims (liabilities) on country j held by banks located in country i, $Y_{i,t}$ is GDP in country i and time t, and $P_{i,t}$ is population in country i at time t. Both measures are bilateral, and contain no information on the direction of capital holdings.

Figure 2 reports the average value of $K_{ij,t}^{pop}$ and $K_{ij,t}^{gdp}$ across country pairs. Even though both variables are normalized, an upward trend clearly survives in both measures. Bilateral goods trade data are collected from the IMF's Direction of Trade data set. The data are expressed in USD, and deflated using the US GDP deflator. Trade intensity is measured as the ratio of bilateral exports and imports, as a proportion of total trade in each country, following Frankel and Rose (1998), among many others.

As in KPP, data are limited to 18 developed economies, in order to minimize structural differences in the cross section.[5] The sample is initially focused on the recent period with data until 2012, but later restricted to the "tranquil" times that preceded 2006.

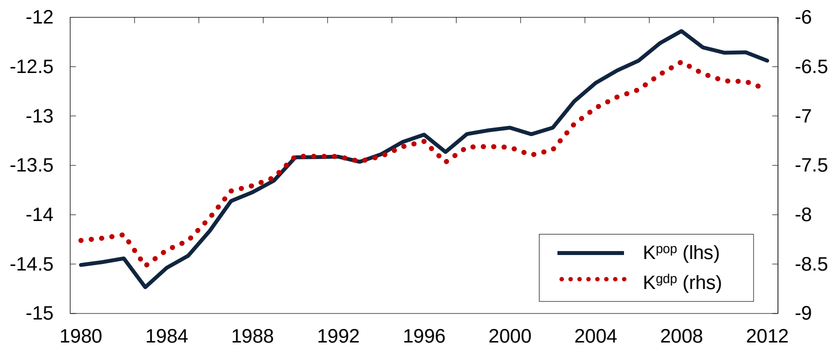

Figure 2 THE EVOLUTION OF BANKING INTEGRATION. The solid and dotted lines plot the evolution over time of the average value of $K_{ij,t}^{pop}$ and $K_{ij,t}^{gdp}$ for the 1980-2012 period. The average is computed across 153 country pairs (our sample spans 18 countries) for each year.

The key argument of the paper rests on the identification of shocks to GDP and to bilateral capital that are common across countries. The decomposition is performed in as simple a manner as possible, using simple factor analysis. In particular, we estimate:

$$y_{i,t} = a_i^y + b_{1,i}^y \mathcal{F}_{1,t}^y + ... + b_{n,i}^y \mathcal{F}_{n,t}^y + \nu_{it}^y,$$

and:

$$K_{ij,t} = a_{ij}^K + b_{1,ij}^K \mathcal{F}_{1,t}^K + ... + b_{n,ij}^K \mathcal{F}_{n,t}^K + \nu_{it}^K,$$

where n is the number of countries in the sample. In both cases, the vector of n factors provides an exact decomposition of the variance in the dependent variable,

[5] The 18 countries are: Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the UK, Ireland, Italy, Japan, the Netherlands, Portugal, Sweden, and the US.

but since each loading is estimated with error, an estimation residual appears in both regressions (ν_{it}^y and ν_{it}^K). Denoting fitted values with a hat, each decomposition can be rewritten as:

$$y_{it} = \hat{a}_i + \hat{b}_{1,i}^y \hat{\mathcal{F}}_{1,t}^y + ... + \hat{b}_{n,i}^y \hat{\mathcal{F}}_{n,t}^y,$$

and:

$$K_{ij,t} = \hat{a}_{ij} + \hat{b}_{1,ij}^K \hat{\mathcal{F}}_{1,t}^K + ... + \hat{b}_{n,ij}^K \hat{\mathcal{F}}_{n,t}^K.$$

Each decomposition creates factors that may or may not be common to two or more countries. A conventional approach to distinguish common from idiosyncratic factors is to consider the eigenvalues associated with each element in the vectors of factors, $\mathcal{F}_t^y$ and $\mathcal{F}_t^K$: idiosyncratic shocks display eigenvalues strictly below one, while they are above one for shocks that affect two countries or more. Since by construction, the eigenvalues associated with $\hat{\mathcal{F}}_{k,t}^y$ and $\hat{\mathcal{F}}_{k,t}^K$ decrease in k, this provides a decomposition of each vector of factors into ones that are common to two countries or more, and ones that are specific to one single economy.

Table 1 provides a summary of the factor estimates for GDP growth rates y_{it} and capital flows $K_{ij,t}$. Two factors are enough to explain almost three-quarters of the variance in GDP growth, and 90 percent of the variance in $K_{ij,t}$. The eigenvalues associated with the two factors are well above unity in both cases, so that it is common shocks that can explain such large proportions of y_{it} and $K_{ij,t}$. This is not surprising: it is simply a reformulation of well known facts in the framework of a simple factor analysis, established for instance by Kose, Otrok, and Whiteman (2003) for GDP growth rates, or by Rey (2013) for financial links. Common shocks matter for GDP growth rates, as they do for financial linkages.

Table 1 FACTOR ESTIMATES FOR GDP GROWTH AND BANKING INTEGRATION

	Eigenvalues		Share of variance		Cum. share of variance	
	$y_i t$	$K_{ij,t}$	$y_i t$	$K_{ij,t}$	$y_i t$	$K_{ij,t}$
$\mathcal{F}_1$	10.67	13.15	59%	73%	59%	73%
$\mathcal{F}_2$	2.21	2.89	12%	16%	72%	89%
$\mathcal{F}_3$	1.02	0.79	6%	4%	77%	93%
$\mathcal{F}_4$	0.89	0.66	5%	4%	82%	97%
$\mathcal{F}_5$	0.83	0.27	5%	2%	87%	99%

Note. Principal components are computed on the panel of 18 GDP growth series (y_{it}) and 153 pair-specific capital instensity series ($K_{ij,t}$).

Table 1 also implies decompositions of y_{it} and $K_{ij,t}$ into common vs. country-specific shocks, according to the estimated eigenvalues associated with each factor. Using Section 2's notation, the first two columns of Table 1 imply the following decomposition:

$$y_{it} = \hat{a}_i + \hat{b}^y_{1,i}\hat{\mathcal{F}}^y_{1,t} + \hat{b}^y_{2,i}\hat{\mathcal{F}}^y_{2,t} + \hat{b}^y_{3,i}\hat{\mathcal{F}}^y_{3,t} + \varepsilon^y_{i,t},$$

and:

$$K_{ij,t} = \hat{a}_{ij} + \hat{b}^K_{1,ij}\hat{\mathcal{F}}^K_{1,t} + \hat{b}^K_{2,ij}\hat{\mathcal{F}}^K_{2,t} + \varepsilon^K_{i,t},$$

So, for GDP growth the first three principal components are common to two countries or more; while for $K_{ij,t}$ the first two principal components are common to two countries or more.

3.2 Estimation results

Equation (5) is the paper's key panel regression. Given the potential importance of common shocks, we use the principal component decomposition just described to run three versions of the estimation. The first simply reproduces results in the literature, where the dependent variable is given by $\mathcal{S}_{ij,t}$ that embeds both common and idiosyncratic shocks. The two alternative specifications condition the estimation on one kind of shock only: on common shocks only, with $\mathcal{S}^{\mathcal{F}}_{ij,t}$ as the dependent variable, and on idiosyncratic shocks only, with $\mathcal{S}^{\varepsilon}_{ij,t}$ as the dependent variable. All three estimations are performed for the two variants of $K_{ij,t}$, normalized by population or by GDP.

Table 2 abstracts from country-pair fixed effects, and estimates β on the cross-sectional dimension of the data, between country pairs.

Table 2 Banking Integration and Business Cycle Synchronization: Cross-sectional ("Between") Estimates

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	0.095	0.106	0.038			
	(0.011)	(0.008)	(0.007)			
	[8.70]	[12.85]	[5.43]			
Banking / GDP (K^{gdp})				0.091	0.082	0.049
				(0.010)	(0.007)	(0.006)
				[9.52]	[11.31]	[7.98]
Observations	4863	4863	4863	4863	4863	4863
R^2	0.092	0.176	0.121	0.095	0.170	0.127
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of year fixed effects. Estimation is performed over the 1980-2012 period.

The estimates are systematically positive, confirming the positive association between finance and synchronization on average. As argued by KPP, caution is in order in interpreting this result if there exist permanent reasons why country pairs display high cycle correlations and high financial integration, such as the practice of a common language, geographic proximity, or common institutions. Hence allowances for country pair effects, α_{ij}, are of the essence.

Table 3 reports the panel estimates of equation (5) allowing for fixed effects. Table 4 includes a control for the intensity of bilateral trade. In both tables, columns (1) and

(4) reproduce the significantly negative estimates of β within country pair, as in KPP. There are permanent reasons why financial links are intense between synchronized economies, captured by α_{ij} in equation (5); but once these are accounted for, a change in financial integration tends to be associated with lower values of $\mathcal{S}_{ij,t}$. But as this paper has argued, $\mathcal{S}_{ij,t}$ embeds the response of GDP to common shocks. Inasmuch as common shocks also affect $K_{ij,t}$, negative estimates of β in columns (1) and (4) could still arise because of features specific to each country pair: in this instance, the responses of $\mathcal{S}_{ij,t}$ and $K_{ij,t}$ to common shocks. Columns (2) and (5) in both tables confirm that negative estimates of β arise when synchronization is conditioned on common shocks only, as in equation (6). As argued in Section 2, this result could be driven by a systematic correlation between $b_i^y - b_j^y$ and b_{ij}^K (together with a positive covariance between $|\mathcal{F}_t^y|$ and $\mathcal{F}_t^K$).

Table 3 Banking Integration and Business Cycle Synchronization: Panel ("Within") Estimates

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	-0.144	-0.154	0.075			
	(0.040)	(0.030)	(0.021)			
	[-3.63]	[-5.05]	[3.54]			
Banking / GDP (K^{gdp})				-0.148	-0.159	0.072
				(0.042)	(0.032)	(0.022)
				[-3.56]	[-4.98]	[3.28]
Observations	4863	4863	4863	4863	4863	4863
R^2	0.099	0.222	0.133	0.099	0.222	0.133
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2012 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

Columns (3) and (6) of Tables 3 and 4 show estimates of β are significantly positive when synchronization is measured by the equilibrium responses of GDP to idiosyncratic shocks, $\mathcal{S}_{ij,t}^{\varepsilon}$ as in equation (3). The synchronization measure captures

Table 4 BANKING INTEGRATION AND BUSINESS CYCLE SYNCHRONIZATION: PANEL ("WITHIN") ESTIMATES WITH CONTROLS

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	-0.102	-0.132	0.060			
	(0.040)	(0.028)	(0.024)			
	[-2.57]	[-4.71]	[2.55]			
Banking / GDP (K^{gdp})				-0.106	-0.137	0.056
				(0.041)	(0.029)	(0.024)
				[-2.55]	[-4.65]	[2.32]
Trade	-0.382	-0.198	0.132	-0.386	-0.203	0.141
	(0.134)	(0.114)	(0.078)	(0.133)	(0.113)	(0.078)
	[-2.86]	[-1.75]	[1.69]	[-2.90]	[-1.79]	[1.81]
Observations	4859	4859	4859	4859	4859	4859
R^2	0.103	0.224	0.134	0.103	0.225	0.134
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2012 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

the equilibrium response of GDP in countries i and j to a country-specific shock: this is the object that most models of the international business cycle have a prediction about. The contagious consequences of finance mirrored by positive estimates of β are consistent with models where financial flows serve to alleviate binding constraints, rather than to chase high returns.

Of course the measurement of country-specific shocks is conditional on a specific decomposition of the panel of GDP growth rates. The actual residuals that serve to measure $\mathcal{S}^{\varepsilon}_{ij,t}$ in Tables 3 and 4 are obtained using a particular method to identify the common factors $\mathcal{F}^{y}_{t}$. It is possible that an alternative decomposition could exist where β would not be significantly positive in the columns (3) and (6) of Table 3 or 4. There is in fact a very large number of methodologies that can be used to identify common vs. idiosyncratic shocks, with different levels of sophistication and generality. Without theory, therefore, there is virtually no limit to the robustness checks the positive estimates of β in Tables 3 and 4 could be subjected to. But the fact that $\mathcal{S}_{ij,t}$ (and $K_{ij,t}$) are contaminated by shocks that are common to two or more countries is a very robust feature of the data, which presumably does not depend on the statistical method used to identify $\mathcal{F}_t^y$. And it has direct bearing on the interpretation of the estimates of β obtained with $\mathcal{S}_{ij,t}$, that can be driven by the systematic responses of GDP to common shocks in countries i and j.

Negative estimates of β and $\beta^{\mathcal{F}}$ arise when the elasticities of GDP and capital to common shocks are systematically related. Section 2 shows this means high b_i^y countries should also display high b_{ij}^K, for all j. Figure 3 plots the estimates of $\hat{b}_{1,i}^y$ against $\hat{b}_{1,i}^K$, where $\hat{b}_{1,i}^K = \frac{1}{J}\sum_j \hat{b}_{1,ij}^K$ is the average capital loading in country i. The correlation is positive and significant, with inelastic countries on both counts like Australia, Japan, and Portugal, and elastic countries on both counts, like the US and most of continental Europe.

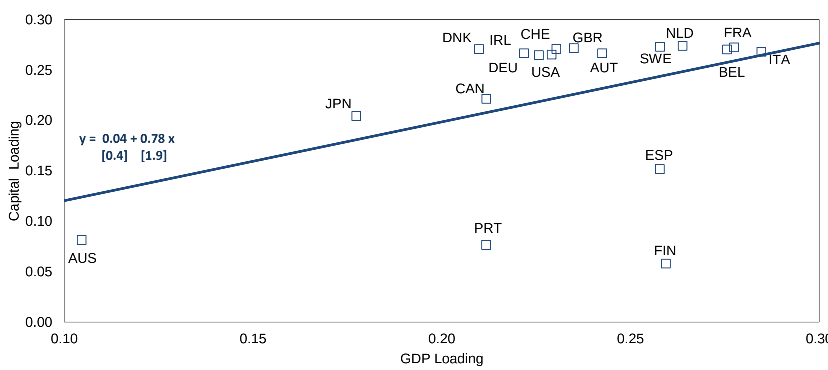

Figure 3 Correlation Between Loadings On GDP And Capital Intensity. On the horizontal axis is the loading on GDP ($\hat{b}_{1,i}^y$). On the vertical axis is the loading on capital $\hat{b}_{1,i}^K$, where $\hat{b}_{1,i}^K = \frac{1}{J}\sum_j \hat{b}_{1,ij}^K$ is the average capital loading in country i. The slope and the constant of the fitted line are reported together with t-Statistics in square brackets.

An implication of such a positive correlation is that capital should go to countries with elastic GDP in periods of global (or regional) booms, but away from them in years of global recession. Figure 4 explores the empirical validity of this implication by plotting the cross-section of $\hat{b}^y_{1,i}$ against measures of the changes in net bank holdings as per the BIS data. We compute the average change in net bank holdings, computed for positive or negative values of $\mathcal{F}^y_t$. Define:

$$KNET_i^+ = \sum_{\mathcal{F}^y_t>0} \Delta_t \left[\sum_j \ln\left(A_{ji,t} + L_{ij,t}\right) - \ln\left(A_{ij,t} + L_{ji,t}\right) \right],$$

and:

$$KNET_i^- = \sum_{\mathcal{F}^y_t<0} \Delta_t \left[\sum_j \ln\left(A_{ji,t} + L_{ij,t}\right) - \ln\left(A_{ij,t} + L_{ji,t}\right) \right],$$

where $\Delta_t[X]$ denotes the first difference of variable X.

Panel (a) of Figure 4 plots the estimates of $\hat{b}^y_{1,i}$ against the average change in net bank holdings computed for positive values of $\mathcal{F}^y_t$ (i.e., $KNET_i^+$).

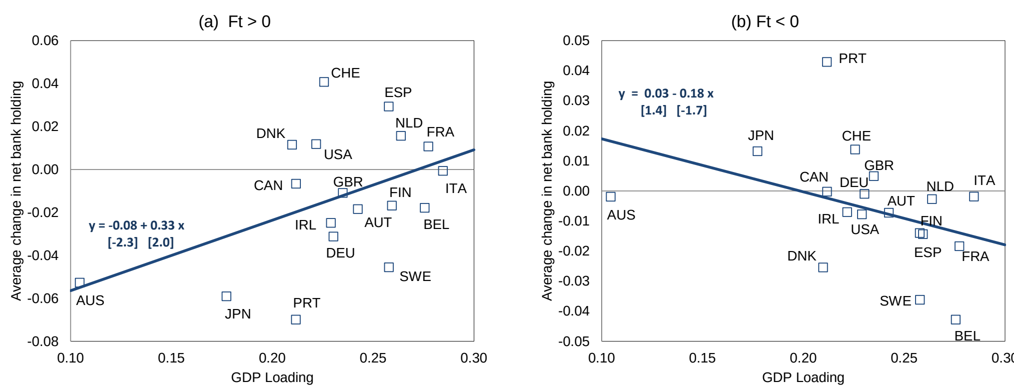

Figure 4 Correlation Between Loadings On GDP And Average Changes In Net Bank Holdings. On the horizontal axis is the loading on GDP ($\hat{b}^y_{1,i}$). On the vertical axis is the change in net bank holdings averaged over periods when $\mathcal{F}_t > 0$ ($KNET_i^+$), in panel (a); and when $\mathcal{F}_t < 0$ ($KNET_i^-$), in panel (b). The slope and the constant of the fitted line are reported together with t-Statistics in square brackets.

A significantly positive correlation exists, which means that on average net capital increases in countries whose GDP is responsive to common shocks in times of global (or regional) booms. Panel (b) of 4 plots the estimates of $\hat{b}^y_{1,i}$ against $KNET^-_i$. A negative relation exists, though it is only weakly significant. There is some tendency for net capital to fall in countries with elastic GDP in times of global (or regional) recessions, but it is less clear cut than the opposite in booms.

Taken together, Figure 4 suggests that (bank) capital tends to flow between countries with different loadings on GDP: from low $\hat{b}^y_i$ to high $\hat{b}^y_j$ in times of booms, and, to a smaller extent, the opposite in times of recessions. This drives a systematic correlation between $\hat{b}^y_{1,i}$ against $\hat{b}^K_{1,i}$, creates negative estimates of $\beta^{\mathcal{F}}$, and ultimately of β. But this tends to always happen between the same countries.

The panel of GDP growth rates used until now include the Great Recession years, until 2012. Arguably, these are years when financial linkages may have been especially contagious. For instance Kalemli-Ozcan, Papaioannou, and Perri (2013) show that estimates of β become less negative if the crisis years are included. They explain the instability in coefficient estimates with the prevalence of credit shocks during the Great Recession. Given the magnitude and globality of the Great Recession, it is likely to affect estimates of common shocks, and thus their loadings on GDP growth rates and bilateral capital flows.

Table 5 repeats the previous three estimations, but on a sample that now stops in 2006.[6] Estimates of β continue to be negative when the dependent variable is $\mathcal{S}_{ij,t}$ or $\mathcal{S}^{\mathcal{F}}_{ij,t}$. They are weakly positive when it is $\mathcal{S}^{\varepsilon}_{ij,t}$, consistent with the prevalence of contagious shocks, and perhaps of credit constraints, in the years post-2006.

[6]The number of factors associated with common shocks rises to 5 when the Great Recession years are omitted. The corresponding estimates are reported in Appendix A.

Table 5 BANKING INTEGRATION AND BUSINESS CYCLE SYNCHRONIZATION: PANEL ("WITHIN") ESTIMATES EXCLUDING THE GREAT RECESSION YEARS

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	-0.280	-0.349	0.029			
	(0.063)	(0.073)	(0.019)			
	[-4.46]	[-4.78]	[1.55]			
Banking / GDP (K^{gdp})				-0.284	-0.349	0.024
				(0.066)	(0.076)	(0.019)
				[-4.33]	[-4.57]	[1.22]
Observations	3945	3945	3945	3945	3945	3945
R^2	0.118	0.183	0.102	0.118	0.181	0.102
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2006 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

Endogeneity is an obvious concern for OLS estimates of equation (5). There is every reason to expect that financial linkages, especially bank linkages, are governed by a diversification motive. Then $K_{ij,t}$ tends to take high values between countries that are out of sync, i.e., where $\mathcal{S}_{ij,t}$ takes large negative values. This endogeneity bias results in estimates of β that are biased downwards: (negative) OLS estimates in columns (1)-(2) and (3)-(5) are biased away from zero, and (positive) OLS estimates in columns (3) and (6) are biased towards zero. Given its dimensions, it is difficult to find instruments for $K_{ij,t}$.

An important contribution of KPP is the introduction of an instrument for $K_{ij,t}$ that is time-varying, and country pair specific. The instrument builds from the existence of European directives, issued by the European Commission at a certain date, and implemented later in member countries, with lags that vary with each country. KPP focus on the 27 directives that pertain to financial regulation, as part of the Financial Services Action Plan launched in 1998 to remove barriers across Europe. At each point in time, and for each country pair they consider the overlap in directives that happen to be implemented in both countries i and j. They argue implementation dates are exogenous to current economic conditions, so that the instrument satisfies standard excludability constraints. The index constitutes a novel and powerful instrument for financial integration $K_{ij,t}$.[7]

Table 6 presents Instrumental Variable estimations of equation (5), once again for the three considered measures of cycle synchronization, $\mathcal{S}_{ij,t}$, $\mathcal{S}^{\mathcal{F}}_{ij,t}$, and $\mathcal{S}^{\varepsilon}_{ij,t}$. Estimates of β are still significantly negative for the measures of synchronization that embed common shocks, $\mathcal{S}_{ij,t}$ and $\mathcal{S}^{\mathcal{F}}_{ij,t}$. Compared with Table 5, point estimates are of the same order of magnitude and have similar value. Estimates of β are also positive and significant when synchronization focuses on idiosyncratic shocks, with $\mathcal{S}^{\varepsilon}_{ij,t}$ as a dependent variable. Compared with the estimates in Table 5, the point estimates are one order of magnitude larger, consistent with an attenuating bias in OLS.

Table 6 Banking Integration and Business Cycle Synchronization: Panel ("Within") IV Estimates Excluding The Great Recession Years

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	-0.487	-0.428	0.220			
	(0.132)	(0.113)	(0.058)			
	[-3.69]	[-3.80]	[3.78]			
Banking / GDP (K^{gdp})				-0.519	-0.457	0.235
				(0.141)	(0.120)	(0.062)
				[-3.69]	[-3.79]	[3.76]
Observations	3951	3951	3951	3951	3951	3951
R^2	0.112	0.188	0.054	0.110	0.185	0.046
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2006 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

[7]Following KPP, the instrument takes value zero for non EU member countries.

4 Extensions

This Section discusses two extensions of our baseline specification.

4.1 Pearson Correlation Coefficient

The measure of cycle synchronization used in most of the literature until recently is the Pearson correlation coefficient. It is problematic in panel regressions, because it is measured with error and because it responds to changes in the variance of the underlying shocks. Still, KPP show that the negative estimates in equation (5) survive this alternative measurement of synchronization.

Consider the consequences of equation (2) on the Pearson correlation ρ_{ij} between the GDP growth rates of countries i and j. By definition:

$$\rho_{ij} = \left(w_i^{\mathcal{F}}\right)^{\frac{1}{2}} \left(w_j^{\mathcal{F}}\right)^{\frac{1}{2}} + \left(1 - w_i^{\mathcal{F}}\right)^{\frac{1}{2}} \left(1 - w_j^{\mathcal{F}}\right)^{\frac{1}{2}} \rho_{ij}^{\varepsilon}, \tag{8}$$

where $w_i^{\mathcal{F}} = \frac{b_i^2 V(\mathcal{F}_t^y)}{V(y_{i,t})}$ is the share of the variance of GDP growth in country i that corresponds to common shocks, and ρ_{ij}^{ϵ} is the Pearson correlation coefficient that captures cycle synchronization conditional on idiosyncratic shocks. As is evident, in the presence of common shocks, the Pearson correlation between GDP growth is an imperfect measure of the actual correlation coefficient implied by country-specific shocks: A corrective term drives a wedge between the two coefficients. Its magnitude depends on the share of the variance in GDP growth that can be explained by common shocks in both countries i and j.

Correlation coefficients were traditionally used in cross-section, since they are computed in the time dimension. As done by KPP, it is also possible to compute them over successive sub-periods, and use the resulting panel as the dependent variable in equation (5). Then the corrective term in equation (8) involving $w_i^{\mathcal{F}}$ and $w_j^{\mathcal{F}}$ can also be time-varying. With an intuition that is analogous to Forbes and Rigobon (2002), changes in the variance of the underlying shocks affect the panel properties of ρ_{ij}. The empirical question posed by this possibility is whether the estimates of β in equation (5) depend whether cycle synchronization is measured by ρ_{ij} or by ρ^{ε}_{ij}.

Table 7 shows that it does: The estimates of β are negative and significant in columns (1) and (4), when the dependent variable in equation (5) is given by $\rho_{ij,t}$, computed over five-year windows. It becomes strongly negative and significant when the correlation coefficient is computed on common shocks only, in columns (2) and (5). But it is essentially zero when the dependent variable is replaced by $\rho^{\varepsilon}_{ij,t}$. This confirms the importance of common shocks for negative estimates of β.

Table 7 Banking Integration and Business Cycle Synchronization: Panel ("Within") Estimates – Pearson Correlation Coefficient

	ρ	$\rho^{\mathcal{F}}$	ρ^{ε}	ρ	$\rho^{\mathcal{F}}$	ρ^{ε}
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop. (K^{pop})	-0.102	-0.031	-0.017			
	(0.061)	(0.015)	(0.020)			
	[-1.67]	[-2.07]	[-0.83]			
Banking / GDP (K^{gdp})				-0.110	-0.033	-0.018
				(0.064)	(0.016)	(0.021)
				[-1.74]	[-2.11]	[-0.85]
Observations	915	915	915	915	915	915
R^2	0.122	0.259	0.001	0.123	0.260	0.001
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2012 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

4.2 Time-Varying Factor Loadings

During the estimation period we consider (1980-2012) global goods and financial markets have grown at fast pace. At the same time, countries have become increasingly integrated into those markets. As a result, the responsiveness country-specific dynamics to global developments are likely to have changed. In this Section we address this issue by estimating a model where country-specific factor loadings are allowed to vary over time.

Consider a version of equation (2) where factor loadings are allowed to be time-varying:

$$y_t = a_t^y + b_t^y \mathcal{F}_t^y + e_t^y, \tag{9}$$

where, for ease of notation, the country subscripts i are ignored. Assume that the coefficients a_t^y and b_t^y evolve as random walks. In state-space form this model can be expressed as:

$$y_t = \mathbf{X}_t \boldsymbol{\beta}_t + e_t^y. \tag{10}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + v_t \tag{11}$$

where $\mathbf{X}_t = (1, \mathcal{F}_t^y)$, $\boldsymbol{\beta}_t = (a_t^y, b_t^y)'$ and $Var(e_t^y) = R$ and $Var(v_t) = Q$.

The model (10)-(11) can be easily estimated *via* Gibbs sampling (see Blake and Mumtaz, 2012). Specifically, if the time-varying coefficients $\boldsymbol{\beta}_t$ are known, then the conditional posterior distribution of R is inverse Gamma, and the distribution of Q is inverse Wishart. Conditional on R and Q the model (10)-(11) is a linear Gaussian state space model. Since the conditional posterior of $\boldsymbol{\beta}_t$ is normal, the mean and the variance of $\boldsymbol{\beta}_t$ can be derived with the Kalman filter.[8]

Figure 5 compares time-varying estimates to their static equivalent for the 18 countries in the sample. While some variation is apparent, time-varying estimates of factor loadings are rarely significantly different from their constant counterparts.

[8] Appendix B provides the details on the Gibbs sampling algorithm, initial conditions and priors.

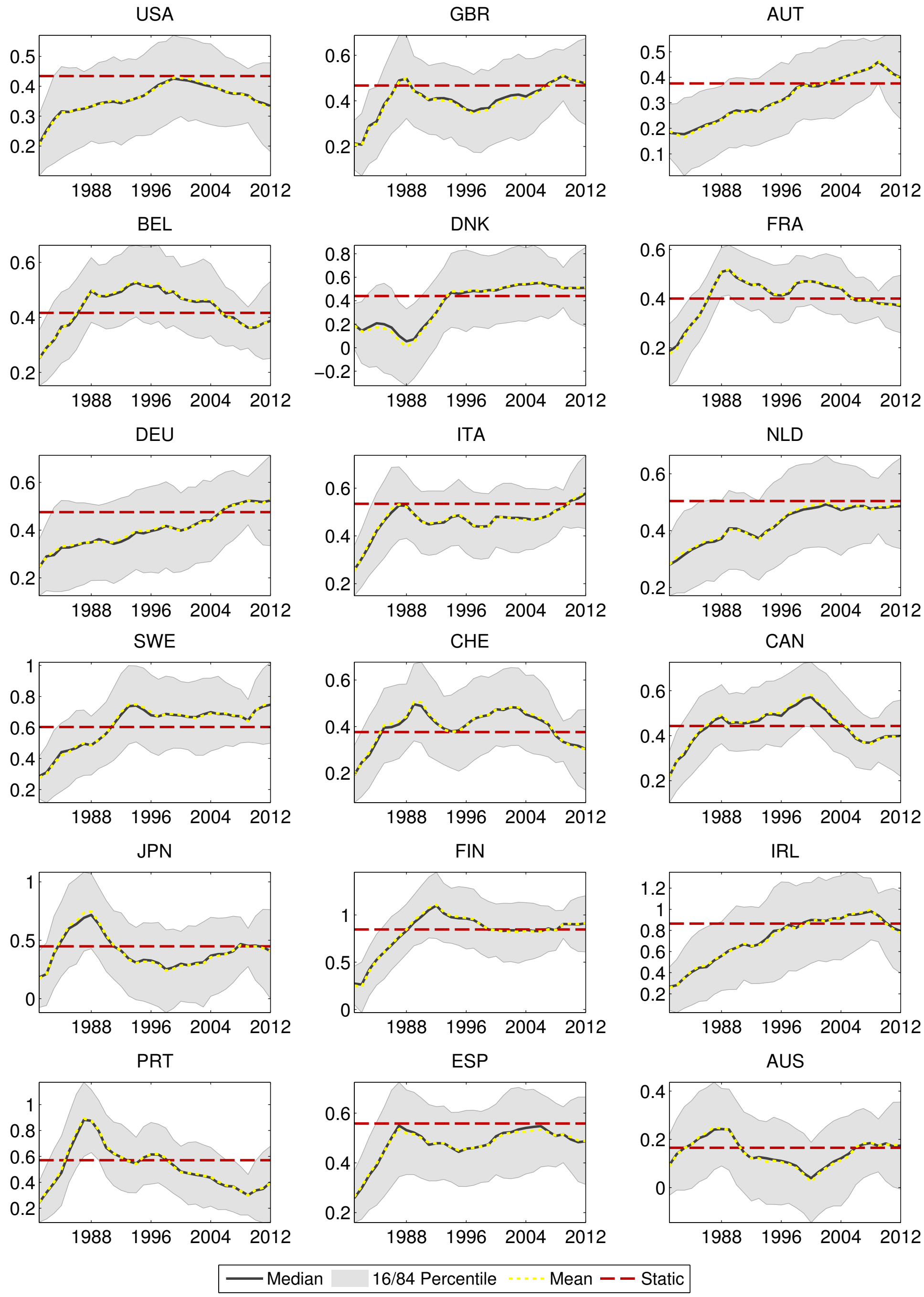

Figure 5 Time-varying Estimates Of The Loadings On The First Principal Component. Mean (dotted line) and median (solid line) estimates of the time-varying parameters in model (10)-(11). Shaded areas display the 68 percent credible intervals. The dashed line reports the OLS fixed estimates.

Tables 8 report the results implied when the time-varying estimates of b_t^y are used to decompose $\mathcal{S}_{ij,t}$ into $\mathcal{S}_{ij,t}^{\mathcal{F}}$, and $\mathcal{S}_{ij,t}^{\varepsilon}$. The estimates of β continue to switch signs as in the results presented above: negative when $\mathcal{S}_{ij,t}$ or $\mathcal{S}_{ij,t}^{\mathcal{F}}$ are the dependent variable, but positive and significant when $\mathcal{S}_{ij,t}^{\varepsilon}$ is. This provides an alternative decomposition where the existence of common shocks obscures the effect of finance on synchronization.

Table 8 Banking Integration and Business Cycle Synchronization: Panel ("Within") Time-Varying Parameter Estimates

	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop.	-0.144	-0.195	0.033			
	(0.040)	(0.037)	(0.012)			
	[-3.63]	[-5.21]	[2.68]			
Banking / GDP				-0.148	-0.199	0.031
				(0.042)	(0.040)	(0.013)
				[-3.56]	[-5.03]	[2.46]
Observations	4863	4863	4863	4863	4863	4863
R2	0.099	0.198	0.161	0.099	0.197	0.161
Country Pairs	153	153	153	153	153	153

Note. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2012 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

5 Conclusion

Most theories of international cycle synchronization investigate the propagation of country-specific shocks across borders. The role of financial linkages in propagating these shocks globally has become particularly relevant for policy-makers and researchers alike. International financial flows could either respond to arising opportunities and flow to the location with highest risk adjusted returns, or they could serve to alleviate local (credit or balance sheet) constraints. The former implies capital flows exacerbate asymmetries in business cycles, whereas the latter implies capital fosters the contagion of binding constraints, and thus of shocks.

This paper argues the well known existence of common shocks in international data has first-order consequences on this debate. In response to common shocks, we show that (bank) capital tends to always flow between the same pairs of countries, which tends to have asymmetric consequences on their business cycles. This happens always between the same countries, and thus hardly constitutes support for the notion that financial flows help "make hay where the sun shines". Instead, the paper documents a positive association between cycle synchronization and financial linkages, provided they are both conditioned on idiosyncratic shocks. Since it is the propagation of idiosyncratic shocks that existing theories have predictions about, this finding provides support for the possibility that idiosyncratic (bank) financial flows serve to alleviate binding financial constraints.

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A Additional results for the 1980-2006 period

Table A.1 provides a summary of the factor estimates for GDP growth rates y_{it} and capital flows $K_{ij,t}$ over the period 1980–2006. As in the our baseline sample period (that runs from 1980 to 2012), two factors are enough to explain 90 percent of the variance in $K_{ij,t}$. However, the percentage of the variance explained by the first two GDP factors is now lower. Moreover, there are now five factors with eigenvalue larger than one for the panel of GDP growth rates.

Table A.1 Factor Estimates For GDP Growth And Banking Integration Excluding The Great Recession Years

	Eigenvalues		Share of variance		Cum. share of variance	
	$y_i t$	$K_{ij,t}$	$y_i t$	$K_{ij,t}$	$y_i t$	$K_{ij,t}$
$\mathcal{F}_1$	7.75	12.70	43%	71%	43%	71%
$\mathcal{F}_2$	3.30	3.21	18%	18%	61%	88%
$\mathcal{F}_3$	1.63	0.96	9%	5%	70%	94%
$\mathcal{F}_4$	1.39	0.56	8%	3%	78%	97%
$\mathcal{F}_5$	1.22	0.29	7%	2%	85%	98%

Note. Principal components are computed on the panel of 18 GDP growth series (y_{it}) and 153 pair-specific capital instensity series ($K_{ij,t}$) over the 1980–2006 period.

B Estimation of time-varying parameters model

Consider the time-varying parameters model in (10)-(11). The Gibbs sampling algorithm consists of the following steps:

1. Set starting values (i.e., $\beta_0,\ Var(\beta_0),\ R_0,\ Q_0$) and priors

$$\begin{aligned}\mathcal{P}(R) &\sim \mathcal{IG}(\frac{T_0}{2},\frac{\theta^R}{2})\\ \mathcal{P}(Q) &\sim \mathcal{IW}(\frac{T_0}{2},\frac{\theta^Q}{2})\end{aligned}$$

2. Sample the state variable β_t conditional on R and Q from its conditional posterior distribution using the Kalman filter

3. Using β_0 and $Var\left(\beta_0\right)$ run Kalman Filter to get mean and variance of β_t at each point in time

4. Conditional on β_t, sample Q and R from their posterior distributions.

5. Repeat steps 1 to 3 until convergence is detected.

Below we describe how we proceed in detail.

Setting $\beta_{0,i}$, $Var\left(\beta_{0,i}\right)$, and $R_{0,i}$.

Using the annual data set we compute a fixed parameter version of model (9) on the full sample for all countries. Therefore, for each country i, we get an estimate of $\beta_{0,i}$, $Var\left(\beta_{0,i}\right)$, and $R_{0,i}$:

$$\begin{aligned}
\beta_0 &= \left(X_t'X_t\right)^{-1}\left(X_t'Y_t\right) \\
Var\left(\beta_0\right) &= R_0 \otimes \left(X_t'X_t\right)^{-1} \\
R_0 &= \frac{\left(y_t - X_t\beta_t\right)\left(y_t - X_t\beta_t\right)'}{(T-K)}
\end{aligned}$$

where T denotes the number of observations.

Setting $Q_{0,i}$.

Since Q_0 is unobserved, one could do a rolling window OLS estimation of the fixed parameter model to get a time-varying estimate of β_0. Then, an estimate of Q_0 can be obtained by running an VAR(1) model on the rolling estimates of β_0:

$$\beta_{0,t} = \Phi\beta_{0,t-1} + \xi_\tau. \tag{B.1}$$

and recovering the covariance matrix of ξ_t in equation (B.1) as:

$$Q_0 = \frac{\left(\beta_{0,t} - \Phi\beta_{0,t-1}\right)\left(\beta_{0,t} - \Phi\beta_{0,t-1}\right)'}{(T-K)}.$$

For the above procedure to work we clearly need a large number of observations. The sample has to be large enough to allow for a rolling window estimation. Therefore, the annual frequency of our data set poses a problem for the implementation of the above strategy. To address this issue we increase the number of available observations using a quarterly data set that is comparable to our annual data set (quarterly real GDP data from the OECD from 1980:Q1 to 2012:Q4).

We then estimate a fixed parameter version of model (9) using a rolling window. To do that, we use a window of 40 quarters.

We then estimate a VAR(1) model as in (B.1) on the rolling estimates and compute variance-covariance $Q_{0,i}$ for each country.

Setting the priors

conditional on β_t the posterior distribution of R is inverse Gamma and the posterior distribution of Q is inverse Wishart:

$$\mathcal{P}(R) \sim \mathcal{IG}(T_0, \theta^R) \qquad \text{and} \qquad \mathcal{P}(Q) \sim \mathcal{IW}(T_0, \theta^Q).$$

We set $T_0 = 32$, i.e. the number of observations in our annual (sample). We then set θ^R so that the mean of $\mathcal{IG}(\frac{T_0}{2}, \frac{\theta^R}{2})$ matches $Var(e_t) \equiv R_0$ and the mean of $\mathcal{IW}(\frac{T_0}{2}, \frac{\theta^Q}{2})$ matches $Var(v_t) \equiv Q_0$. Therefore, for $\mathcal{P}(R_i) \sim \mathcal{IG}(T_{0,i}, \theta_i^R)$ we set $\theta_i^R = R_{0,i}(T_{0,i} - 1)$. For $\mathcal{P}(Q_i) \sim \mathcal{IW}(T_0, \theta_i^Q)$ we set the diagonal element $\theta_{nn,i}^Q = Q_{0,i}(T_0 - n - 1)$.

Implementation

We run 100,000 replications, discard the first 99.000, and use the remaining 1.000 draws to form the empirical distribution of the parameters of (10)-(11)