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Informational economic transmission between countries ☆

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ABSTRACT

Informational economic transmission is crucial even after accounting for countries' fundamental real and financial connections. Informational connections emerge from anomalous interdependence in agents' beliefs about countries' economic activity. We propose measuring this interdependence through the correlation (between countries) of analysts' one-year forecast errors about countries' economic performance. Our measure is based on a learning model in which informational transmission occurs when agents incorrectly assess the quality of new information regarding common factors that affect multiple countries simultaneously, due to learning frictions. Informational interdependence remains substantial under various validity analyses and robustness checks, and after addressing endogeneity concerns in several dimensions. Additionally, we demonstrate considerable higher-order spillovers of economic shocks.

1. Introduction

There are three channels for the propagation of economic shocks across countries, that is, the real, financial and informational channels of economic transmission. Transmission of shocks can arise because countries are fundamentally connected through trade (in the case of the real channel of interdependence) or through common investors who have investments in two or more countries (in the case of the financial channel of interdependence). Economic transmission can also occur through informational linkages, which reflect anomalous interdependence in agents' beliefs about the economic variables characterizing countries, even if those countries are not connected through the fundamental real and financial links. However, informational linkages are difficult to measure empirically, as they crucially depend on the learning dynamics followed by agents and their information sets, which are typically unobservable.

In this paper, we propose a novel measure of informational linkages between economies. This measure is based on a stylized learning model, where agents learn new information about the unknown future values of a variable that characterizes the economic performance of countries. Due to learning frictions, agents incorrectly assess the quality of new information regarding common factors that affect multiple countries simultaneously. As a result, we show that informational linkages emerge, manifesting as anomalous co-movements in agents' forecast errors regarding the economic variable describing economies.

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Based on this motivating framework, we propose a measure of informational linkages between economies, which is based on the correlation of analysts' forecast errors regarding a variable that characterizes the economic performance of countries, after considering (and cleaning from the data) the interdependence induced by the fundamental real and financial links. Our measure relies on the intuition that any additional correlation of analysts' belief errors between countries should not be observed (after accounting for the fundamental links), unless there is informational interdependence.

We begin our empirical analysis by quantifying the informational linkages. Precisely, first, we compute, on a monthly basis, the average gross domestic product (GDP) one-year-ahead forecast errors (in relation to the actual future value) of the analysts following each country. Then, we calculate the correlations (between country pairs) of the GDP one-year-ahead forecast errors. Afterward, we orthogonalize these correlations relative to the fundamental real and financial channels of economic interdependence to obtain our measure of informational linkages. This is because we want to have a 'pure' measure of informational linkages that is not confounded by the real and financial connections.

In the case of the real links, we construct a measure of trade intensity between countries based on annual bilateral trade data (see Kaminsky et al., 2004; Caramazza et al., 2004). We then instrument the trade intensity measure using gravity variables, which are standard in the trade literature, such as common language, common borders and preferential trade agreements, among others (Frankel and Romer, 1999; Frankel and Rose, 2002; Cavallo and Frankel, 2008).[1] To proxy for the financial links, we examine whether a country relies on investment funds that are overexposed to other countries (see Broner et al., 2006); specifically, we consider the monthly evolution of the assets under management of investment funds.[2]

To examine whether our measure of informational interdependence explains economic spillovers across countries, we rely on a spatial econometric model. Spatial econometric methods focus primarily on modeling the interaction effects among geographical units (e.g. countries or regions). They rely on interdependence (or connectivity) matrices to capture the relationships between these units. In the context of our study, the use of spatial econometrics is appealing since it enables us to analyze the spillover mechanisms stemming from multiple sources of economic transmission.

We have access to a detailed monthly data set covering 30 countries between 2007 and 2019. The dependent variable is the default risk of the sovereign debt in each country, which is proxied by the credit default swap (CDS) spread.[3] Thanks to our spatial econometric model, we allow for the possibility that sovereign risk in one country affects the sovereign risks in other economies. We include an interdependence matrix proxying for informational linkages, but also two additional interdependence matrices measuring the (fundamental) real and financial sources of economic transmission. This arises from the fact that two countries' CDS spreads can be linked due to their fundamental connections through real and financial interdependence channels, which we want to control for in our empirical analysis.

We also include common shocks related to market volatility, and we allow for country-specific sensitivities to these common shocks, which help us to mitigate the impact of global factors related to risk pricing on CDS spreads (since Longstaff et al., 2011 document that sovereign credit risk can be affected by global dynamics). To control for local fundamental factors, we include lagged country-specific variables (e.g. inflation and external debt, among others), which have been used in the previous literature (see, e.g., Longstaff et al., 2011; Lucas et al., 2014; Blasques et al., 2016). We also control for *unobserved* variables that might influence CDS spreads, which can be cross-sectional and time-variant, by including country-fixed effects and time-fixed effects.

We reduce endogeneity concerns in several dimensions. First, we estimate our model using an instrumental variable procedure through a spatial two-stage least squares (S2SLS) estimation method, which accounts for endogeneity issues, including the impact of *unobserved* common factors. Intuitively, in the S2SLS estimation method, we instrument the CDS spread of a given economy i with the macroeconomic characteristics of the countries linked with economy i.[4] Second, to mitigate endogeneity concerns between CDS spreads and the informational linkages, we measure the informational linkages by calculating the correlations (between country pairs) of the analysts' one-year-ahead GDP forecast errors for each country (rather than using variables related to the analysts' views about the default risk of sovereign debt).

Third, we include lagged control variables (i.e. macroeconomic indicators and common shocks) to mitigate any reverse causality because, at any point in time, these variables are not likely to be affected by the future values of CDS spreads. Fourth, to avoid potential endogeneity arising from simultaneity between CDS spreads and the interdependence matrices, as well as to prevent endogeneity issues related to the lagged country-specific variables used as controls, we construct the interdependence matrices for informational,

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1 As a robustness check, we consider alternative proxies for the real channel of interdependence, including (i) bilateral exports only, over the total GDP of the two countries, (ii) bilateral exports and imports over the total trades of the two countries, (iii) bilateral exports and imports over the GDP of one of the two countries and (iv) current account over GDP.

2 We also examine an alternative way of measuring financial interdependence, in which we quantify the financial linkages of each country with a common creditor, in terms of the country being highly indebted to the common creditor and being highly represented in the creditor's portfolio. For this exercise, we rely on data on cross-border bank flows from the international banking locational statistics of the Bank of International Settlements.

3 Thus, we follow the studies that rely on CDS data to study the economic interdependence between countries. This literature has increased since the recent subprime and European sovereign debt crises; see, for instance, Longstaff et al. (2011); Kalbaska and Gątkowski (2012); Lucas et al. (2014); Blasques et al. (2016); Tabak et al. (2016); Buchholz and Tonzer (2016).

4 The S2SLS estimation method was developed in a series of articles by Kelejian and Prucha (1998, 1999, 2004). The instrumental variable procedure contained in the 2SLS estimation method has been used in diverse studies to examine, for example, peer effects (Bramoullé et al., 2009), the role of geographical, cultural and relational proximity in the automotive industry (Schmitt and Van Biesebroeck, 2013), spillovers in institutional development (Kelejian et al., 2013), mafia-type organizations in Sicily's municipalities (Buonanno et al., 2015) and tax competition (Agrawal, 2015), among others.

real and financial linkages using data from the period January 2002 to October 2007. Our estimation period for the spatial econometric model spans from December 2007 to December 2019.[5]

Fifth, to avoid cross-sectional dependence in the series of analysts' forecast errors (e.g. due to analyst consensus bias), we compute their cross-sectional averages and extract them from each observation (i.e. analysts' forecast errors are 'de-factored'), which accounts for *unobserved* global fundamental factors. Sixth, to avoid any endogeneity issue between the three sources of interdependence, which may simultaneously capture common information, we adopt a Gram-Schmidt orthogonalization procedure for the informational, real and financial interdependence matrices.

We present strong evidence of the existence of the informational channel of interdependence. We show that the parameter that measures the strength of the informational channel of economic transmission is positive and statistically significant, after controlling for the (fundamental) real and financial linkages. Moreover, the informational links remain substantial under numerous robustness checks. This means that larger sovereign risk in one country, say country i, is accompanied by larger CDS spreads in countries that are informationally linked to country i.

While our measure of informational linkages is based on a stylized learning model, an important question remains: How can we ascertain the effectiveness of this measure in reflecting informational interdependence? We cannot definitively answer this question due to the unobservability of both learning dynamics and agents' information sets, which constitutes one of the primary challenges in studies examining informational links. Nevertheless, to indirectly address this question, we develop a set of hypotheses to investigate the behavior of our measure across various scenarios, which we subsequently test using economic data. These hypotheses draw upon previous studies that offer potential explanations for the existence of informational interdependence. This analysis is crucial as it provides insights into whether our proposed measure adequately captures informational linkages by generating outcomes that align with actual economic transmission dynamics.

Our first hypothesis is grounded on previous studies emphasizing that costs related to learning and information production should incentivize agents to follow common factors rather than acquiring costly country-specific information (Calvo and Mendoza, 2000). This over-reliance on common factors should in turn generate informational links. According to this perspective, the production and learning of new country-specific information should increase in periods of stress, when distinguishing between countries becomes more relevant (Gorton and Ordoñez, 2014, 2020), consequently reducing informational interdependence. This is because agents may perceive the economic gains from learning new country-specific information (rather than relying on signals related to common factors) to be larger during periods of stress. Mistakes in investment decisions (due to a lack of country-specific information) during crises might lead to larger economic losses (than during tranquil times). In line with this first hypothesis, we do find a decrease in the strength of the informational channel in periods of economic stress (which include the global financial crisis and the European sovereign debt crisis), when compared to normal times.

The second hypothesis is based on studies highlighting agents' limited attention capacity (Mondria and Quintana-Domeque, 2013; Kacperczyk et al., 2016), which suggest that agents are more likely to learn about common factors that describe groups of *apparently* similar countries than to learn country-specific information (see Barberis and Shleifer, 2003; Ashby and Maddox, 2005; Peng and Xiong, 2006). Thus, we expect that informational links should be stronger between countries that belong to groups of apparently similar economies. We show that informational links are stronger between countries that are either within the group of emerging economies or within the group of advanced economies, which is consistent with this second hypothesis.

Our third hypothesis concerns the potential influence of common analysts on our proposed measure of informational interdependence. Actually, the informational connections captured by our proposed measure may be contaminated, or driven, by the presence of common analysts delivering GDP forecasts. This is because analysts' forecasts may be biased by both conflicts of interests (e.g. due to career concerns) and the amount of information available in each country, which should be important when there are common analysts. While we acknowledge that common analysts may introduce bias into the measurement of informational linkages, four factors mitigate this concern. First, because we use the *errors* in the GDP forecasts rather than the predicted values *per se* of such forecasts, issues of bias should matter less. Second, as explained above, analysts' forecast errors are 'de-factored' to mitigate the potential impact of analyst consensus bias induced by career concerns (which can be relevant when there are common analysts). Third, our measure of informational links is the *correlation* of the forecast errors, which should reduce the bias issue even more. Fourth, substantial differences in information availability between two countries should reduce, rather than inflate, the correlation between their forecast errors. Taken together, these considerations support the argument that our empirical approach is not subject to biases introduced by common analysts. We therefore hypothesize that our proposed measure for informational linkages is not affected by the presence of common analysts.

In line with this third hypothesis, we find that the strength of the informational linkages, as captured by our measure, remains unaffected when we control for an interdependence matrix capturing links between countries when they share a significant number of common analysts delivering GDP forecasts. This suggests that our measure is not significantly influenced by overlapping analyst coverage. Moreover, we find that the strengths of the real and financial linkages diminish once we control for common analysts. This result is expected though, as common analysts tend to operate in countries that are already connected through fundamental real and financial connections, thereby partially capturing the same underlying interdependencies.

[5] There are two reasons for having interdependence matrices that do not vary over time: because we are interested in the long-term relationships between the countries and to avoid introducing an undesirable degree of randomness into the analysis. However, as a robustness check, we also report an analysis in which the interdependence matrices change over time. The findings observed under this robustness check are qualitatively similar to the results reported when the interdependence matrices do not vary over time.

In the last part of the paper, we analyze the marginal direct and indirect effects and amplifications that occur through spillovers. This analysis is important because local shocks in one country i not only economically affect the same country i (i.e. 'direct' effects) but may also have an impact, through 'indirect' (i.e. spillover) effects, on other economies that may be connected (or not directly connected) to country i. We find that the indirect effects have a similar magnitude to (and in some cases are greater than) the direct effects. Thus, the effective economic impact on one country, from idiosyncratic shocks, may be amplified through the economic interdependence of countries.[6]

Our study relates to the few empirical investigations of the informational channel of interdependence. The small number of such studies may stem from the fact that informational links depend on investors' learning processes and their information sets, which are not observable. Within this literature, Kaminsky and Schmukler (1999) investigate the effects of news across various Asian markets during the 1997–1998 Asian crisis. They find that some of the largest one-day market swings and volatility increments could not be explained by any apparent substantial news, while specific news items from one country significantly affected financial markets in other economies. They interpret these findings as evidence of informational spillovers between countries and investor herding behavior.[7]

Our study is also connected to Basu (2002) and Bekaert et al. (2014), who analyze the transmission of economic shocks from the crisis in Hong Kong (in 1997) and the global financial crisis (between 2007 and 2009), respectively. They find residual persistence in spillovers of the negative shocks, after controlling for fundamental links, which is interpreted as indicative of the informational channel. Debarsy et al. (2018) also present evidence suggesting informational linkages. They measure the informational channel using, as proxies for the informational links, variables capturing potential *connections* between pairs of countries, such as similarity of macro indicators or socioeconomic-institutional proximity.

The paper is organized as follows. Section 2 presents the motivating framework. Section 3 describes the empirical methodology and data. Section 4 reports the main results. In turn, Section 5 presents a validation analysis to investigate the behavior of our proposed measure of informational links under different scenarios. Section 6 presents the spillover effects. Finally, Section 7 concludes. The internet appendix contains proofs, technical details, robustness checks and a model application to the 2014 Ukrainian revolution (absent from the main text).

2. Motivating framework for the informational linkages

We begin with a description of the potential (complementary) explanations for the *existence* of the informational channel of interdependence. Afterward, in the next section, we present a motivating learning model that is based on these explanations for informational links. The objective of this motivating learning model is to provide microfoundations for the sources of informational transmission and to develop intuition behind our novel measure of informational interdependence.

2.1. Potential explanations for informational economic transmission

Potential explanations for informational links are related to both the costs of learning and limited attention capacity of agents. In relation to the learning costs, they include the costs of producing new information and the costs associated with the energy and time spent in the learning process. For instance, Calvo and Mendoza (2000) argue that globalization may reduce the willingness to produce costly information, and may increase incentives to follow common factors such as the ones observed in global market portfolios, which should induce herding dynamics. There are also studies arguing that the costs and benefits of learning change over time. This is because investors' benefits from costly production (and learning) of country-specific information are larger during crisis periods than in tranquil times. Thus, production and learning of new country-specific information should increase during crisis periods when distinguishing between countries is more relevant (i.e. there are fewer incentives to follow common factors), while production and learning of new knowledge should be lower in calm periods (see Gorton and Ordoñez, 2014, 2020).

Within the strand of literature on learning costs, Ahnert and Bertsch (2020) argue that a crisis in one country is a signal, i.e., a 'wake-up call', to investors in other countries that induces them to acquire information and to reassess their beliefs about other countries' fundamentals. In addition, the costs of learning can generate incomplete information, which might also induce informational links (see, e.g., Manz, 2010; Trevino, 2020). The intuition behind this literature is that, if investors do not have precise information on how a crisis in a given country is related to their investments in other countries, they may withdraw their investments in the latter countries.

Furthermore, there are explanations for the existence of informational linkages that are valid even if there are zero costs related to learning new information. The rationale for these alternative explanations is that individuals have a limited attention capacity (e.g.

[6] In the internet appendix, we also perform an application of our spatial model estimates to quantify the economic transmission of one particular shock: the Ukrainian revolution in 2014. This application is particularly appealing, given the current Ukrainian war (starting in February 2022), which has already greatly impacted the world economy. The application can hence shed some light on the likely international economic transmission of the current war.

[7] Similar to Kaminsky and Schmukler (1999), we provide evidence of informational linkages during crisis periods. However, we also demonstrate that informational interdependence exists during normal times. Interestingly, we observe that informational linkages weaken during periods of economic stress (such as the global financial crisis and the European sovereign debt crisis) compared to tranquil periods. This occurs because investors have stronger incentives to acquire and learn country-specific information in stressful times, as distinguishing between individual country characteristics becomes more critical (Gorton and Ordoñez, 2014, 2020). Such behavior is consistent with the heightened costs of investment mistakes during crises, when limited country-specific knowledge can lead to substantial economic losses. Consequently, during periods of stress, investors tend to rely less on common signals affecting multiple countries and place greater emphasis on country-specific information than in normal times.

Mondria and Quintana-Domeque, 2013; Kacperczyk et al., 2016). This limited attention capacity might induce agents either to have a 'specialized learning' behavior (as in Van Nieuwerburgh and Veldkamp, 2010) or to learn in terms of groups of elements (i.e. 'category learning', as in Barberis and Shleifer, 2003; Ashby and Maddox, 2005; Peng and Xiong, 2006). Applied to the context of economic interdependence, in relation to the 'specialized learning' behavior, agents might choose to learn information about common factors rather than country-specific information, which would artificially increase the economic links between countries. Complementarily, in relation to 'category learning', given that agents' ability to process information is limited, they may prefer to learn about common factors that simultaneously describe a group of apparently similar countries.[8]

It is important to point out that our objective is not to test each of these complementary explanations (mentioned above) for the informational linkages, as doing so is outside the scope of this paper. Instead, our main objective is to analyze empirically the impact of the informational channel on the economic transmission between countries using a novel measure of informational links. Nevertheless, our measure of informational links is based on a stylized learning model that captures intuitions about the costs of learning new information and limited attention capacity. Moreover, we perform a validity analysis that is based on the potential explanations for informational linkages.

2.2. Motivating learning model

Consider two countries, A and B, where $i = A, B$ is a country indicator variable. There is an infinite number of periods ($t = 0, 1, \ldots, \infty$). A representative agent would like to learn at t about the unknown future values at $t+1$ of a variable that characterizes the economic performance of each of the countries (e.g. the one-year-ahead value of each country's GDP). Let $f_{i,t+1}$ be the unknown future value of the variable that characterizes the economic performance of country i. The variable $f_{i,t+1}$ for each country is normally distributed, and is a linear combination of two independent random factors:

$$f_{i,t+1} = g_{t+1} + v_{i,t+1} \tag{1}$$

where g_{t+1} is a common factor that has a simultaneous impact on both economies, while $v_{i,t+1}$ is a country-specific factor for each economy i.

We assume that these factors are identically and independently distributed across periods, and follow normal distributions. The common factor follows $g_{t+1} \sim N(\bar{g}, 1/\tau_{g,0})$, where $\bar{g}$ and $\tau_{g,0}$ are its expected value and precision, respectively. The country-specific factor for each country follows $v_{i,t+1} \sim N(\bar{v}_i, 1/\tau_{v,0})$. Here, $\bar{v}_i$ is the expected value of the country-specific factor, while $\tau_{v,0}$ is its precision (which, for simplicity, is the same for both countries).

At time t, the agent receives signals about the future values of random factors at $t+1$:

$$s_{g,t} = g_{t+1} + \epsilon_{g,t}, \qquad \epsilon_{g,t} \sim N\left(0, \frac{1}{\tau_{g,\epsilon}}\right), \tag{2}$$

$$s_{v,i,t} = v_{i,t+1} + \epsilon_{i,v,t}, \qquad \epsilon_{v,i,t} \sim N\left(0, \frac{1}{\tau_{v,\epsilon}}\right). \tag{3}$$

All signals are normally distributed and independent of each other, with $\tau_{g,\epsilon}$ and $\tau_{v,\epsilon}$ the precision of the signals corresponding to the common factor and country-specific factor, respectively.

However, the agent has a learning bias that affects the learning process, leading to anomalous interdependence in agents' beliefs about the future value of the variable that characterizes the economic performance of countries. We make this simplification since the learning model described in this section primarily serves as a motivating framework. Our main objective is to highlight potential sources of informational linkages and to provide intuition underlying our novel measure of informational connections, which we later use to empirically assess whether the informational channel contributes to cross-country economic transmission. We incorporate this learning bias into our model by assuming that the agent misperceives the precision of the signal regarding the common factor as $\lambda\tau_{g,\epsilon}$. Thus, the agent perceives at time t the following biased signal about the future value of the common factor:

$$s^*_{g,t} = g_{t+1} + \epsilon^*_{g,t}, \qquad \epsilon^*_{g,t} \sim N\left(0, \frac{1}{\lambda\tau_{g,\epsilon}}\right), \tag{4}$$

where $\epsilon^*_{g,t}$ is the noise in the perceived signal with variance denoted by $Var(\epsilon^*_{g,t}) = 1/(\lambda\tau_{g,\epsilon})$. Thus, we require $\lambda > 0$ to ensure that $Var(\epsilon^*_{g,t})$ remains positive.

In equation (4), the agent underweights the precision of the signal related to the common factor when $0 \le \lambda < 1$ and overweights this signal's precision when $\lambda > 1$. Additionally, the agent exhibits no learning bias when $\lambda = 1$.

Using Bayesian updating, the agent's posterior beliefs at time t regarding the future values at $t+1$ of the country-specific factor for each country and the common factor are characterized in the following proposition.

[8] An example of information about common factors related to groups of economies is the knowledge concerning the dynamics of 'regional' financial indexes (see, e.g., MSCI regional market indexes: www.msci.com/end-of-day-data-regional). These regional indexes provide financial information about groups of apparently similar countries that are located in the same region (e.g. Emerging Eastern Europe, Emerging Latin America, Emerging Africa, among others).

Proposition 1. *The agent's posterior beliefs about the common factor and the country-specific factors are given by* $g_{t+1}|s^*_{g,t} \sim N(\hat{g}_{t+1}, 1/\tau_g)$ *and* $\upsilon_{i,t+1}|s_{\upsilon,i,t} \sim N(\hat{\upsilon}_{i,t+1}, 1/\tau_\upsilon)$*, respectively, with:*

$$\hat{g}_{t+1} = \frac{\tau_{g,0}}{\tau_g}\bar{g} + \frac{\lambda\tau_{g,\varepsilon}}{\tau_g}s^*_{g,t} \quad \text{and} \quad \tau_g = \tau_{g,0} + \lambda\tau_{g,\varepsilon} \tag{5}$$

$$\hat{\upsilon}_{i,t+1} = \frac{\tau_{\upsilon,0}}{\tau_\upsilon}\bar{\upsilon}_i + \frac{\tau_{\upsilon,\varepsilon}}{\tau_\upsilon}s_{\upsilon,i,t} \quad \text{and} \quad \tau_\upsilon = \tau_{\upsilon,0} + \tau_{\upsilon,\varepsilon} \tag{6}$$

where τ_g *and* τ_υ *are the corresponding precisions.*

Proof. See internet appendix A.

In Proposition 1, and similarly to Peng and Xiong (2006), we treat learning about each of the independent factors as a separate task. Then, the forecast of $f_{i,t+1}$ at time t, $forecast_t(f_{i,t+1})$, is:

$$forecast_t(f_{i,t+1}) = \hat{f}_{i,t+1} = \hat{g}_{t+1} + \hat{\upsilon}_{i,t+1}. \tag{7}$$

Expression (7) and Proposition 1 show that $forecast_t(f_{i,t+1})$ equals the agent's expected value of the posterior beliefs regarding $f_{i,t+1}$, $\hat{f}_{i,t+1}$. In addition, if $\lambda \neq 1$, the agent has biased values for $forecast_t(f_{i,t+1})$ because posterior beliefs about $f_{i,t+1}$ are affected by the wrongly perceived precision regarding the common factor. If $\lambda = 1$, we obtain the learning-unbiased case.

To analyze the biases in posterior beliefs, we can write the expression for the root squared error of the agent's forecast of $f_{i,t+1}$, $RootSqErr_{f,i,t}$, in relation to its future actual value:

$$\begin{aligned} RootSqErr_{f,i,t} &= \sqrt{\left(Error_{f,i,t}\right)^2} \\ &= \sqrt{\left(\hat{f}_{i,t+1} - f_{i,t+1}\right)^2} = \sqrt{\left(Error^{NoLearnBiases}_{f,i,t} + Error^{LearnBiases}_{f,i,t}\right)^2} \end{aligned} \tag{8}$$

where

$$Error^{NoLearnBiases}_{f,i,t} = \hat{f}^{NoLearnBiases}_{i,t+1} - f_{i,t+1} \quad \text{and} \tag{9}$$

$$Error^{LearnBiases}_{f,i,t} = \hat{f}_{i,t+1} - \hat{f}^{NoLearnBiases}_{i,t+1} = \frac{\tau_{g,0}\tau_{g,\varepsilon}(\lambda-1)(s_{g,t}-\bar{g})}{(\tau_{g,0}+\lambda\tau_{g,\varepsilon})(\tau_{g,0}+\tau_{g,\varepsilon})}. \tag{10}$$

Here, $\hat{f}_{i,t+1}$ is given in expression (7), while $\hat{f}^{NoLearnBiases}_{i,t+1}$ reflects the learning-unbiased version of $\hat{f}_{i,t+1}$ (i.e. when $\lambda = 1$). We use the root squared error of the agent's forecast, $RootSqErr_{f,i,t}$, rather than the simple forecast error because $RootSqErr_{f,i,t}$ corresponds to the single-observation case of the root mean squared error used in the empirical analysis in the following sections, where multiple agents (i.e., analysts) produce economic forecasts for a given country (see equation (16) in Section 3.1). In the empirical implementation, we use the root mean squared error of forecasts to avoid the possibility of positive and negative errors offsetting each other, which can occur when calculating the mean of simple forecast errors from multiple analysts.

Equations (8)-(10) show that the root squared errors can be decomposed into two components. The first component is $Error^{LearnBiases}_{f,i,t}$, which reflects the forecast errors under a scenario without learning biases. The second component is $Error^{LearnBiases}_{f,i,t}$, which represents the additional forecast errors induced by the agent's learning biases (i.e. when $\lambda \neq 1$). Thus, $Error^{LearnBiases}_{i,t} = 0$ if there are no learning biases (i.e., if $\lambda = 1$).

The following lemma reflects the correlation between the root squared errors of the agent's forecasts for countries A and B under a scenario with learning biases.

Lemma 1. *The correlation between* $RootSqErr_{f,A,t}$ *and* $RootSqErr_{f,B,t}$ *is given by:*

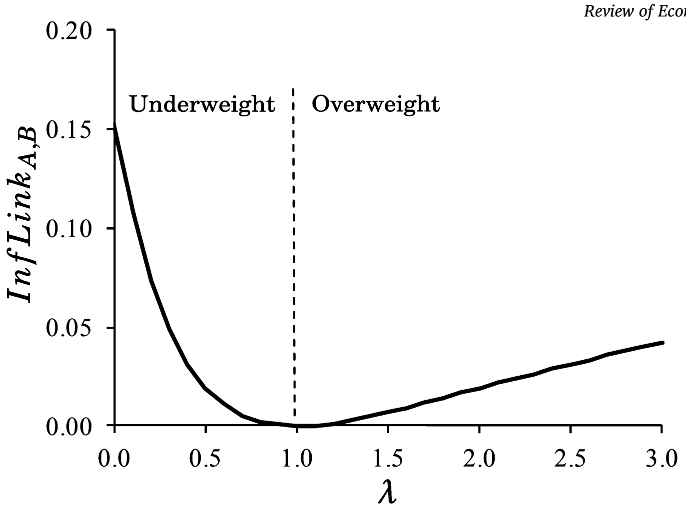
$$Corr(RootSqErr_{f,A,t}, RootSqErr_{f,B,t}) = \frac{\frac{2}{\pi}\left[\sqrt{1-\rho^2} + \rho \cdot arcsin(\rho) - 1\right]}{1 - \frac{2}{\pi}}, \tag{11}$$

$$\text{with} \quad \rho = Corr(Error_{A,i,t}, Error_{f,B,t}) = \frac{Var(Error_{g,t})}{Var(Error_{g,t}) + Var(Error_{\upsilon,t})}, \tag{12}$$

$$\text{where} \quad Var(Error_{g,t}) = \frac{\tau_{g,0} + \lambda^2\tau_{g,\varepsilon}}{(\tau_{g,0}+\lambda\tau_{g,\varepsilon})^2} \quad \text{and} \quad Var(Error_{\upsilon,t}) = \frac{1}{\left(\tau_{\upsilon,0}+\tau_{\upsilon,\varepsilon}\right)}.$$

Proof. See internet appendix A.

In expression (12) of Lemma 1, $Var(Error_{g,t})$ and $Var(Error_{\upsilon,t})$ are the variances of the agent's forecast errors in $\hat{g}_{t+1}$ and $\hat{\upsilon}_{i,t+1}$, respectively (i.e. $Error_{g,t} = \hat{g}_{t+1} - g_{t+1}$ and $Error_{\upsilon,i,t} = \hat{\upsilon}_{i,t+1} - \upsilon_{i,t+1}$). Here, $Var(Error_{\upsilon,t}) = Var(Error_{\upsilon,A,t}) = Var(Error_{\upsilon,B,t})$, which



Notes: This figure illustrates the measure of information links between countries A and B, $InfLink_{A,B}$ (see equation (13)). We assume that $\tau_{v,0} = \tau_{v,\epsilon} = 0.2$ and $\tau_{g,0} = \tau_{g,\epsilon} = 0.3$, while λ changes.

Fig. 1. Measurement of informational links among countries under a learning bias.

can be obtained from Proposition 1. In equation (12), the numerator takes the form $Var(Error_{g,t})$, reflecting that the overlapping component of the variance in both $Error_{A,i,t}$ and $Error_{B,i,t}$ arises from the forecast error of the common factor (see equation (7)).

Let's define a measure of informational links between countries A and B, denoted by $InfLink_{A,B}$, induced by the agent's learning bias, which generates anomalous interdependence in agents' beliefs. Specifically, let $InfLink_{A,B}$ equal the correlation between the root squared errors of the agent's forecasts for countries A and B under a scenario with learning biases, minus the corresponding correlation calculated under a scenario without learning biases. Then:

$$\begin{aligned} InfLink_{A,B} = {} & Corr(RootSqErr_{f,A,t}, RootSqErr_{f,B,t}) \\ & - Corr(RootSqErr^{Fundamental}_{f,A,t}, RootSqErr^{Fundamental}_{f,B,t}), \end{aligned} \tag{13}$$

where

$$RootSqErr^{Fundam}_{f,A,t} = RootSqErr^{NoLearnBiases}_{f,A,t} \quad \text{and}$$

$$RootSqErr^{Fundame}_{f,B,t} = RootSqErr^{NoLearnBiases}_{f,B,t}.$$

Here $Corr(RootSqErr^{Fundamental}_{f,A,t}, RootSqErr^{Fundamental}_{f,B,t})$ is the correlation between the root squared errors of the agent's forecasts for countries A and B, where such agent's forecasts (and thus, their root squared errors) are obtained under a scenario without learning biases (i.e. when $\lambda = 1$).

Consequently, $InfLink_{A,B}$ reflects the *additional* correlation between the root squared errors of the agent's forecasts for countries A and B—beyond the fundamental correlation between the root squared errors of the forecasts—generated by the agent's learning frictions. The following proposition describes the behavior of $InfLink_{A,B} > 0$, when the agent has a learning bias.

Proposition 2. *If the agent exhibits a learning bias that affects the learning process regarding information about the common factor (i.e., when $\lambda \neq 1$), then the measure of informational links between countries A and B, denoted by $InfLink_{A,B}$, is positive ($InfLink_{A,B} > 0$). In the absence of a learning bias (when $\lambda = 1$), $InfLink_{A,B}$ equals zero.*

Proof. See internet appendix A.

Proposition 2 means that, either if the agent underweights the information about the common factor (i.e. $0 \leq \lambda < 1$), or if the agent overweights such information (i.e. $1 < \lambda$), the measure of information links between countries A and B will be larger than zero, $InfLink_{A,B} > 0$. This is because, as shown in equation (10), the value of the *additional* error generated by the agent's learning bias for each country i, $Error^{LearnBiases}_{f,i,t}$, is a random variable that is simultaneously observed in both economies. Thus, the *additional* forecast errors induced by the agent's learning biases for the two countries co-move perfectly, as $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ are both affected by the wrongly perceived precision regarding the common factor (which induces the same *additional* forecast error in both economies). Fig. 1 illustrates this empirical implication, as it shows that $InfLink_{A,B} > 0$ when $\lambda \neq 1$, while $InfLink_{A,B} = 0$ when $\lambda = 1$.

2.3. Empirical implication

We now derive a testable implication, which is based on the main intuitions behind informational linkages between countries. Let $Corr(\hat{f}_{A,t+1}, \hat{f}_{B,t+1})$ be the correlation between the posterior beliefs $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ for countries A and B, respectively, which is described in the following lemma.

Lemma 2. *The correlation between $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ is given by:*

$$Corr(\hat{f}_{A,t+1}, \hat{f}_{B,t+1}) = \frac{Var(\hat{g}_{t+1})}{Var(\hat{g}_{t+1}) + Var(\hat{v}_{t+1})}, \tag{14}$$

$$\textit{where} \quad Var\left(\hat{g}_{t+1}\right) = \frac{\lambda^2\left(\tau_{g,0}+\tau_{g,\varepsilon}\right)\tau_{g,\varepsilon}}{\left(\tau_{g,0}+\lambda\tau_{g,\varepsilon}\right)^2\tau_{g,0}} \quad \text{and} \quad Var(\hat{v}_{t+1}) = \frac{\tau_{v,\varepsilon}}{\left(\tau_{v,0}+\tau_{v,\varepsilon}\right)\tau_{v,0}}.$$

Proof. See internet appendix A.

Here, $Var(\hat{g}_{t+1})$ and $Var(\hat{v}_{t+1})$ are the variances of $\hat{g}_{t+1}$ and $\hat{v}_{t+1}$, respectively. In Lemma 2, similarly to Lemma 1, $Var(\hat{v}_{A,t+1}) = Var(\hat{v}_{B,t+1}) = Var(\hat{v}_{t+1})$, which can also be obtained from Proposition 1. The numerator of equation (14) is $Var(\hat{g}_{t+1})$ because the shared part of the variance in $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ is related to the common factor (see equation (7)).

We now introduce a metric for the abnormal interdependence between the agent's forecasts for countries A and B, denoted by $AbnInterd_{A,B}$, which is driven by the agent's learning bias, affecting the processing of information about the common factor. Specifically, $AbnInterd_{A,B}$ is defined as the correlation between the posterior beliefs $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ for countries A and B when learning biases are present (i.e., when $\lambda \neq 1$), minus the corresponding correlation when learning biases are absent (i.e., when $\lambda = 1$). Formally:

$$AbnInterd_{A,B} = Corr(\hat{f}_{A,t+1}, \hat{f}_{B,t+1}) - Corr(\hat{f}^{Fundamental}_{A,t}, \hat{f}^{Fundamental}_{B,t}) \tag{15}$$

with

$$\hat{f}^{Fundam}_{A,t} = \hat{f}^{NoLearnBiases}_{A,t} \quad \text{and} \quad \hat{f}^{Fundam}_{B,t} = \hat{f}^{NoLearnBiases}_{B,t}.$$

Consequently, similarly to $InfLink_{A,B}$ in equation (13), $AbnInterd_{A,B}$ captures the abnormal correlation between the posterior beliefs $\hat{f}_{A,t+1}$ and $\hat{f}_{B,t+1}$ for countries A and B—beyond their fundamental correlation—resulting from the agent's learning bias. We can now derive the following empirical implication that reflects the anomalous interdependence among the agent's beliefs concerning the two economies.

Empirical implication. *The abnormal interdependence between the agent's forecasts for countries A and B, denoted by $AbnInterd_{A,B}$, increases with λ (i.e., $\partial AbnInterd_{A,B}/\partial\lambda > 0$). Moreover, $AbnInterd_{A,B} < 0$ when the agent underweights the information about the common factor (i.e., $0 \leq \lambda < 1$), while $AbnInterd_{A,B} > 0$ when the agent overweights this information (i.e., $\lambda > 1$).*

Proof. See internet appendix A.

Fig. 2 illustrates this empirical implication, showing that the correlation between the posterior beliefs for countries A and B increases with λ. This figure shows that $AbnInterd_{A,B}$ is negative when $0 \leq \lambda < 1$ and positive when $\lambda > 1$.

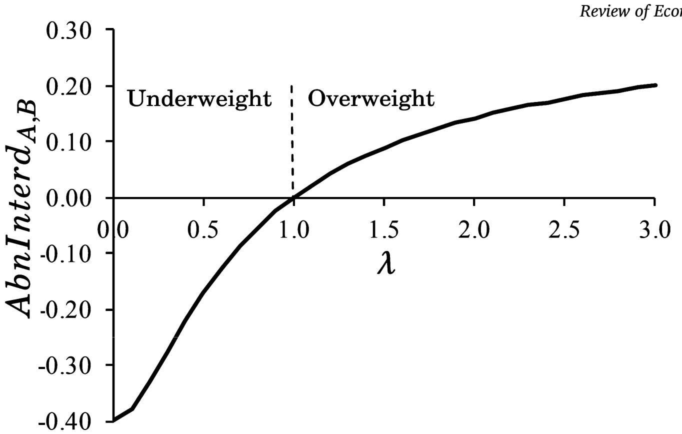
This empirical implication highlights a distinct pattern of anomalous interdependence in an agent's beliefs about economic variables across countries, depending on whether the agent underweights or overweights the quality of information regarding the common factor. Specifically, when the agent underweights the information quality about the common factor (i.e., $0 \leq \lambda < 1$), the abnormal interdependence between the agent's forecasts for countries A and B, $AbnInterd_{A,B}$, is negative. Conversely, when the agent overweights the information quality about the common factor (i.e., $\lambda > 1$), $AbnInterd_{A,B}$ is positive.

This implication connects to the potential explanations for informational economic transmission discussed previously in this section. For example, as described in Section 2.1, in the context of explanations related to learning frictions, abnormal interdependence may arise due to learning costs and/or limited attention capacity, which may lead agents to overweight new information concerning the common factor that simultaneously affects both economies.

3. Empirical implementation and data

In this section, we empirically analyze the existence of informational linkages. To do so, first, we present our new measure of informational links between economies. Second, we introduce a spatial econometric model for empirically examining whether this measure of informational interdependence effectively explains spillovers (beyond and above the real and financial links).

In the spatial econometric model, each channel of economic transmission takes the form of an interdependence matrix, which we denote by the matrices $\mathbf{W}_I$, $\mathbf{W}_R$ and $\mathbf{W}_F$, proxying for the informational, real and financial sources of interdependence, respectively.



Notes: This figure depicts abnormal interdependence among countries, $AbnInterd_{A,B}$ (see equation (15)). We assume that $\tau_{v,0} = \tau_{v,\varepsilon} = 0.2$ and $\tau_{g,0} = \tau_{g,\varepsilon} = 0.3$, while λ changes.

Fig. 2. Abnormal interdependence among countries under a learning bias.

The intuition behind the construction of the interdependence matrices is simple. A pair of countries are connected according to one source of interdependence when the mean value of the corresponding (standardized) linkage measure is sufficiently strong in a statistical sense (in such a case, the corresponding element in the matrix under consideration takes a non-zero value); otherwise, the two countries are not connected (hence, there is a value of zero in the corresponding element of the matrix). Section 3.1 details how we construct our new measure of informational linkages.

Sections C.2 and C.3, in the internet appendix, detail the construction of the measures of the real and financial linkages of economic interdependence, respectively. In short, to measure the real channel of interdependence, we rely on a bilateral trade intensity measure, which corresponds to the sum of exports and imports between each country pair, divided by the sum of their outputs. We instrument the trade intensity measure, relying on standard variables used in the trade literature (Frankel and Romer, 1999; Frankel and Rose, 2002; Cavallo and Frankel, 2008), allowing for the possibility of trade being endogenous.[9] To proxy for the financial channel of interdependence, we use as the linkage measure an index of common investors, as in Broner et al. (2006). Furthermore, we consider alternative proxies for the real and financial links in the internet appendix.

3.1. *Informational linkages*

To quantify the informational linkages between any pair of countries (as reflected in the matrix $\mathbf{W}_I$), we analyze whether their GDP forecast errors are abnormally correlated. We use data from professional forecasters provided by Consensus Forecast (Country Reports). Therefore, following Carroll (2003), we assume that investors (who are the actual decision-makers) learn from professional forecasters.[10]

Firstly, following the intuitions provided by equation (8), we calculate on a monthly basis the root mean squared error, $RootSqErr_{GDPi,t}$, of the one-year-ahead GDP forecasts made by analysts covering country i, as follows:

$$RootSqErr_{GDP,i,t} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(forecast_{k,t}\left(GDP_{i,t+1}\right) - GDP_{i,t+1}\right)^2} \tag{16}$$

where k is the analyst index and $GDP_{i,t+1}$ is the realized true value. We require a minimum of six analysts per month in each country to calculate the GDP forecast errors.

To correct for cross-sectional dependence in $RootSqErr_{GDP,i,t}$, we de-factor the GDP forecast errors. Thus, we follow Bailey et al. (2016b) and estimate the specification below:

$$RootSqErr_{GDP,i,t} = \alpha_i + \gamma_i \overline{RootSqErr}_{GDP,t} + \xi_{DFact,i,t} \tag{17}$$

where $\overline{RootSqErr}_{GDP,t} = N^{-1}\sum_{i=1}^{N} RootSqErr_{GDP,i,t}$, which is calculated using the N countries in our data set. We then compute the residuals from equation (17), yielding a panel series of the de-factored GDP forecast errors, which we denote by $\xi_{Dfact,i,t}$ for any country i. It is important to stress that, by de-factoring the GDP forecast errors in equation (17), we eliminate the influence of cross-sectional dependence (e.g. due to analyst consensus bias), which accounts for *unobserved* global fundamental factors.

[9] In particular, we consider the log of the product of the land areas, the log-distance, and indicator variables for whether the two countries in a pair have a common language, common borders, preferential trade agreements, regional trade agreements, are landlocked and are part of a currency union, respectively.

[10] The use of data from professional forecasters as a proxy for the behavior of actual decision-makers has been employed in various studies in economics and finance (see, e.g., Johnson, 2004; Ilut and Schneider, 2014; Zhao, 2017; Baker et al., 2018; Ilut and Saijo, 2020).

In line with equation (11) of the motivating framework, we define $\widehat{\epsilon}_{I,i:j}$ as the sample estimate of the (de-factored) pairwise correlation between the GDP forecast errors of any two countries i and j over $t \in \{1, 2, \cdots, T\}$:

$$\widehat{\epsilon}_{I,i:j} = \frac{\sum_{t=1}^{T}(\xi_{DFact,i,t} - \bar{\xi}_{DFact,i})(\xi_{DFact,j,t} - \bar{\xi}_{DFact,j})}{\sqrt{\sum_{t=1}^{T}(\xi_{DFact,i,t} - \bar{\xi}_{DFact,i})^2 \sum_{t=1}^{T}(\xi_{DFact,j,t} - \bar{\xi}_{DFact,j})^2}} \tag{18}$$

with $\bar{\xi}_{DFact,i} = T^{-1}\sum_{t=1}^{T}\xi_{DFact,i,t}$.

Finally, in order to consistently estimate the non-zero elements of $\mathbf{W}_I$, we follow Bailey et al. (2016b)'s methodology and apply a multiple testing procedure (Holm, 1979):

$$w_{I,ij} = I\left(\widehat{\epsilon}_{I,i:j} > T^{-\frac{1}{2}} c_p(n_{ij})\right) \tag{19}$$

where $c_p(n_{ij}) = \Phi^{-1}\left(1 - \frac{p}{2f(n_{ij})}\right)$, p is the size of the test, which we set to $p = 0.01$, $\Phi^{-1}(.)$ is the inverse cumulative standard normal distribution and $f(n_{ij})$ is a function linearly increasing in n_{ij}, the number of country pairs, that is, $n_{ij} = N \times (N-1)$.

Intuitively, equation (19) indicates that an element $w_{I,ij}$ is non-zero when the informational link measure between countries i and j is sufficiently strong, that is, when it is statistically different from zero. In addition, to allow for varying degrees of intensity of the significant informational connections, we multiply each element of $\mathbf{W}_I$, $w_{I,ij}$, by its corresponding $\widehat{\epsilon}_{I,ij}$ and then row-normalize.

Then, following the intuition provided in equation (13) in the stylized learning model, we aim to obtain a 'pure' measure of informational linkages that is not confounded by the *fundamental* real and financial connections. Thus, the values in $\mathbf{W}_I$ are orthogonalized with respect to the real and financial linkages. We adopt the sequential Gram-Schmidt orthogonalization procedure (for an illustration, see Iacoviello and Navarro, 2019), where the variables are treated in a specific order.

One advantage of the Gram-Schmidt orthogonalization procedure, compared to other methods such as principal component analysis, is that the resulting orthogonal variables are easier to interpret, particularly when the ordering of the original variables carries meaningful information. Thus, we sequentially regress the elements of the p^{th} matrix, $\widehat{\epsilon}_{p,i:j}$, over the elements of the previously orthogonalized matrices, $\left\{\widehat{\epsilon}^{\perp}_{h,i:j}\right\}_{h=1}^{p-1}$, yielding the orthogonalized residuals, $\widehat{\epsilon}^{\perp}_{p,i:j}$.

The sequential Gram-Schmidt method aligns well with our analysis, given that our theory provides clear guidance on the appropriate ordering of variable orthogonalization. In particular, informational linkages must appear last in the sequential orthogonalization procedure. This ordering ensures that our measure of informational links between countries is free from any confounding effects stemming from *fundamental* (real and financial) connections.

In terms of ordering, we first run a regression with the financial links as the dependent variable and real links as the explanatory variable. Next, we run a regression with the informational links as the dependent variable, using two explanatory variables: the real links and the residuals obtained from the previous regression (representing the financial links orthogonal to the real links). The residuals from this second regression yield our final measure of the informational links, which are orthogonal to both the real and the financial links. Thus, our measure of informational links captures the abnormal interdependence that operates beyond the *fundamental* real and financial linkages (see equation (13) in the motivating framework), which should not drive the international transmission of shocks in CDS spreads in the absence of learning biases.

Although we know informational linkages should appear last in the sequential Gram-Schmidt orthogonalization procedure, there remains some flexibility regarding the ordering of the fundamental real and financial links. Therefore, as a robustness check presented in the internet appendix, we consider an alternative ordering of these fundamental real and financial connections, while still keeping informational linkages last in the sequential procedure. Specifically, in this robustness exercise, we first regress the real links on the financial links. Next, we regress the informational links on two explanatory variables: the financial links and the residuals from the initial regression (representing the real links orthogonal to the financial links). Finally, the residuals from this second regression again provide our final measure of the informational links, again orthogonal to both the real and financial links. The outcomes of this robustness check are qualitatively similar to those reported here.

3.2. Measuring the spillover mechanisms

We rely on a spatial econometric model to analyze whether our measure of informational interdependence is able to explain the propagation of economic shocks across countries, controlling at the same time for the (fundamental) real and financial linkages between countries. The dependent variable is the default risk of the sovereign debt in each country, which is proxied by the CDS spread. There is a large literature that relies on CDS data to study the economic interdependence between countries.[11] This way, the spatial econometric model allows us to analyze whether changes in the sovereign risk in one country affect the sovereign risk in other countries, where such shock propagation is generated by informational, real or financial linkages.

We use monthly data on the 5-year sovereign CDS spreads. The data on CDS spreads come from Datastream. Whenever available, we use sovereign CDS contracts denominated in US dollars. Otherwise, as in Buchholz and Tonzer (2016), we use contracts specified

[11] See, e.g., Longstaff et al. (2011); Kalbaska and Gątkowski (2012); Leschinski and Bertram (2013); Lucas et al. (2014); Blasques et al. (2016); Tabak et al. (2016); Buchholz and Tonzer (2016); Oh and Patton (2018).

in euros (since CDS spreads are measured in basis points, currency differences are of minor concern; see, e.g., Longstaff et al., 2011; Ang and Longstaff, 2013).[12] Details of the sample period will be described later in Section 3.3.

Consider N countries over T periods. Denote by $\mathbf{y}_t$ the vector of CDS spreads at period $t \in T$. The spatial baseline model specification is written as:

$$\mathbf{y}_t = \rho_I \mathbf{W}_I \mathbf{y}_t + \rho_R \mathbf{W}_R \mathbf{y}_t + \rho_F \mathbf{W}_F \mathbf{y}_t + \gamma g_{t-1} + \mathbf{X}_{t-1}\beta + \mu + \delta_t + \mathbf{v}_t \tag{20}$$

where $\mathbf{W}_p$ represents an interdependence matrix of size $N \times N$ with p the sub-index for the three sources of interdependence, namely, the informational (sub-index $p = I$), real ($p = R$) and financial ($p = F$) channels; hence, $p \in \mathscr{P}$ and $\mathscr{P} = \{I; R; F\}$. Thus, an element of $\mathbf{W}_p$, which we denote by $w_{p,i:j}$, represents the extent of the corresponding interdependence between the two countries i and j, where informational, real and financial links are obtained from the Gram-Schmidt orthogonalization procedure as described in Section 3.1. The parameter ρ_p then captures the average strength of the informational, real or financial linkages (depending on the sub-index p).

Countries cannot be connected with *themselves* in any of the channels of interdependence; thus, $w_{p,i:i} = 0$ or, equivalently, each diagonal element in each $\mathbf{W}_p$ is zero. This means that the economic variable $y_{i,t}$ of a country i (i.e. $y_{i,t} \in \mathbf{y}_t$ on the left-hand side) is not used as an explanatory variable for the same country (i.e. $y_{i,t}$ on the right-hand side). Conversely, if two *different* countries i and j are linked in informational, real or financial terms, then $w_{p,i:j} \neq 0$; otherwise, $w_{p,i:j} = 0$.

It is important to highlight that we not only include the informational interdependence matrix, but also the real and financial interdependence matrices. Thus, by following the intuitions provided in equation (15) of the motivating framework, our objective is to analyze the abnormal *additional* interdependence after taking fundamental real and financial connections into account. In other words, CDS spreads would exhibit a fundamental connection between countries that are economically and financially integrated—which we explicitly control for in equation (20). This approach allows us to isolate and evaluate the strength of informational spillovers.[13]

Furthermore, we control for potential global dynamics that might affect CDS spreads across countries, by including a variable related to common shocks in equation (20). The variable g_{t-1} is a lagged common shock, with γ representing a vector of country-specific slopes for the lagged values of that common shock; thus, we consider country-specific sensitivities to common dynamics. As a lagged common shock, g_{t-1}, we use the monthly logarithm of the average of the Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX), lagged by one month, which helps us to mitigate the impact of global factors related to risk pricing on CDS spreads. We also control for *unobserved* fundamental characteristics that might influence CDS spreads, which can be cross-sectional and time-variant, by including country-fixed effects and time-fixed effects. Thus, in equation (20), μ is a vector of country-fixed effects and δ_t denotes time-fixed effects.[14]

In equation (20), $\mathbf{X}_{t-1}$ denotes a matrix of k lagged country-specific macroeconomic variables used as controls for local fundamental factors, and β the vector of their k parameters. Following the literature on international economics (see, e.g., Longstaff et al., 2011; Lucas et al., 2014; Blasques et al., 2016), we include the following lagged macroeconomic variables: the quarterly growth of real GDP (as a measure of economic activity); the quarterly external debt; the quarterly consumer price inflation (to proxy for the monetary policy stance); the quarterly foreign exchange reserves; the quarterly foreign direct investment net flows; and the annual fiscal balance. To mitigate any endogeneity bias due to simultaneity, all country-specific macroeconomic variables are lagged by one period (which corresponds to one quarter or one year, depending on the frequency of the variable). Finally, we assume that the error terms $v_{i,t} \in \mathbf{v}_t$ are identically and independently distributed with mean 0 and variance σ_i^2.

3.3. Sample period, estimation method, orthogonalization and discussion

The sample covers 30 countries, of which 14 are advanced economies and 16 emerging economies.[15] The spatial model described in equation (20) and its extensions are estimated with data from December 2007 to December 2019. However, to construct the matrices for the real, financial and informational linkages, we rely on data from January 2002 to October 2007. This is done to avoid potential endogeneity arising from simultaneity between the reduced-form spatial model for the CDS spreads (equation (20)) and the interdependence matrices, as well as to prevent endogeneity issues related to the one-month-lagged country-specific variables used as controls. There are two additional reasons for having interdependence matrices that do not vary over time: first, because we are interested in the long-term relationships between the countries, and second, to avoid introducing an undesirable degree of randomness into the analysis. Nevertheless, as a robustness check, we report in the internet appendix an analysis where the interdependence matrices change over time, and show that the main results presented in the body of our manuscript do not change qualitatively. Table 1 reports the summary statistics of our data set.

[12] CDS data have an advantage over yield spreads on sovereign bonds, in that they represent a risk premium without the need to lose data on the benchmark sovereign yields (typically, those from Germany or the USA). Additionally, in contrast to bond yields, CDS spreads lead price discovery (Palladini and Portes, 2011) and exclude inflation or currency risk premia since CDS contracts primarily insure against credit risk.

[13] An alternative approach would be to consider a convex combination of the interdependence matrices to form a single composite weighting structure as in Debarsy and LeSage (2022). However, this procedure would counteract our objective of examining the importance of the informational channel, beyond that of the fundamental channels.

[14] Note that, by including country-specific coefficients for the common shock, together with the fixed effects, we are implicitly *de-factoring* the CDS spreads as well.

[15] The advanced economies are Australia, the Czech Republic, Germany, Spain, France, Great Britain, Italy, Japan, Korea, the Netherlands, Norway, Slovakia, Sweden and the USA. The emerging economies are Brazil, Chile, China, Colombia, Hong Kong, Hungary, Indonesia, Mexico, Malaysia, Peru, Poland, Romania, Russia, Thailand, Turkey and Ukraine.

Table 1
Summary statistics.

	Mean	St. Dev.	p25	p50	p75	Obs.
GDP forecast errors	1.6	1.2	0.7	1.1	2.3	1815
Financial links (common investors)	0	0.3	−0.1	0	0	64380
Real links (bilateral trade/GDP)	0.4	0.7	0.0	0.1	0.4	6960
5y-CDS sov. spread (log bp)	4.3	1.1	3.7	4.4	5.0	4350
Reserves/GDP	18.8	21.5	3.6	14.2	24.5	4350
Ext. Debt/GDP	112.4	116.7	34.7	69.5	148.2	4350
Δ GDP	2.4	3.4	1.1	2.5	4.3	4350
Δ CPI	0.8	1.3	0.2	0.6	1.2	4350
FDI/GDP	−0.8	3.3	−2.4	−0.9	1.0	4350
FB/GDP	−2.0	3.9	−3.8	−2.4	−0.1	4350
VIX	18.1	1.4	14.0	16.9	22.1	4350

Notes: The one-year-ahead GDP forecast errors are calculated using equation (16). Real linkages correspond to the sum of exports and imports between a country pair, divided by the sum of their outputs, at an annual frequency (equation (33)). The common investors' index is calculated monthly following Broner et al. (2006), as in equation (40). 5y-CDS sov. spread, y in equation (20), corresponds to the five-year sovereign credit default swap spread, expressed in log of basis points; Reserves/GDP corresponds to the stock of international reserves divided by GDP; Ext.Debt/GDP is the ratio of total external debt stock to GDP; Δ GDP is the real GDP growth; Δ CPI is the inflation rate; FDI/GDP is the net foreign direct investment inflows over GDP; FB/GDP is the net fiscal balance over GDP; VIX is the volatility index of the CBOE. Sources: Consensus Economics, Datastream, EPFR, International Monetary Fund and World Bank.

It is important to note that, when calculating informational linkages using correlations of one-year-ahead GDP forecast errors, we impose the condition that the number of analysts providing forecasts must be greater than six, thereby reducing noise in the measurement of informational links. The unit of measurement for the one-year-ahead GDP forecasts for each country is the percentage change in nominal GDP for the entire economy relative to the previous calendar year's value. In addition, Table C.1 in the internet appendix presents summary statistics for the one-year-ahead GDP forecasts, including the number of analysts per country-month, the dispersion in the number of analysts per country and the frequency of analysts' revisions per country.[16]

To produce consistent estimates of the spatial econometric model in equation (20), we implement an S2SLS estimation method, allowing for multiple spatial weight matrices (see Kelejian and Prucha, 1998, 1999, 2004). The S2SLS estimation method is an instrumental variable procedure, which accounts for endogeneity in the dependent variable. The intuition behind the S2SLS estimation, in the context of our spatial econometric model, is that the CDS spread of a given country i is instrumented with the macroeconomic characteristics of the economies linked (in information, real and financial terms) to country i. The internet appendix provides details of this estimation method.

An alternative approach to our spatial econometrics model would be to use a global vector autoregressive (GVAR) model (see, e.g., Pesaran et al., 2004). One of the main differences between spatial econometric and GVAR models is that spatial econometric models focus on potentially sparse levels of interdependence between countries (as described above). This is an important feature for our study since we want to focus on those connections that are effectively strong from an econometric point of view, and that are long term. Conversely, the GVAR model usually operates with dense interdependence matrices, containing no or hardly any zero off-diagonal elements (see, e.g., Elhorst et al., 2018).[17]

4. Empirical results

The main objective of this section is to examine whether there is an informational channel of interdependence between countries. Section 4.1 starts by quantifying the strength of the informational channel of interdependence. In Section 4.2, we perform a battery of robustness checks.

4.1. The existence of the informational channel

Table 2 presents the estimation of the spatial model explained in Section 3.2. Columns 1, 3 and 5 report the estimations of restricted versions of the model described in equation (20), where there is only one interdependence matrix, representing either the

[16] Table C1 shows that, on average, 16.4 analysts cover a country in a given month, indicating that our measure of informational linkages is not driven by only a few analysts. Additionally, the dispersion in the number of analysts covering each country is relatively low, and forecasts are consistently revised, with analysts updating their estimates approximately every 1.5 months on average.

[17] The difference with respect to the sparsity or density of the interdependence matrix also has consequences for the choice of estimation method. If the number of zero off-diagonal elements in the connectivity matrix is high, either multiple-stage least squares, maximum likelihood, instrumental variables or the generalized method of moments is required. Instead, if the number of zero off-diagonal elements is low, ordinary least squares can be used. Another difference between the two approaches is that spatial methods have been developed with a focus on univariate dependent-variable vectors, and involving spatial dependence between a large set of cross-sectional units (LeSage and Pace, 2009). GVAR models introduce cross-unit dependence in otherwise standard VARs where the traditional focus is on the time dimension.

Table 2
Informational interdependence.

Variable	Restricted model	T-stat.	Restricted model	T-stat.	Restricted model	T-stat.	Baseline model	T-stat.
W_I	0.27	6.10					0.21	5.61
W_R			0.27	8.68			0.26	10.01
W_F					0.53	23.65	0.43	18.52
Reserves/GDP	-0.31	-2.50	-0.39	-3.40	-0.43	-3.85	-0.43	-3.97
Ext. Debt/GDP	0.27	6.16	0.41	10.30	0.26	6.63	0.27	6.75
Δ GDP	-4.74	-17.38	-3.96	-15.04	-4.35	-17.49	-3.98	-16.10
Δ CPI	6.71	12.22	7.14	13.87	6.01	11.93	6.13	12.50
FDI/GDP	-0.13	-0.59	-0.40	-1.98	-0.45	-2.24	-0.37	-1.90
FB/GDP	-5.36	-15.88	-4.90	-15.10	-4.16	-13.27	-3.60	-11.69
Observations	4640		4350		4350		4350	
Log-likelihood	124.58		390.73		494.54		563.25	
Akaike crit.	170.84		-361.46		-569.08		-702.5	

Notes: Estimates include country- and time-fixed effects. The model is estimated with data from December 2007 to December 2019. Estimation period for the interdependence matrices: January 2000 - November 2007. The dependent variable corresponds to the five-year sovereign credit default swap spread, expressed as the log of its basis points. To compute W_I, we use the correlation (between countries) of analysts' GDP one-year-forecast errors, which are de-factored. To compute W_R, trade intensity data is instrumented for the possibility of trade being endogenous using gravity variables (e.g. common language, common borders and preferential trade agreements, among others). To compute W_F, financial interdependence data are based on an index of common investors. All the interdependence matrices are row-normalized, allowing for varying degrees of intensity of the significant connections. To avoid any endogeneity issue between the three sources of interdependence, we adopt a Gram-Schmidt orthogonalization procedure for the informational, real and financial matrices of interdependence. We also include common shocks related to market volatility that control for the impact of global factors on CDS spreads. We also account for the impact of country-specific variables, which are all lagged by one period and explained in Table 1.

informational, the real or the financial channel, respectively. Column 7 exhibits the estimates of the complete model (i.e., the baseline specification). Here, the parameter of interest is ρ_I, which measures the strength of the informational linkages.

The last two columns of Table 2 reflect one of the main results of the paper as they show that informational linkages are positive and strongly significant for the CDS spreads, after accounting for the real and financial channels of interdependence. It is important to notice that informational linkages are significant, even after controlling for endogeneity issues through an instrumental variable methodology, avoiding simultaneity between CDS spreads and the interdependence matrices (which are calculated prior to the period of analysis) and cleaning the influence of cross-sectional dependence on GDP forecast errors through the de-factoring process (see equation (17)), among other procedures used to mitigate endogeneity concerns, as described in previous sections.

The last two columns of Table 2 show that the average strength of informational interdependence is 0.21. In terms of economic significance, a one-standard-deviation shock in a given country i induces, on average, a 9.4% change in the mean CDS spread of an informationally connected country $j \neq i$.[18] This means that a negative shock in a given country i not only negatively affects the economy of that country, but also other countries which may be informationally linked to country i.[19]

The positive cross-sectional linkages in CDS spreads due to the informational channel that we document in Table 2 are consistent with the empirical implication we developed using the motivating learning model (see Section 2.3), where we explained that agents' over-reliance on common factors leads to an abnormal positive interdependence of agents' beliefs.

4.2. Robustness checks

To analyze the robustness of our results, we perform a battery of checks. These robustness checks are described in the following paragraphs, and the results are presented in Section D of the internet appendix.

First, although informational linkages should appear last in the sequential Gram-Schmidt orthogonalization procedure (as explained in Section 3.1), there is some flexibility in the ordering of the fundamental real and financial links. To account for this, we implement an alternative ordering as a robustness check. In this alternative approach, we first regress the real links on the financial links. Next, we regress the informational links on the financial links and the residuals from the previous regression (which capture the real links orthogonal to the financial links). The residuals from this second regression provide an alternative measure of informational links, again orthogonal to both the fundamental real and financial links. The results obtained from this robustness exercise, reported in Table D1, are qualitatively similar to those presented in the main analysis.

[18] Section E of the Internet Appendix details the calculation of the economic significance for parameters in spatial econometric models, with results normalized by the mean CDS spread.

[19] Moreover, the informational channel, with a value of 0.21, is of a similar order of magnitude to the fundamental real linkages, which have a value of 0.26. One possible explanation may relate to learning frictions faced by investors, which tend to reinforce informational linkages. For instance, analysts often rely on shared information to fill in missing monthly country-specific data when producing GDP forecasts, thereby creating informational connections. This potential explanation will be further developed in Section 4.2.

Second, we conduct a placebo test in which the real and financial linkages remain unchanged, while the informational linkages are assumed not to exist, following the approach of Bailey et al. (2016a). Specifically, in this placebo test, we assign random values to the informational links within the interdependence matrix, while keeping the real and financial matrices intact. Thus, instead of computing the (de-factored) pairwise correlation of GDP forecast errors between countries (using equation (18)), we substitute the informational link values with random numbers drawn from a uniform distribution with support $[-1, 1]$.

In this placebo test, if the strength of the informational channel remained significant after randomization, it would indicate that the effects attributed to the informational channel might, in fact, stem from other factors, such as spurious correlations related to the real or financial channels. Conversely, if the strength of the informational channel were no longer significant after randomization, this would reinforce the robustness of the informational linkage. Table D2 in the internet appendix presents the results of this placebo test. This table shows that the strength of the informational interdependence is no longer significant in the placebo test, suggesting that the informational links are unlikely to be driven by other unobserved factors, including potential spurious links arising from real or financial connections.

Third, we re-estimate the same baseline model specification as in the last two columns of Table 2, but this time we allow the informational interdependence matrix to change over time. Specifically, we dynamically compute the informational interdependence matrix using a rolling window of three years, lagged by one year, when estimating the spatial econometric model in equation (20). We report the results of this robustness check in the first two columns of Table D3.

This third robustness check yields qualitatively similar results to those reported earlier in our study, in the sense that the informational linkages remain positive and significant for CDS spreads. However, the strength of these informational linkages decreases when the informational interdependence matrix is allowed to vary over time. This reduction possibly reflects the impact of major crisis episodes during our analysis period, namely, the global financial crisis and the European sovereign debt crisis. We expect that the production and learning of country-specific information intensifies during periods of stress, as distinguishing among countries becomes increasingly important (Gorton and Ordoñez, 2014, 2020). Consequently, informational interdependence among countries should diminish. This is likely to happen because agents will likely perceive there are greater economic gains to be had from acquiring new country-specific information—rather than relying solely on signals tied to common factors—during stressful periods. Indeed, investment mistakes arising from inadequate country-specific knowledge can lead to larger economic losses during crises compared to tranquil times. Consistent with this reasoning, we demonstrate in the next section that the informational channel weakens in periods of economic stress relative to normal times.

Fourth, we modify the sparsity levels of the interdependence matrices by considering an alternative threshold above which a linkage between two countries is deemed significant for a given source of interdependence. Specifically, we use $p = 0.10$ instead of $p = 0.01$ for each pair of countries across each of the three interdependence matrices (see equation (19), applied separately for each interdependence channel). The last two columns of Table D3 in the internet appendix report the results of this additional analysis. Estimates show that our main findings continue to hold, although the strength of the informational linkages decreases. This reduction can be explained by the additional noise resulting from the inclusion of weaker informational connections, as we relax the criterion for identifying potential informational links between countries.

Fifth, we construct informational links using forecast errors from an alternative set of analysts' projections. Specifically, instead of computing correlations across countries based on the root mean squared error (RMSE) of one-year-ahead GDP forecasts, as defined in equation (16), we use the correlation of one-year-ahead consumer price index (CPI) forecast errors. The use of GDP forecasts and corresponding GDP forecast errors, which underpins the baseline measure of informational links explained in Section 3.1, is primarily motivated by superior data quality. During the sample period used to quantify informational links, the average share of missing country-month observations is 13.6% for GDP forecasts, compared with 23.6% for CPI forecasts.

Despite the greater incidence of missing observations in CPI forecasts, we construct the alternative informational linkage measure using the RMSE of one-year-ahead CPI forecasts. The measurement unit for the one-year-ahead CPI forecasts for each country is the percentage change in the CPI relative to its value from the previous calendar year. The first two columns of Table D4 report the results. The outcomes are qualitatively similar to the baseline estimates: informational linkages remain positive and strongly significant when using CPI forecasts, reinforcing the robustness of our findings.[20]

Sixth, as additional robustness checks, we recalculate the informational channel matrix using correlations based on five alternative error measures and then re-run the baseline specification (equation (20)). Precisely, we replace the root mean squared error of the one-year-ahead GDP forecast (as shown in equation (16)), with five alternative measures. First, we use the quantile-based dispersion ($QUANT$) of the one-year-ahead GDP forecast, which reduces sensitivity to skewness from outliers; the results for this specification appear in columns 3–4 of Table D4. Second, we employ the root winsorized mean squared error ($RootSqErr_{Win}$) of the one-year-ahead GDP forecast, which is less sensitive to extreme values; columns 1–2 of Table D5 show the results. Third, we use the root median squared error ($RootSqErr_{Med}$) of the one-year-ahead GDP forecast, another measure robust to outliers, as reported in columns 3–4 of Table D5. Fourth, we apply the mean absolute error (MAE) of the one-year-ahead GDP forecast, with corresponding results in columns 1–2 of Table D6. Fifth, we use the dispersion ($DISP$) of the one-year-ahead GDP forecast, whose outcomes are presented in columns 3–4 of Table D6. Across all five specifications, the results are qualitatively consistent with those of the main analysis, further supporting the robustness of the informational channel.

[20] Alternatively, we considered using the RMSE of one-year-ahead unemployment forecasts to compute correlations, following the same procedure, used in Table D4. However, we did not pursue this robustness check because only 13 out of the 30 countries analyzed in our study consistently reported unemployment forecasts during the sample period used to quantify informational links.

Seventh, as described in Section 3.1, we use monthly data to measure informational links. However, analysts might not always have timely access to all country-specific monthly data because, for example, some macroeconomic variables are released on a quarterly basis in certain countries. As a result, analysts may rely on common information to fill in missing monthly country-specific data when preparing their *monthly* GDP forecasts, thus creating informational links (as explained in the motivating framework in Section 2). To assess this possibility, as a robustness check, we use quarterly rather than monthly data to measure informational links and re-run the baseline specification (see equation (20))

Intuitively, if informational links were measured using quarterly data, we would expect to observe weaker links. The reason is that analysts would have more timely access to country-specific data at the quarterly frequency, reducing their reliance on common information to fill gaps. The first two columns of Table D7 in the internet appendix present the results of this robustness check. Indeed, results show weaker informational linkages when using quarterly data, consistent with our previous arguments. Interestingly, the fundamental real and financial linkages remain largely unchanged when comparing the last two columns of Table 2 with the first two columns of Table D7.

Consequently, a potential explanation for the similarity in the magnitudes of the coefficients for informational linkages (0.21) and real linkages (0.26), as reported in Table 2, could be related to investors' learning frictions, which give rise to informational linkages—for instance, when analysts do not have timely access to comprehensive monthly country-specific information, and they may rely on common information to fill these gaps when producing monthly GDP forecasts.

Most importantly, the results in the first two columns of Table D7 further support the empirical implications derived from the stylized learning model. Specifically, the model suggests that agents' excessive reliance on common factors generates abnormally strong positive interdependence in their beliefs. Nevertheless, it is noteworthy that the informational linkages remain positive and statistically significant even when quarterly data are used.

Eighth, as explained in Section 3.1, we quantify informational linkages between country pairs by examining whether their monthly GDP forecast errors exhibit abnormal contemporaneous correlations. This rests on the assumption that informational linkages operate contemporaneously (on a monthly basis). However, informational linkages may not always be contemporaneous due to differences in forecast deadlines, publication schedules or other country-specific factors that can introduce delays in the transmission of information. To account for this possibility, we consider the potential for a lagged structure in informational linkages. As a robustness check, we modify our baseline approach and, instead of applying equation (18) to compute the de-factored pairwise correlation of GDP forecast errors, we introduce the following lagged correlation structure designed to capture the potential delayed transmission of information across countries:

$$\widehat{\epsilon}^*_{I,i:j} = \frac{\sum_{t=2}^{T}(\xi_{DFact,i,t} - \bar{\xi}_{DFact,i})(\xi_{DFact,j,t-1} - \bar{\xi}_{DFact,j})}{\sqrt{\sum_{t=2}^{T}(\xi_{DFact,i,t} - \bar{\xi}_{DFact,i})^2 \sum_{t=2}^{T}(\xi_{DFact,j,t-1} - \bar{\xi}_{DFact,j})^2}}.$$

The last two columns of Table D7 in the internet appendix present the estimates. The table shows that our key results remain valid, although the strength of informational connections weakens slightly. This finding suggests that informational interdependence primarily involves contemporaneous transmission. Additionally, in an unreported analysis available from the authors upon request, we examine whether the decreased strength in lagged informational effects is more pronounced during crisis periods or primarily observed among emerging-country pairs rather than advanced-country pairs. This unreported analysis indicates that the reduction in the strength of lagged informational effects is similar between crisis and tranquil periods. Furthermore, the decline in informational connection strength is more pronounced among emerging-country pairs compared to advanced-country pairs.

Finally, as additional robustness checks, we consider alternative proxies for the real channel of interdependence, in unreported results, which are available upon request. Specifically, instead of relying on the share of bilateral exports and imports over the total GDP (of the two countries), we alternatively use (i) the fraction of bilateral exports only, over the total GDP of the two countries, (ii) bilateral exports and imports over the total trade of the two countries, (iii) bilateral exports and imports over the GDP of one of the two countries and (iv) current account over GDP. In the latter case, we compute the pairwise correlation of current account over GDP and apply the same multiple testing procedure that we use for the informational interdependence channel (as, in this case, we are also using the pairwise correlation), to determine which countries are linked in real terms.

Furthermore, as an alternative way of measuring financial interdependence, we follow Kaminsky and Reinhart (2000); Caramazza et al. (2004) and examine the role of common creditors, given that countries may suffer financial interdependence due to portfolio adjustments made by the major lender to a country early on in a crisis. Specifically, we follow Caramazza et al. (2004) and measure the financial linkages of each country with a common creditor, in terms of being highly indebted to them and highly represented in their portfolio. To implement the common creditor measure, we rely on data on cross-border bank flows from the international locational banking statistics (LBS) of the Bank of International Settlements. The results of these unreported robustness checks are qualitatively no different from the results presented in Table 2.

5. Validity analysis

The main objective of our study is to propose a novel measure of informational interdependence, which is used to empirically examine the informational economic transmission. Therefore, a natural question comes up: How do we know that this measure effectively captures informational links? In spite of the fact that our measure of informational linkages is based on a stylized model under frictions in the agent's learning process, we cannot offer a definite answer to this question. This is because learning dynamics and agents' information sets are not directly observable.

Table 3
Validity analysis.

Variable	Model extension	T-stat.	Model extension	T-stat.	Model extension	T-stat.
W_I	0.24	6.49	0.09	2.06	0.21	6.21
W_R	0.26	9.99	0.27	11.01	0.16	5.49
W_F	0.43	18.53	0.38	15.61	0.38	15.90
$W_I * Crisis$	-0.03	-3.28				
W_I^{EME}			0.17	2.19		
W_I^{ADV}			0.22	4.56		
W_A					0.28	6.29
Reserves/GDP	-0.35	-3.15	-0.40	-3.60	-0.16	-1.50
Ext. Debt/GDP	0.25	6.24	0.24	5.96	0.21	5.44
Δ GDP	-4.03	-16.29	-4.02	-16.27	-3.99	-16.22
Δ CPI	6.12	12.47	6.24	12.76	6.15	12.68
FDI/GDP	-0.34	-1.74	-0.30	-1.54	-0.16	-0.85
FB/GDP	-3.70	-11.97	-3.62	-11.56	-3.32	-10.91
Observations	4350		4350		4350	
Log-likelihood	534.64		576.77		632.06	
Akaike Crit.	-641.28		-725.54		-838.11	

This table reports three model extensions of the baseline specification (see equation (20)) reported in the last two columns of Table 2. These model extensions are used in the validity analysis of the measure of informational interdependence, as described in Section 5.

To indirectly address this question, we develop a set of hypotheses to investigate the behavior of our proposed measure of informational links under different scenarios, which we subsequently test using financial and economic data. These hypotheses rely on previous literature offering potential explanations for the *existence* of the informational channel of interdependence. Such analysis can provide some insights into whether our proposed measure is able to capture informational linkages by generating results that are consistent with actual economic transmission dynamics.

Our first hypothesis is based on previous work highlighting that learning costs incentivize agents to follow common factors rather than learning country-specific information (Calvo and Mendoza, 2000). However, during crisis periods, the production and learning of new country-specific information are expected to increase, as distinguishing between countries becomes more crucial (see Gorton and Ordoñez, 2014, 2020). This is because mistakes in investment decisions (due to a lack of country-specific information) are likely to lead to larger economic losses during crisis times (compared to tranquil times). As a result, agents' reliance on common signals should go down during periods of stress.[21]

Hypothesis 1. *The strength of the information links should be smaller during periods of stress.*

We test Hypothesis 1 in the first two columns of Table 3, where we extend the baseline specification (see equation (20)) reported in the last two columns of Table 2. In this model extension, we interact the informational interdependence matrix with a dummy variable, $Crisis$, that takes the value one during the crisis period, encompassing both the subprime and European sovereign debt crises (i.e. from December 2007 to April 2013).

In line with this first hypothesis, the first two columns of Table 3 show that the strength of the informational channel of interdependence decreases in the crisis period. The parameter associated with the interaction term $\mathbf{W}_I * Crisis$ is significant, with a value of -0.03. In terms of economic significance, this implies that a one-standard-deviation shock in a given country i induces, on average, a 1.6% reduction in the mean CDS spread of an informationally connected country $j \neq i$ during periods of stress.[22] As explained above, this result can be interpreted by changes in investors' perceptions regarding the benefits of improving the process of learning country-specific information during crises (relative to calm periods).

It is important to note that, despite the strength of informational links decreasing during crisis periods, these links remain positive and strongly significant (i.e. $0.24 - 0.03 > 0$). Thus, our study supports previous empirical literature that provides evidence of informational linkages during periods of stress, such as Kaminsky and Schmukler (1999) during the Asian crisis (in 1997 and 1998), Basu (2002) during the Hong Kong crisis (in 1997), and Bekaert et al. (2014) during the global financial crisis (between 2007 and 2009).

As a robustness check, in Table D8 of the internet appendix, we conduct two additional analyses. In columns 1–2 of Table D8, we use an alternative definition of the dummy variable $Crisis$, which takes the value one when the monthly average of the VIX falls in the upper quartile of the sample distribution. The results from this robustness check are qualitatively similar to those reported in the first two columns of Table 3.

[21] The additional production of country-specific information in stressed periods can additionally be triggered by the fact that investors have a behavioral bias in that they assign more importance to negative news than positive (e.g. Kuhnen, 2015). This bias enhances the value of information. Therefore, a crisis in one country serves as a signal (i.e. a 'wake-up call') to investors in other countries, inducing them to produce more information about these economies (e.g. Ahnert and Bertsch, 2020).

[22] Section E in the internet appendix explains how to calculate the economic significance of spatial econometric parameters, with values normalized by the mean CDS spread.

Additionally, in columns 3–4 of Table D8, we estimate an alternative extension of the baseline specification (see equation (20)). In this extension, we interact the three interdependence matrices —reflecting informational, real and financial links—with the $Crisis$ dummy variable, as defined in Table 3. Again, the results are qualitatively similar to those presented in the main analysis. Notably, this robustness check shows that real links significantly strengthen during crisis periods, while financial links marginally weaken in such times (and this is only significant at the 10% level). The finding that real links increase significantly during crises is consistent with Forbes and Rigobon (2002), who shows that fundamental contagion tends to intensify during periods of stress. This is because, as argued in our first hypothesis, the production and learning of information regarding fundamental channels of interdependence are likely to increase during crisis periods. Specifically, investment mistakes stemming from insufficient knowledge of these fundamental links (in this case, real links) can lead to greater economic losses during crises than during tranquil times.

The second hypothesis is grounded on the literature emphasizing agents' limited attention capacity (e.g. Mondria and Quintana-Domeque, 2013; Kacperczyk et al., 2016), which in turn should induce agents to learn in terms of groups of *apparently* similar countries (i.e. 'category learning', as in Barberis and Shleifer, 2003; Ashby and Maddox, 2005; Peng and Xiong, 2006).[23]

Hypothesis 2. *The informational links should be stronger between countries that are part of a group of apparently similar economies, than between countries that belong to dissimilar groups.*

We test this second hypothesis in columns 3 and 4 of Table 3. In these columns, we extend the baseline specification in equation (20) to incorporate the marginal effects of informational linkages, when two countries are part of either the group of emerging economies (EME) or the group of advanced countries (ADV). The model specification becomes:

$$\mathbf{y}_t = \rho_I \mathbf{W}_I \mathbf{y}_t + \rho_I^{EME} \mathbf{W}_I^{EME} \mathbf{y}_t + \rho_I^{ADV} \mathbf{W}_I^{ADV} \mathbf{y}_t + \rho_R \mathbf{W}_R \mathbf{y}_t + \rho_F \mathbf{W}_F \mathbf{y}_t + \gamma g_{t-1} + \mathbf{X}_{t-1} \boldsymbol{\beta} + \boldsymbol{\mu} + \delta_t + \mathbf{v}_t, \tag{21}$$

where $\mathbf{W}_I^{EME}$ and $\mathbf{W}_I^{ADV}$ are the information interdependence matrices for the pairs of emerging economies and pairs of advanced countries, respectively. Let $w_{I,i:j}^{EME}$ be an element of $\mathbf{W}_I^{EME}$. Thus, $w_{I,i:j}^{EME} = w_{I,i:j}$ if i and j are both emerging economies (where $w_{I,i:j}$ is an element of $\mathbf{W}_I$, as described in Section 3.1); otherwise $w_{I,i:j}^{EME} = 0$. Similarly, let $w_{I,i:j}^{ADV}$ be an element of $\mathbf{W}_I^{ADV}$. Then $w_{I,i:j}^{ADV} = w_{I,i:j}$ if i and j are both advanced countries; otherwise $w_{I,i:j}^{ADV} = 0$.

The parameters ρ_I^{EME} and ρ_I^{ADV} in equation (21) capture the marginal effect of informational linkages when a pair of countries are part of the same group (i.e. emerging economies or advanced countries). Columns 3 and 4 of Table 3 present the estimates of this model extension.

Columns 3 and 4 of Table 3 show that the informational interdependence is stronger within each group (i.e., within the group of emerging economies and within the group of advanced countries), than in the baseline model (see Table 2), which is consistent with hypothesis 2. For instance, in column 3 of Table 3, the informational interdependence between countries within the group of advanced economies has an estimated parameter of 0.31 (i.e. $0.09 + 0.22 = 0.31$), while the parameter measuring the strength of the informational interdependence is 0.21 in column 7 of Table 2. In terms of economic significance, a one-standard-deviation shock in a given country i within the group of emerging (advanced) economies induces, on average, an 11.7% (a 13.9%) change in the mean CDS spread of an informationally connected country $j \neq i$ within the group of economies.

Our third hypothesis relates to the potential impact of common analysts on our proposed measure of informational interdependence. Specifically, the informational links captured by our proposed measure may be contaminated (or driven) by the presence of common analysts reporting GDP forecasts. This is because analysts' forecasts may be biased due to conflicts of interest, such as career concerns, and the varying amount of information available in each country, which becomes particularly relevant when common analysts are present.

While we acknowledge the importance of the potential bias induced by common analysts, it is important to note four key points. First, by using the *errors* in GDP forecasts, rather than the forecasts themselves, concerns regarding such biases should be mitigated. Second, analysts' forecast errors are de-factored to alleviate potential biases arising from analyst consensus induced by career concerns, which can be significant when there are common analysts. Third, our metric for the informational channel relies on the *correlation* of GDP forecast errors rather than on the analysts' forecasts, further diminishing such bias concern. Fourth, in cases where the information available in two countries varies significantly, the correlation between forecast errors should diminish instead of increasing. Therefore, we argue that our empirical strategy allows us to clean our estimates from potential biases due to common analysts. Hence, we hypothesize the following:

Hypothesis 3. *The proposed measure of informational interdependence is not affected by common analysts producing simultaneous economic forecasts for diverse economies.*

We test this third hypothesis by extending the baseline specification in equation (20) to include the influence of common analysts providing economic forecasts about countries' GDP. This model extension is reflected in the following equation:

[23] Agents' learning propensity of focusing on groups of similar countries can also be explained by the concept of 'specialized learning' behavior (as in Van Nieuwerburgh and Veldkamp, 2010). Thus, agents might choose to acquire information about common factors that characterize groups of related countries rather than investing in learning country-specific information.

Table 4
Impact of a unit increase in country-specific variables.

	Res./GDP	Ext. Debt/GDP	Δ GDP	Δ CPI	FDI/GDP	FB/GDP
Direct	-0.55	0.31	-4.74	7.33	-0.45	-4.31
	(0.02)	(0.01)	(0.03)	(0.04)	(0.00)	(0.02)
Indirect	-1.25	0.77	-12.06	18.64	-1.12	-10.96
	(0.12)	(0.06)	(0.69)	(1.05)	(0.07)	(0.62)
Total	-1.81	1.08	-16.80	25.97	-1.57	-15.27
	(0.13)	(0.06)	(0.72)	(1.08)	(0.07)	(0.64)

Notes: Estimates correspond to the average marginal effects of a unit increase in the corresponding domestic (country-specific) variables of a given country i on itself (direct effect) and the average of the effects on other countries $j \neq i$ (indirect effects). Standard errors are in parentheses; they are obtained from 1000 simulated coefficients drawn from the multivariate normal distribution implied by the estimated variance-covariance matrix obtained from the estimates in the last two columns of Table 2.

$$\mathbf{y}_t = \rho_I \mathbf{W}_I \mathbf{y}_t + \rho_A \mathbf{W}_A \mathbf{y}_t + \rho_R \mathbf{W}_R \mathbf{y}_t + \rho_F \mathbf{W}_F \mathbf{y}_t + \gamma g_{t-1} + \mathbf{X}_{t-1}\boldsymbol{\beta} + \boldsymbol{\mu} + \delta_t + \mathbf{v}_t. \tag{22}$$

Here $\mathbf{W}_A$ is a new interdependence matrix that reflects the connection between countries due to *common* analysts providing GDP forecasts. We construct $\mathbf{W}_A$ by using the same periods as for the other interdependence matrices ($\mathbf{W}_I$, $\mathbf{W}_R$ and $\mathbf{W}_F$). We calculate *per* month for the pair of countries (i, j) the following ratio $q(i, j)$: the number of common analysts that countries (i, j) share divided by the total number of analysts in country i.[24] Let $w_{A,i:j}$ be an element of $\mathbf{W}_A$. Then, $w_{A,i:j} = 1$ if the monthly average of $q(i, j)$, $\bar{q}(i, j)$, is in the upper quartile; otherwise $w_{A,i:j} = 0$. Therefore, $w_{A,i:j}$ is a dummy variable that reflects whether country i has, on average, a high proportion of analysts that are also providing GDP forecasts for country j.

Columns 5 and 6 of Table 3 present the estimates of the model extension described in equation (22). The parameter associated with $\mathbf{W}_A$, which captures the average strength of connections between countries due to *common* analysts, is 0.28. In terms of economic significance, a one-standard-deviation shock in a given country i induces, on average, a 15.0% change in the mean CDS spread of a country $j \neq i$ that is connected through common analysts.

Most importantly, column 5 shows that the informational interdependence has an estimated parameter of 0.21 when we include $\mathbf{W}_A$, capturing the connection between countries due to *common* analysts providing GDP forecasts. The value of 0.21 for the informational interdependence in column 5 is the same as the estimated parameter for the informational interdependence in column 7 of Table 2, where we did not include $\mathbf{W}_A$. This means that the strength of informational linkages does not change when we control for common analysts, confirming Hypothesis 3.

To ensure the robustness of our results, we perform an additional analysis related to common analysts, reported in Table D8 of the internet appendix. In columns 5–6 of Table D8, we extend the baseline specification in equation (20) by incorporating the influence of common analysts providing GDP forecasts for countries, similarly to the last two columns of Table 3. However, unlike in Table 3, we construct $\mathbf{W_A}$ by calculating, for each month and country pair (i, j), the ratio $q^A(i, j)$ as follows: the number of analysts common to both countries (i, j) divided by the geometric mean of the total number of analysts covering country i and the total number covering country j. We use the geometric mean in the denominator of this ratio to follow the same logic as in the calculation of the correlation between two variables (i.e., $Corr(x, y) = Cov(x, y)/(\sigma_x \sigma_y)$), since the informational links are based on the correlation of forecast errors. We then set $w_{A,i:j} = 1$ if the monthly average of $q^A(i, j)$, denoted by $\bar{q}^A(i, j)$, is in the upper quartile; otherwise, we set $w_{A,i:j} = 0$. The results of this robustness check are consistent in both direction and significance with those presented in the main analysis.

6. Marginal direct and indirect effects, and amplifications through spillovers

6.1. Direct and indirect effects of transmission due to domestic economic shocks

We now compute the direct and indirect effects of shocks on each of the domestic variables used in our empirical model in equation (20). A direct effect corresponds to the impact of a change in country i in one domestic variable (i.e., one of the country-specific economic variables in the matrix $\mathbf{X}_{t-1}$) on the CDS spread of the same country i. In contrast, an indirect (or spillover) effect comprises the impact of a change in one domestic variable of country i on the CDS spreads of other countries. Section F in the internet appendix provides the details of the computations.

Table 4 presents the marginal effects of the country-specific macroeconomic variables, based on the estimates from the last two columns of Table 2. Specifically, Table 4 reports the average direct marginal effects, the average indirect marginal effects, and the average total marginal effects for each domestic variable k. The standard errors of the marginal effects are obtained through a simulation approach, using the empirical distribution of the parameter estimates.

Table 4 shows that all marginal effects have the expected signs. Regarding both the direct marginal effects and the indirect marginal effects, we observe an increase (reduction) in the CDS spreads when there is an increase in foreign debt and inflation (reserves, GDP,

[24] Consequently, $q(i, j)$ and $q(j, i)$ are not equivalent as they have different denominators.

Table 5
Indirect effect of a simultaneous shock to all countries in the respective group.

	Impact of a shock to:	
	Emerging economies	Advanced economies
Emerging economies	0.68	0.39
	(0.02)	(0.03)
Advanced economies	0.27	0.66
	(0.02)	(0.02)

Notes: Estimates correspond to the average marginal indirect effects of a standard-deviation exogenous shock ε to a given country i on other countries $j \neq i$. Each column considers simultaneous exogenous shocks to all the countries in the corresponding category. Standard errors are in parentheses; they are obtained from 1000 simulated coefficients drawn from the multivariate normal distribution implied by the estimated variance-covariance matrix obtained from the estimates in the last two columns of Table 2.

FDI and fiscal balance). Most interestingly, we observe in Table 4 that the indirect effects have larger magnitudes than the direct effects due to changes in the domestic variables. This last result is important because it quantifies the extent to which each country is not only economically affected by its own local shocks but also by the economic transmission of shocks that occur in other economies.

6.2. Economic transmission of shocks in the CDS spreads

A related interesting question is the assessment of the impact that an idiosyncratic exogenous shock to the CDS spread of one country, or a group of countries, may have on the CDS spreads of other economies. Thus, we perform a simulation analysis to examine such economic interdependence between countries, which is based on our econometric model, described in equation (20).

It is important to note that, as explained in our specification given in equation (20), the CDS spread of country i (on the left-hand side of the equation) cannot be explained by the CDS spread of the same country i (on the right-hand side of the equation). Therefore, we analyze shocks to the CDS spread of a given country in terms of their *indirect* impacts on the CDS spreads of other countries.

Table 5 illustrates the average marginal indirect impacts of simultaneous one-standard-deviation shocks to the CDS spreads of all the countries that are part of either the group of emerging economies or the group of advanced countries. In this table, we also distinguish between shocks to CDS spreads in emerging and advanced economies, and we report the average marginal indirect impacts on other countries belonging to either group. For the computations, we rely on the model estimates from the last two columns of Table 2. Table 5 shows that the indirect impacts of shocks to CDS spreads are significant between countries that belong to the same country group, as well as between those that belong to different country groups.

Finally, in the internet appendix, Section G, we present a model application where we analyze the economic interdependence among CDS spreads given an idiosyncratic, exogenous shock to the CDS spreads in one country. Specifically, we examine the effects of a CDS spread shock to Ukraine on the world economy. Interestingly, we find that the shock induced by the Ukrainian revolution affected unlinked (to Ukraine) countries, due to higher-order transmission effects. Given the current Ukrainian war (starting in February 2022), this exercise is appealing because, by identifying the countries that were most sensitive to Ukraine in the past, we can infer which countries are likely to transmit the shock of the ongoing Ukrainian war to the world economy in the future.

7. Final remarks

We propose a novel measure of informational interdependence: the correlation between analysts' forecast errors regarding countries' one-year-ahead GDP, after controlling for the fundamental real and financial channels of interdependence. This measure is based on a stylized learning model, where informational links emerge when agents incorrectly assess the quality of new information regarding common factors that affect multiple countries simultaneously, due to learning frictions in agents' learning process. We present strong evidence that the informational linkages are important.

To conclude, it is important to notice that the methodological approach used in our paper is simple and intuitive. Most importantly, our study opens the door to a future research agenda on the impact of the informational channel of interdependence. For instance, interesting avenues for future studies include examining whether financial markets (or even assets) are informationally connected, after controlling for fundamental links, and analyzing bank runs that may be generated (or exacerbated) by informational linkages.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.red.2025.101302.

Data availability

I have made data available at the attach step

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