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ESTIMATING THE CONTAGION EFFECT THROUGH THE PORTFOLIO CHANNEL USING A NETWORK APPROACH

by Alessandro Schiavone*

Abstract

This work studies the contagion risk through the portfolio investment channel using network analysis and simulation on cross-country bilateral data. The importance of the portfolio channel in the transmission of financial shocks reflects the high interconnectedness of the global financial system, which diminished in the aftermath of the global financial crisis, but has resumed in recent years. The network representing cross-country portfolio investments turns out to be highly concentrated around the main financial centres, which act as global hubs connecting nodes that are not directly linked. Using a network simulation model based on the assumption that international investors rebalance their portfolios after an idiosyncratic shock, reducing investments in countries they are overexposed to, we find that contagion effects may be significant even when the shock originates in a peripheral country. In addition, the model suggests contagion risk has risen since the global financial crisis, owing to the increasing centralization of the portfolio investment network and the greater financial integration of emerging economies.

JEL Classification: F21, F36, G01, G11.

Keywords: financial contagion, network analysis, portfolio investments.

Contents

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1. Introduction[1]

The global financial crisis has rekindled the debate on the potential benefits and risks of financial integration. The main arguments in this debate can be summarized as follows: on the one hand, financial liberalization brings benefits in terms of risk diversification, consumption smoothing and financing/investment opportunities; on the other hand, it entails enhanced risks for the stability of the international financial system stemming from the cross-border transmission of financial shocks.

In this paper we focus on the concept of contagion borrowed from epidemiology, which has been widely used since the late 'nineties to describe the mechanism of cross-border propagation of financial crises (Claessens and Forbes, 2001). Yet the definition of contagion is not straightforward as it overlaps with the concept of economic and financial interdependence. For example, Kaminsky and Reinhart (2000) refer to shock propagation as the result of the optimal response of economic agents to changes in countries' economic fundamentals; on the other hand, because of market imperfections, countries may be subject to 'pure contagion' effects even in the absence of changes in their economic fundamentals (Moser, 2003). There are two main mechanisms that help to explain pure contagion: first, because of information effects, when a country is hit by a financial crisis, investors tend to reassess the economic fundamentals of other economies and reduce their exposure to them (Goldstein, 1998). The second explanation refers to the existence of 'domino effects' that may occur when a crisis originating in one country spreads to others as a result of direct or indirect financial linkages.[2] Domino effects may be associated with 'cascading defaults' when losses spread across creditors via direct claims; this mechanism is used, for example, to simulate contagion in the interbank market (see Upper (2010) for a review of the literature on this kind of contagion). Another mechanism for pure contagion relates to portfolio rebalancing, when international investors affected by a crisis in one country unwind positions in other markets owing to capital and liquidity constraints (Schinasi, 2000).

After the global financial crisis, the focus on systemic risk prompted many researchers to use network analysis to describe the financial system and infer under what conditions an idiosyncratic shock could lead to large-scale disturbances. From a macro perspective, it is often assumed that the nodes of the network are the individual economies (or their respective financial systems), while the links stand for the financial inter-linkages across them. Adopting this framework, Minoiu and Reyes (2013) show that the interconnectedness of the global banking system increased during the period 1978-2010, and that it tends to diminish during international financial crises. They also find that the more an economy is interconnected with the rest of the network, the more it is exposed to financial shocks, suggesting that a negative relationship between integration and financial stability.

Another approach to assess the stability of financial networks is to estimate contagion effects using simulation models. Typically, under this approach, an idiosyncratic shock hitting one country causes the contagion to spread throughout the network, affecting the economies whose banking systems are less capitalized and more exposed to banks domiciled in the crisis country. According to Espinosa-Vega et al. (2010), this type of simulation model tends to underestimate contagion risk, which becomes significant only when the shock originates in a core economy, such as the United States or the United Kingdom (Degryse et al., 2010). They emphasize that, as occurred in the great financial crisis, when funding markets freeze, banks

[1] Thanks go to Nicola Branzoli, Pietro Catte, Valerio Nispi Landi, Francesco Paternò and Massimo Sbracia for their helpful comments and assistance with the data.

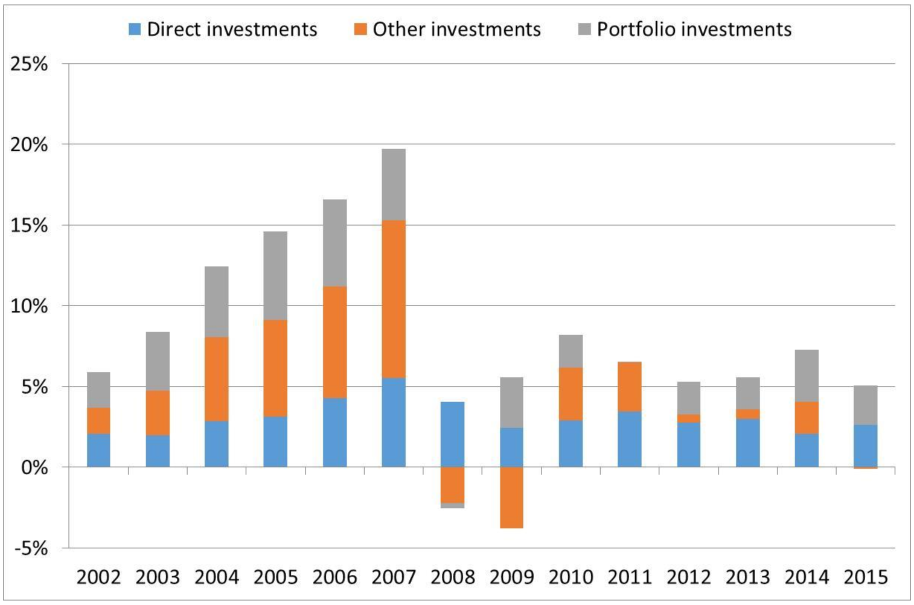
[2] Note that some authors (see Claessen and Forbes, 2001) consider domino effects due to direct financial linkages between economies, a particular mechanism of financial interdependence.

relying on short-term liabilities are forced to sell assets to obtain liquidity; if many banks do this, the ensuing large-scale assets may trigger a downward price spiral, further eroding banks' capital. Indeed, by using a more complex transmission mechanism that also takes into account the funding channel, they prove that contagion risks can be significant even when the crisis originates in a peripheral economy.

Most works relying on network simulation models have focused on financial linkages across the national banking systems for two main reasons: first, aggregate data broken down by country counterparties were available only for cross-border banking claims (source BIS); second, before the global financial crisis cross-border banking claims used to account for a large portion of capital movements. Both aspects now need to be reassessed: as regards the type of data required in network simulation, the survey on portfolio investments conducted by the International Monetary Fund (Coordinated Portfolio Investment Survey, CPIS) provides, at the country level, stock data broken down by country counterparties, and is increasingly used for research and analysis. As regards the composition of capital movements, after the global financial crisis, the share of portfolio investments increased while the 'other investment' component (which includes cross-border banking claims; see Chart 1) contracted. This reshuffle reflects the world-wide shift in financial resources from the banking sector to the asset management industry (IMF, 2015). Note that portfolio investments, in particular the debt component, are highly volatile, like cross-border banking claims; therefore, recipient countries continue to be exposed to the risk of 'sudden stops', with implications for the stability of their domestic financial systems.[3]

Chart 1 Breakdown of gross capital movements

(net acquisitions of financial assets as a percentage of aggregate GDP)



Source: Balance of payments statistics, IMF.

Taking into account the changes in the composition of capital movements, in this paper we aim to assess contagion risks through the channel of portfolio investments using a simulation model built on the concept of financial interdependence across economies. We assume that an idiosyncratic shock hitting an economy brings about a generalized fall in the prices of domestic financial assets; the investors that are overexposed to this economy will make losses (relatively more than other investors) and will subsequently rebalance their portfolios, reducing investments in the other countries they are overexposed to. Finally, we assume that if the reduction of portfolio investments into a given economy exceeds an appropriate threshold representing its

[3] See 'Dealing with large and volatile capital flows', IRC Task Force on IMF issues, *ECB Occasional Paper 180*, September 2016.

shock absorption capacity, then this economy will also be affected by contagion, and will itself contribute to the propagation of the crisis, reiterating the process of portfolio rebalancing.

The simulation is carried out using cross-country bilateral data on portfolio investments, assuming implicitly that each economy acts as a representative investor; as a consequence the results of the simulation could be biased as we do not take into account the heterogeneity between investors in a given country. Given this limitation, the objective of this paper is not to provide a new methodology for measuring systemic risk, rather to shed light on the portfolio channel in the transmission of financial shock, and assess whether it has become more important since the global financial crisis.

The outcomes of the simulation suggest that contagion effects depend crucially on the intensity of the portfolio rebalancing mechanism, which reflects international investors' risk aversion and their financial constraints. Following an idiosyncratic shock, global investors rebalance their portfolios, liquidating other investments and spreading contagion to third countries. One insight of our model is that, if global investors are affected by an idiosyncratic shock, contagion may spread even when the crisis originates in a peripheral country.

From a policy perspective, there are two main options to reduce contagion risk: first, recipient economies whose absorption capacity is limited in case of a sudden stop should make their financial markets more liquid and resilient to external shocks; second, regulators should aim to contain the risk of sudden stops, by reducing the intensity of the portfolio rebalancing mechanism. In this respect, taking into account the evolution of the global financial system and loopholes in financial regulation (see Signorini, 2016),[4] competent authorities should consider adopting measures targeted to specific types of global investors (e.g. those addressing the vulnerabilities of open-ended funds).

The structure of the paper is as follows: in Section 2 we review the literature on financial shock contagion, focusing on the relationship between financial integration and stability. In Section 3 we describe the evolution of the investment portfolio network. In Section 4 we illustrate the simulation model and in the final section we present the main outcomes.

2. A short review of the literature on financial shock contagion

There are several definitions of contagion in the literature on financial crises. According to Moser (2003) 'pure contagion' refers to situations in which financial shocks spread cross-border independently of fundamental factors (fundamental-spillover contagion) and in absence of common causes (common cause contagion). In theoretical models, pure contagion is often associated with market imperfections; for example, Calvo and Mendoza (1997) show that when information is costly financial integration can lead to herding phenomena, even if economic agents are rational. A financial crisis in one economy may also act as a wake-up call, leading international investors to reassess the fundamentals of other economies (Goldstein, 1998).

The importance of pure contagion mechanisms has been questioned from an empirical standpoint. According to Forbes and Rigobon (2002), who analyse co-movements in financial cross-country returns, spillover effects are driven by common economic factors. Other studies, which use data on quantities instead of prices, suggest that pure contagion phenomena are not rare. For example, Van Rijckeghem et al. (2000) point out that an important factor is the structure of the international banking system and the presence of common lenders, particularly for emerging economies; analysing aggregate cross-border banking claims, they find that during the crises in Mexico and Thailand, the countries most exposed to these economies reduced

[4] 'The financial landscape is changing apace. The growth of intermediaries outside the banking sector points to the need for new micro- and macro-prudential tools. Work has begun in this area but much remains to be done.' (Economic Challenges Facing Europe and the World, Università degli Studi di Torino, 19 December 2016).

positions in other economies as well. According to Kaminsky and Reinhart (2000), the presence of common lenders helps to explain why some countries are relatively more exposed to contagion risk; for instance, with regard to the Asian financial crisis, the idiosyncratic shock in Thailand spread to the economies (such as Malaysia) that relied more on Japanese banks, which were heavily overexposed to Thailand.

Kaminsky et al. (2004) empirically verify the process of portfolio rebalancing by analysing data on emerging markets funds; they find that during the crises in Mexico (1994), Thailand (1997) and Russia (1998), fund managers undertook 'contagion trading' by selling third countries' assets. Broner et al. (2006) develop a model of portfolio rebalancing, assuming that fund managers are remunerated on the basis of their performance against a benchmark. When a country is in crisis, the managers of the funds overexposed to it become more risk averse and reduce their investments in third countries they are also overexposed to. Financial interdependence across economies arises because they share international investors. To empirically verify the model the authors use microdata on emerging market mutual funds during the financial crises of the 'nineties. In addition, they compute an index of financial interdependence across economies, which accounts for common lenders and funding concentration, and find that this indicator performs well as a proxy for country contagion risk.

Galystan and Lane (2013), using aggregate data on portfolio investments after the global financial crisis, find evidence of a 'mean-reversion' mechanism in cross-border country bilateral positions, which is consistent with contagion literature; during the global financial crisis, investing countries disproportionally reduced their positions in countries they were overexposed to. The authors' findings suggest that the portfolio rebalancing mechanism also works at the aggregate level; this outcome continues to hold after controlling for variables relating to institutions, geography and cultural factors, which are used as determinants of bilateral investments in gravity equations (Portes and Rey, 2005).

Among the factors that can enhance contagion effects through the portfolio rebalancing mechanism, an issue that has received particular attention in the literature is institutional investors' financial constraints. Schinasi et al. (2000) develop a model of asset allocation and show that the effects of portfolio rebalancing after a 'capital event' (that is, when investors incur in losses due to an idiosyncratic shock) may be amplified if intermediaries are leveraged. According to Kaminsky et al. (2003), international investors play a crucial role in the propagation of financial crises; by analysing episodes of 'fast and furious' contagion during the eighties and nineties, such as devaluations or defaults triggering an immediate adverse chain reaction in other countries, the authors claim a common denominator is given by the presence of common leveraged creditors.

With regard to the role of mutual funds in contagion dynamics, particular attention has been paid to the mechanism of forced sales, i.e. when fund managers, fearing that end-investors will redeem their shares, liquidate assets causing spillover effects (Shleifer et al., 1997). Raddatz et al. (2011) find empirical evidence of contagion trading during the global financial crisis; using microdata on American mutual funds, they find that neither managers nor investors act counter-cyclically, trying to benefit from potential long-term arbitrage opportunities, and thus performing a stabilizing role. Instead, they seem to amplify crises and transmit shocks across countries, which is also consistent with the contagion literature.' Jotikasthira et al. (2012), using data on global funds domiciled in developed economies from 1996 to 2010, find that such funds substantially alter portfolio allocations in emerging markets in response to funding shocks in their investor base.

2.1 The contribution of network analysis

As mentioned above, the global financial system can be represented as a network in which the nodes are the economies and the links stand for their financial linkages. A crucial aspect of networks is their density (or interconnectedness), which can be computed as the number of existing links over all possible ones. Note that interconnectedness and interdependence are two different concepts and have different implications in terms of contagion risk; in fact, two economies that are not directly connected may be financially interdependent if they share common investors; conversely, they can be directly connected even in the absence of common investors.

The relationship between the density of the network and its stability has been discussed extensively in the literature. According to Allen et al. (2000), the more the financial system is interconnected, the more opportunities investors have to diversify portfolio risk, thus increasing the stability of the network. Glasserman et al. (2016) provide an extensive review of the literature mainly at micro level, arguing that one lesson we can draw is that the stability of the network is not determined uniquely by its structure per se; it also depends on the interaction with the characteristics of the financial intermediaries, such as their leverage, their reliance on short-term liabilities, their exposure to common risks and so on. For example, Nier et al. (2007) test the resilience of different banking networks to shocks and find that the relationship between the degree of interconnectedness and the stability of the networks is not monotone and hinges on the degree of heterogeneity across the nodes and the level of banks' capital. Gai et al. (2010) point out that financial networks share the properties of robust-yet-fragile structures; by simulating random shocks, they find that in most cases the high degree of interconnectedness observed in the interbank markets enables banks to diversify idiosyncratic risks. However, in the very few cases in which the contagion risk materializes, the probability of it spreading throughout the network is very high.

Among the first network analysis applications on aggregate data, Von Peter (2007), using BIS banking statistics for a sample of 40 countries, finds that the international banking system is strongly interconnected (i.e. each node is on average connected with 15 other nodes). Interestingly, there are only a few nodes acting as global hubs, which intermediate claims between the other nodes that are not directly connected. Minoiu and Reyes (2013) analyse the evolution of the international banking system from 1978 to 2010, finding that financial integration, measured by means of network centrality indicators, follows a pro-cyclical path, in line with the evolution of global capital movements. They also find that the probability of banking crises in each country is strongly correlated with centrality indicators, but they do not address the issue of causality between the interconnectedness of the network and its stability.

Cerutti et al. (2017) claim that the shrinkage of cross-border banking claims observed after the global financial crisis cannot be interpreted as a retreat in financial globalization. Using network indices computed using BIS banking statistics, they find that the degree of interconnectedness of the global banking network has not declined across the board; indeed, after the global financial crisis some European countries turn out to be less interconnected, whereas emerging economies now appear more financially integrated.

Unlike cross-border banking claims, network analysis has not been used extensively for analysing other types of capital movements, mostly owing to data constraints. Kubelec & Sa (2010) address this gap, using gravity equations to create a dataset covering different types of asset class (foreign direct investments, equity and debt) from 1980 to 2005 for a sample of 18 advanced economies. They find that the degree of interconnectedness of the network has increased for all types of capital movements; the network looks like robust-yet-fragile structures with a strong heterogeneity across nodes in terms of number of interconnections and a strong concentration around very few nodes.

In the last decade, researchers have started to apply network analysis to portfolio investments using the CPIS data. An IMF study[5] provides a description of the portfolio network, underlining the following aspects: i) advanced economies are considerably more interconnected than emerging economies; and ii) while

[5] 'Mapping Cross-Border Financial Linkages: A Supporting Case for Global Financial Safety Nets'. International Monetary Fund, 2011.

individual advanced economies tend to be interconnected with other nodes in both ways (on the investing and the borrowing sides), emerging economies tend mainly to borrow from advanced economies. It is also shown that during the global financial crisis the recession was more intense for economies with a strong concentration of funding sources (that is, very few countries investing in these economies); this outcome highlights the importance of the funding channel and suggests that the diversification of funding sources helps to mitigate the domestic impact of international financial crises.

Chinazzi et al. (2013) analyse the evolution of the portfolio investments network from 2001 to 2010 and find that the global financial crisis resulted in a decline in the network's density, but this effect was short-lived. They investigate whether the degree of financial integration of each country, measured by means of several network indices, affected the impact of the global financial crisis, finding that more interconnected countries suffered less in terms of output contraction as higher interconnectedness helped to dissipate adverse shocks.

One approach to estimating contagion effects using a network approach consists in simulating an idiosyncratic shock triggering domino effects through the financial linkages between the nodes. This approach has been used mainly to investigate the stability of the global banking network. For example, Degryse et al. (2010), using aggregated data on cross-border banking claims and taking into account the average level of capitalization of each banking system in the sample, find that a banking crisis in central nodes like the United States or the United Kingdom may cause a global crisis via the losses on bilateral claims (credit channel).

This approach has been examined closely by Espinosa-Vega et al. (2010), who claim that simulation models like those mentioned, which focus uniquely on the credit channel, are too simplistic and tend to underestimate the contagion risk. They develop an alternative simulation model allowing for funding shocks and fire sales. Using data on 18 countries at the end of 2007, and comparing the results of different models, they state that 'the addition of the funding channel raises the vulnerability of all banking systems significantly, and helps explain why numerous papers in the network literature — which focus only on credit events — have shown little contagion.'

Tressel (2010) adopts a similar set-up with funding shocks and fire sales, but instead of considering extreme events like a banking crisis in one country, he explores the adjustment mechanism following an aggregate shock, assuming that banks reduce the size of their balance sheets, selling foreign assets in order to keep the leverage ratio constant. The contraction in cross-border claims turns out to be a multiple of the original shock (about 5 times), a finding in line with the decrease in banks' foreign assets observed in the aftermath of the global financial crisis.

Čihák et al. (2011) use an algorithm to shape the global banking network in a flexible way, carrying out multiple simulations. They find that the relationship between the degree of interconnectedness of the network and the likelihood of contagion is not linear and exhibits an 'M' path: when the density of the network is low, the sign of the relationship is positive; it becomes ambiguous for intermediate degrees of interconnectedness and finally turns negative when the network is highly interconnected.

3. An application of network analysis

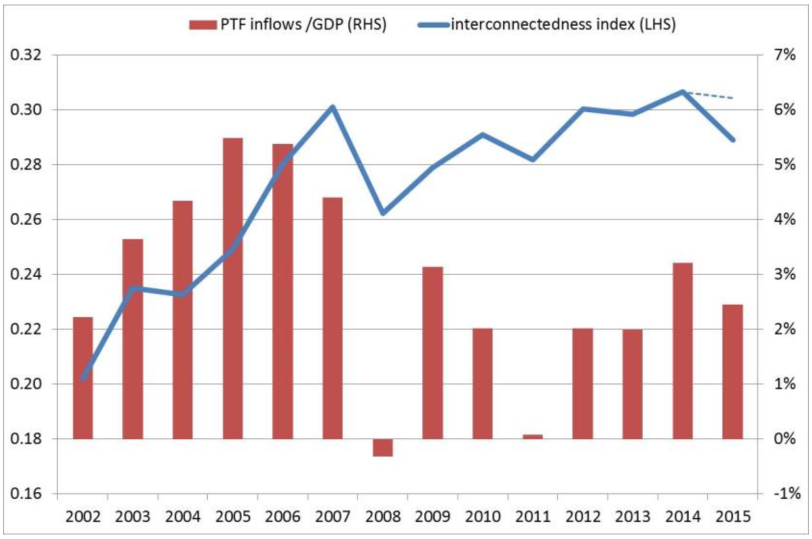
In this section we describe the evolution of the network of international portfolio investments from 2002 to 2015, analysing various indicators of centrality (see Annex A1) computed using bilateral data on portfolio investment stocks. Our sample comprises 50 reporting countries accounting for 83 per cent of the amount outstanding of aggregate portfolio investments reported in CPIS data.[6]

The main outcomes of our analysis are the following: i) the degree of interconnectedness, which had decreased significantly during the global financial crisis, has recently risen again and now hovers around the level recorded before the crisis; ii) the network has become more concentrated around the main financial centres;[7] and iii) these nodes act as global hubs, intermediating resources across the network and creating financial interdependence between economies that are not directly connected.

Our estimate of the interconnectedness index varies over time from 20 to 30 per cent (see Chart 2), a range of values coherent with other studies.[8] The density of the network increased until 2007, mirroring the trend of global portfolio investments; the index declined in 2008 and only in 2012 returned to the levels recorded before the crisis.[9] Overall, the density of the network of portfolio investments seems to follow a pro-cyclical path, a behaviour similar to that found by Minoiu and Reyes (2013) with regard to the international banking system.

Chart 2 Density of the international portfolio investment network(1)

(indices and net incurrence of liabilities as % of global GDP)



(1) The dashed line indicates the interconnected index for 2015 obtained keeping constant the out-degree index of Ireland with respect to the previous year (see footnote 9).

Source: IMF World Economic Outlook and calculations based on CPIS data.

Like Chinazzi et al. (2013), we find that the density of the global portfolio investment network, which diminished during the global financial crisis, has since recovered, suggesting that the effect of the crisis on financial integration was only temporary. Note that this pattern is not common across all types of capital movements; for cross-border banking claims, for example, Cerutti et al. (2017) find that, overall, the degree

[6] The number of reporting countries in the CPIS dataset varies over time, with an average of 70; our sample includes only countries that have regularly contributed to the survey.

[7] This outcome is driven in part by the fact that the data we use in this work are based on the residence principle. For a discussion of the implications for financial integration measures in global banking see McCauley et al. (2017).

[8] See, for example, IMF 2011.Their estimate of the interconnection index is 18 per cent for a sample of 56 countries and is obtained using a cut-off value of 0.2 per cent of the recipient‘s GDP. Our estimate refers to a smaller sample (50 countries) and is obtained by dropping observations relating to bilateral investments worth less than USD 1 bn.

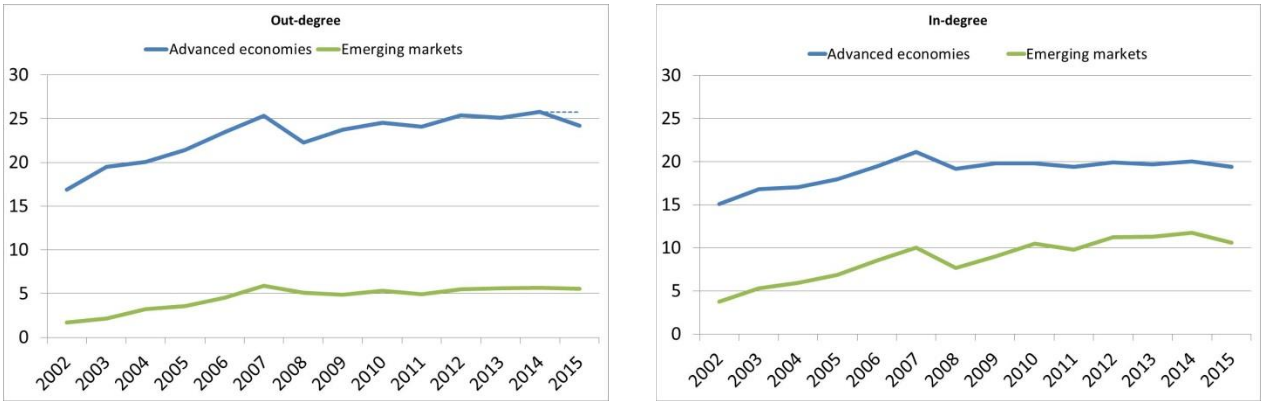
[9] Note that in 2015 Ireland had not contributed to the CPIS; as a consequence indicators using information on the out-degree for that year are biased downwards as Ireland notably represents an important financial centre.

of interconnectedness, which fell significantly during the global financial crisis, has recovered only to a limited extent.

We describe the network of portfolio investments using several indicators (see Annex A1 for a brief description) in order to shed light on different aspects of its structure. The density of the network is found to be heterogeneous across countries and regions (see Table 1a in the annex); for example, the in-degree indicator, that is, the number of other economies investing in a given country, is on average about twice as large for advanced economies as for emerging economies (see Chart 3); however it is also worth noting that on average these economies are more integrated than they were before the global financial crisis. The out-degree (that is, the number of other economies the investors domiciled in a given country invest in) shows a wider gap between advanced and emerging economies, suggesting that the latter are more financially integrated in the role of borrowers than in the role of investors.

Chart 3 Degree index by country groups(2)

(simple averages)

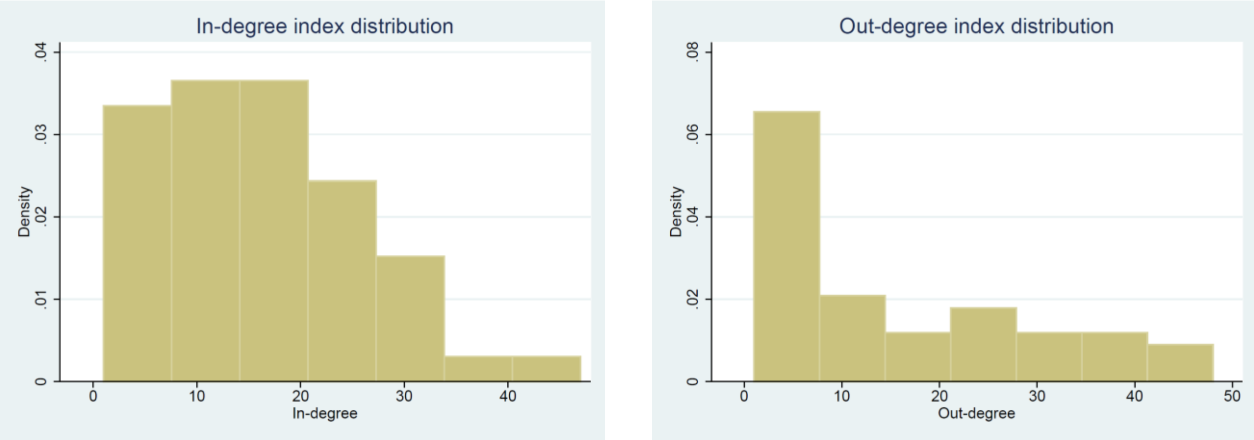


(2) In left panel, the dashed line for advanced economies indicates the average for 2015 obtained keeping constant the out-degree index for Ireland with respect to the previous year (see footnote 9).

Source: Calculations based on CPIS data.

The distributions of in-/out-degree indices (Chart 4), like other centrality indicators, tend to be asymmetric, suggesting that only a few economies are strongly interconnected, while most economies have a limited number of connections. The distribution of the out-degree index recalls the shape of a power-law distribution, which is associated in the network literature with the occurrence of extreme events (Strogatz, 2001). Such network structures (dubbed scale-free as the relative frequencies of different degrees depend only on their ratio and not on their absolute size) can be considered as an intermediate case between regular structures (in which, for example, each node is interconnected with all its neighbours owing to geographical or cultural factors) and random networks, in which the probability that two nodes are interconnected is independent of their characteristics.

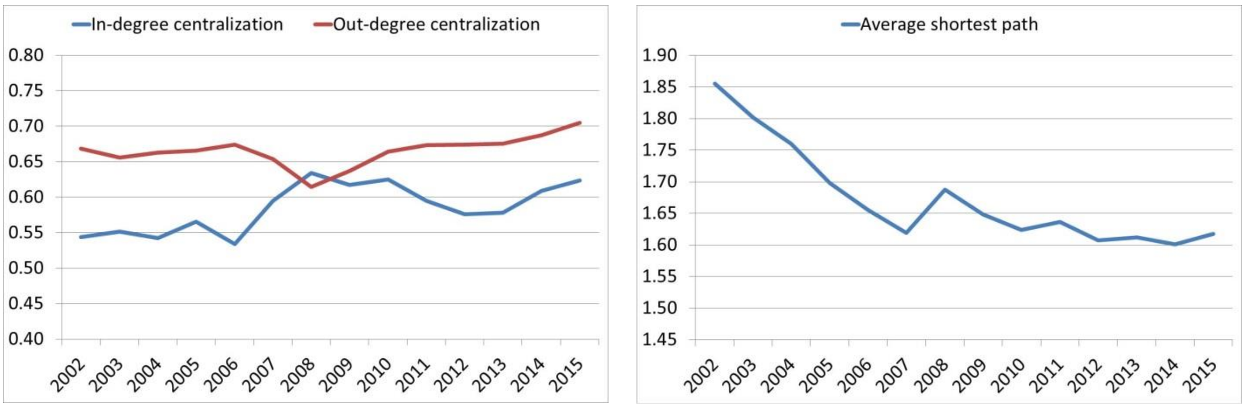
Chart 4 Distribution of degree indices (year 2014)



Source: Calculations based on CPIS data.

The heterogeneity in terms of degree indices between the central nodes and the others is also captured by the centralization index, which turns out to be very high particularly for the main investor countries (Chart 5, left panel); the three economies that are the most interconnected (using the eigen-centrality index, which is a measure of the influence of each node in a network) account for about 40 per cent of the sum of portfolio assets and liabilities. Another major feature is the limited number of separation degrees between nodes; the corresponding indicator (i.e. the average shortest path), which tends to move inversely with the interconnectedness index (Chart 5, right panel), has decreased over time; the small number of separation degrees implies that, when a shock hits a node, the contagion may swiftly spread to the rest of the network. These two properties (high centralization and short distance) characterize 'small world' networks and are considered to be particularly important from a financial stability perspective as they increase the likelihood of local disturbances producing global effects (Haldane, 2009). If global investors localized in the central nodes of the network are exposed to an idiosyncratic shock in the periphery, then contagion may spread throughout the network, also affecting the nodes that are not directly linked to the one where the crisis originates.

Chart 5 Centralization and average shortest path indices



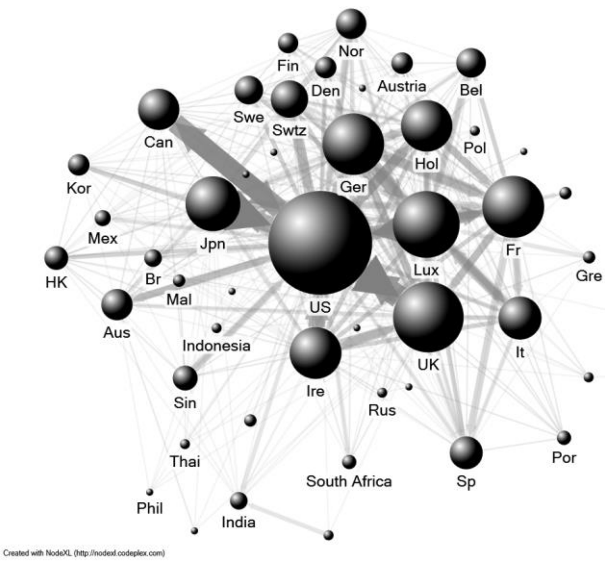
Source: Calculations based on CPIS data.

The centrality indicators (see Table 1a in the Annex) allow us to identify the central nodes of the network. The correlation between indicators (see Table 2a) is high (around 0.8 on average); in particular, the betweenness index, which captures the intermediation role played by each node in the network, presents a very skewed distribution, exhibiting very high levels for three countries (US, UK and Luxembourg), which not surprisingly account for 40 per cent of global portfolio investments. For these economies, net positions are very tiny compared with gross positions, confirming their role as intermediaries in the network.

Chart 6 depicts the network, representing the size of each node as proportional to the country's share in global portfolio investment and the thickness of the links as proportional to the size of bilateral investment positions between each country pair. This representation highlights the density of the network around the main financial centres.

The intermediation role played by the financial centres may be a source of financial interdependence between countries even when they are not directly connected. One famous example in the literature is that of the Southeast Asian economies in 1997, which, although not directly linked to one another, were all financially dependent on Japanese banks.

Chart 6 The network of portfolio investments in 2014



Source: Calculations based on CPIS data.

According to the International Monetary Fund (GFSR 2016), financial interdependence across economies is on the rise owing to the increasing role of global funds in capital movements; after the global financial crisis both emerging and advanced economies increased the reliance on these intermediaries. In particular, emerging economies have become more integrated and might therefore cause spillover effects in advanced economies.

The concept of financial interdependence constitutes a sort of bridge between network analysis and the simulation model we have developed to estimate contagion risk. To illustrate this point, we compute an indicator of financial interdependence (see Annex A3) and then check it against network indicators using the same dataset. As mentioned above, we assume that each country acts as a representative investor as, owing to lack of data, we cannot take into account the heterogeneity between funds domiciled in a given country.[10]

[10] The implications of this assumption on the interdependence index (and on the estimate of contagion risk) are not obvious. There may be situations in which using aggregate data leads to overestimation of the degree of interdependence between two economies, and other cases in which the effect is the opposite. Imagine two funds domiciled in country A investing each in one country (respectively B and C); using aggregate data, economies B and C will show up as being financially interdependent even if they have no common investor. On the other hand, imagine that three funds (x, y and z) domiciled in country A invest each in three destination countries (B, C, D), but with different allocations (fund x is overexposed to B and C; fund y to C and D; and fund z to B and D). For the sake of simplicity, imagine that the benchmark portfolio corresponds to country A's overall portfolio. In this case, using aggregate data, economy A will appear not to be overexposed to any country, and hence countries B, C and D will appear as not mutually interdependent, even though in fact each pair shares common (overexposed) investors.

The financial interdependence index between two economies (say A and B) is given by the combination of two factors: the reliance of economy A on third countries (acting as common investors) and the degree of overexposure[11] of these countries to economy B (see Annex A2). This index can be considered a proxy of potential spillover effects to economy A from economy B.

Table 1 Interdependence matrix (*)

Country	US	Can	UK	Swz	Aus	Bel	Lux	Net	Ger	Fra	Ita	Sp	Por	Gre	Ire	Cz	Slvk	Hun	Pol	Arg	Bra	Chi	Col	Mex	Pan	Ur	Ven	HK	Ind	Indo	Kor	Mal	Phil	Sing	Tha
United States	-	1	31	6	28	43	226	47	150	133	86	41	8	5	43	2	2	3	4	1	16	1	1	4	-	1	1	32	45	16	33	14	5	19	6
Canada	357	-	524	216	16	21	118	54	55	60	43	22	4	1	124	1	1	5	2	9	55	14	11	74	17	2	4	60	50	22	86	14	12	47	14
United Kingdom	524	260	-	137	33	53	323	92	105	109	132	79	13	1	101	3	3	4	5	6	35	9	7	48	11	2	3	41	40	16	60	11	8	38	10
Switzerland	484	316	395	-	20	36	165	62	100	105	83	39	8	4	113	2	2	6	4	7	48	10	9	58	13	2	3	45	27	15	58	7	8	34	10
Austria	288	35	61	20	-	119	732	205	203	308	256	195	25	4	54	11	28	4	26	2	9	3	2	8	1	1	1	7	3	3	7	1	1	4	2
Belgium	380	83	125	45	77	-	378	182	230	198	281	167	26	4	53	3	12	6	13	3	17	3	3	19	4	2	2	13	7	7	15	2	3	9	4
Luxembourg	357	29	98	18	83	60	-	164	122	300	251	216	31	5	132	11	12	3	13	4	11	2	1	8	1	0	2	13	11	3	15	4	2	10	2
Netherlands	451	151	204	80	56	79	472	-	133	175	225	144	22	6	94	6	7	5	10	4	28	6	4	29	6	1	2	24	13	8	29	4	4	17	5
Germany	634	110	167	61	36	71	324	90	-	158	158	89	15	6	90	6	5	5	6	4	25	4	4	23	5	1	2	25	20	10	30	7	5	14	6
France	599	119	150	64	53	47	536	78	155	-	130	80	15	5	91	8	7	6	10	4	26	5	4	24	5	1	2	22	10	7	23	3	4	14	5
Italy	360	54	95	30	66	115	537	202	204	221	-	188	46	7	61	8	7	5	12	2	20	2	2	14	2	1	1	12	5	5	10	1	2	6	3
Spain	356	79	124	43	75	105	710	197	193	238	271	-	23	8	78	8	7	5	12	4	17	3	3	16	3	1	2	16	11	6	18	3	3	8	4
Portugal	165	70	106	38	67	111	760	197	182	253	475	182	-	5	79	6	6	5	10	3	22	2	3	17	3	1	2	12	6	6	13	2	2	7	3
Greece	346	129	170	68	41	66	425	128	185	196	184	160	14	-	132	2	2	6	6	5	41	4	4	24	5	1	2	31	11	7	22	4	4	15	5
Ireland	383	187	274	99	42	51	516	103	151	174	145	95	16	6	-	5	5	5	6	5	35	7	5	35	8	1	2	32	21	11	38	6	5	22	7
Czech Republic	190	59	96	34	112	70	819	188	287	439	246	184	17	5	66	-	31	7	58	2	16	2	2	12	2	1	1	13	5	4	12	2	2	6	3
Slovak Republic	47	-	5	-	369	220	###	236	334	388	249	188	20	1	14	41	-	10	144	0	1	1	0	1	-	0	0	-	-	1	-	-	0	-	0
Hungary	257	210	262	109	44	74	194	97	192	202	148	71	12	6	90	5	8	-	12	5	39	7	7	41	9	2	3	33	18	13	36	5	5	22	8
Poland	439	125	166	68	99	85	436	140	200	229	177	124	14	5	64	19	34	7	-	3	24	5	4	25	5	1	2	20	11	7	24	3	4	13	5
Argentina	112	407	499	210	5	27	443	29	54	120	43	53	6	4	161	0	-	6	1	-	56	13	11	74	17	3	5	52	35	20	70	9	9	42	13
Brazil	644	279	346	147	12	30	126	45	114	99	97	22	11	6	117	1	0	6	2	6	-	9	8	53	12	2	3	59	24	14	52	7	7	33	9
Chile	433	330	407	175	29	26	157	58	84	101	48	21	4	3	107	1	2	5	4	7	48	-	9	60	14	2	3	44	28	15	60	7	9	34	10
Colombia	284	348	428	183	29	39	115	54	110	124	61	22	5	2	108	1	2	6	4	8	48	12	-	64	15	3	4	45	30	17	62	8	9	36	11
Mexico	510	310	385	164	21	37	175	58	97	107	94	31	11	3	106	1	1	5	3	7	47	10	9	-	13	2	3	43	26	15	56	7	8	32	10
Panama	132	512	629	264	15	21	57	49	43	65	35	15	3	0	139	0	1	6	3	11	64	16	14	91	-	3	5	63	44	23	89	11	12	52	15
Uruguay	170	353	433	182	-	73	-	28	110	121	110	1	9	-	95	-	-	9	1	9	48	11	11	70	15	-	5	43	30	22	61	8	8	36	12
Venezuela	87	415	510	214	5	37	389	29	56	118	56	46	7	2	147	-	-	6	1	12	54	13	12	77	17	3	-	51	35	21	72	9	10	42	13
Hong Kong	853	244	304	130	11	24	69	35	94	73	41	12	3	4	93	1	0	5	1	6	51	8	7	45	10	2	3	-	279	40	104	35	15	85	18
India	736	202	264	107	6	21	31	24	64	49	34	8	3	2	68	0	0	4	1	5	31	7	6	37	8	1	2	223	-	51	136	58	21	87	23
Indonesia	897	238	299	126	14	33	50	31	104	94	50	9	4	3	81	1	1	5	2	6	36	8	7	45	10	2	3	104	155	-	132	54	20	110	24
Korea	871	266	354	142	13	23	83	40	77	63	41	16	3	3	89	1	1	4	2	6	42	9	7	48	11	2	3	88	126	41	-	44	18	41	20
Malaysia	###	202	270	107	14	27	60	33	89	82	44	13	3	4	76	1	1	4	2	5	33	7	6	38	8	2	2	118	220	67	175	-	27	31	30
Philippines	778	257	333	140	16	28	58	35	95	96	45	13	4	4	91	1	1	5	3	6	40	9	7	48	11	2	3	86	138	45	128	48	-	35	22
Singapore	760	269	374	141	9	17	69	30	69	61	28	7	2	3	93	0	0	4	1	6	46	9	7	49	11	2	3	122	156	54	68	9	8	-	9
Thailand	896	249	319	132	13	30	34	28	101	96	44	8	3	4	90	1	1	5	2	6	40	8	7	46	10	2	3	78	119	40	112	41	17	31	-

(*) Values are obtained by multiplying funding and investment (percentage) shares by 10^2.
Source: Calculations based on CPIS data.

Table 1 shows the interdependence matrix for a sample of 50 countries in 2014 (some countries have been dropped to allow the table to fit on one page). The columns indicate countries originating spillover effects while the rows denote countries undergoing these effects; note that the main economies generating financial interdependence are the United States, Luxemburg and the United Kingdom, which, not surprisingly, are also the countries with the highest centrality scores.[12]

[11] The degree of overexposure of country A to country B is computed, if positive, as the share of investments of country A in country B less the share of aggregate investments in B (see Annex A1). It is set equal to zero when the difference is negative.

[12] A way to measure spillover effects generated by each economy to all other economies is to compute means by column. This indicator turns out to be highly correlated with the relative share and centrality indicators, in particular with the eigenvalue (R^2=0.95).

The heat-map obtained by highlighting in green for each column the values above the 95th percentile and in yellow those above the median (with different shades of the colours denoting intermediate percentiles) reveals that financial interdependence tends to be relatively higher within some regions, such as the European Monetary Union (EMU), Central Eastern European countries (CEECs), South America and Southeast Asian economies. There is also some evidence of spillover effects across regions, mainly between the EMU and CEECs, and between the US and Southeast Asian economies; this finding suggests that there are countries belonging to different regions that share common investors. For example, Southeast Asian economies are strongly interdependent with the US[13] as around 60 per cent of their portfolio investments originate from countries that are overexposed to the US (such as Singapore and the UK). By comparison, the fraction of portfolio investments in CEECs[14] from countries overexposed to the US is much lower (on average 31 per cent); indeed, these countries rely more on countries overexposed to Luxembourg (51 per cent of their inward portfolio investments).

4. The simulation model

In order to estimate the contagion effect, we use a simulation model based on the concept of financial interdependence described in the previous section. We aim to capture the mechanics of pure contagion events, in which an idiosyncratic shock hits one economy and then spreads through the network as a result of the portfolio rebalancing process. In our model, as in Broner et al. (2006), we assume that investors have heterogeneous preferences on countries' assets; in particular, investors are overexposed (underexposed) to countries they are relatively more optimistic (pessimistic) about relative to the average of other investors.

Generally, fund managers care about their performance against a benchmark; when they perform relatively worse, they reduce investments in countries they are overexposed to, feeding contagion dynamics. As we mentioned in Section 2, empirical evidence confirms that, when a country undergoes a financial shock, international investors implement contagion trading strategies, selling third countries' assets. Coherently with this evidence, we assume that when an economy undergoes a financial crisis, investors overexposed to this economy will reduce investments in other countries they are overexposed to.

Note that in our model countries act as representative investors and therefore the results of the simulation might be biased as we do not take into account the heterogeneity between investors in a given country (as discussed in the previous section with regard to the indicator of financial interdependence).

We also assume that the portfolio rebalancing mechanism works as an asymmetric process, that is, investors do not increase investments in countries they are underexposed to. This assumption takes into account the fact that, because of financial constraints, when global investors incur losses as a result of financial shocks, they react not only by changing portfolio allocation but also by reducing the overall size of their assets.

Note also that in our model price effects are not explicitly considered, even though they are incorporated through the effect of portfolio rebalancing on recipient economies. Consider the case in which an idiosyncratic shock leads international investors to unwind positions in some economies (reflected in a negative inflow); for any recipient economy, if the reduction in portfolio liabilities exceeds a given threshold, representing its capacity of shock absorption, we assume domestic asset prices fall, in turn bringing about another round of losses and changes in global investors' portfolio allocation. To account for this effect, once the portfolio adjustment process is complete, we compute for each recipient economy the negative inflows and then verify the following condition: if the reduction in portfolio liabilities (equivalent to negative

[13] Indonesia, Korea, Malaysia, Philippines, Singapore and Thailand.
[14] Czech Republic, Slovakia, Hungary, Slovenia and Poland.

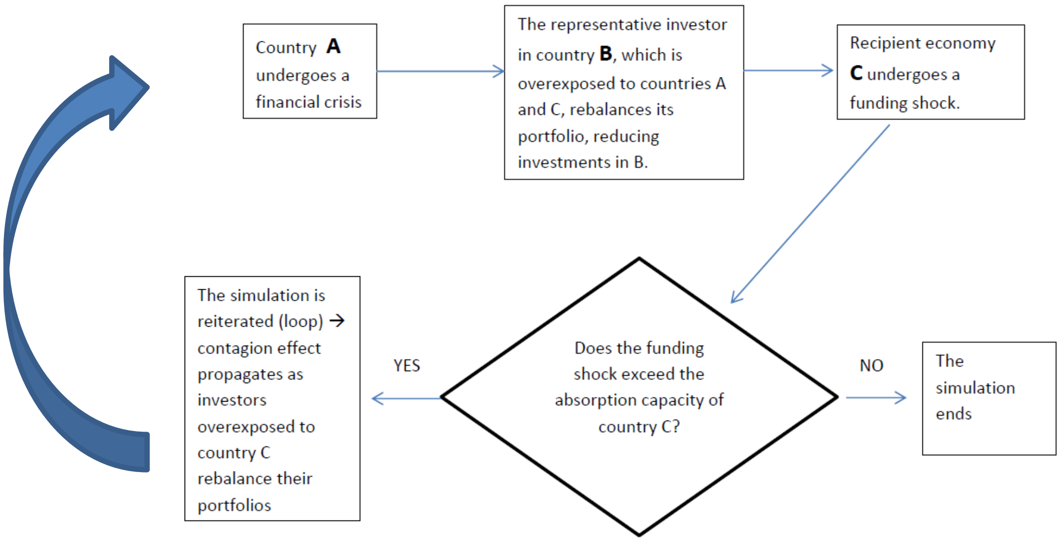
inflows) exceeds the standard deviation of portfolio investments[15] multiplied by a parameter α, then we assume that the recipient economy also undergoes a financial shock, and the simulation is reiterated.

The logic underlying the above condition is the following: based on the methodology in use in empirical works to identify sudden stop episodes (see, for example, Forbes and Warnok, 2011), we verify whether or not the simulated effects of the portfolio rebalancing are important from the perspective of the recipient economies; we assume that if an economy undergoes a sudden stop as a result of the portfolio rebalancing, then this economy itself becomes a potential source of contagion. Implicitly, we assume that when the above condition is verified, foreign investors' sales of domestic financial assets are not offset by domestic investors' purchases, causing a generalized fall in their prices.

To sum up, we run the simulation in three stages (see Chart 7): first, an idiosyncratic shock hits a generic economy (say country A); second, countries overexposed to economy A rebalance their portfolios, reducing investments in third economies they are overexposed to. For the sake of simplicity, in Chart 7 we illustrate the case in which country B is the only one overexposed to economy A; as it is also overexposed to economy C, country B will rebalance its portfolio, reducing investments in country C, thus causing a funding shock; to the extent that country C is unable to absorb this funding shock, the contagion will propagate and the simulation will loop.

Note that in this set-up we do not consider either domestic policies to contain contagion risks or recourse to global safety nets. We therefore do not take into account either the amount of official reserves held by each country or their access to IMF facilities, swap lines and regional financing arrangements.

Chart 7 Model set-up



A crucial aspect of the simulation is the intensity of the portfolio rebalancing mechanism, which depends on the reaction function of international investors. Broner et al. (2006) argue that an idiosyncratic shock feeds contagion by increasing the risk aversion of international investors; however, in their model risk aversion is exogenous and the portfolio rebalancing is driven uniquely by the funds' relative performance. A way to make risk aversion endogenous is to assume it is influenced by wealth. We build on Kyle et al. (2004), who develop a model in which risk aversion is decreasing in net worth for some investors (i.e. short-term traders):

[15] We compute this using balance of payments statistics from 2005 to 2014 for each country in the sample used in the simulation (see Section 5).

when they incur losses, they become more risk averse and reduce total investments, stoking contagion dynamics.

Following the model of Broner in which investors are overexposed to economies about which they are relatively more optimistic, one can expect that if one of these economies undergoes a financial crisis, investors will also become more skeptical about the goodness of their model and hence reduce investments in other countries they were relatively optimistic about. We apply this mechanism at the macro level by assuming that countries act as representative investors in the presence of an idiosyncratic shock affecting one economy; we incorporate wealth effects in our model, linking, for each representative investor, the intensity of the portfolio rebalancing mechanism to its exposure to the crisis economy. Consider the case depicted in Chart 7, where economy B is overexposed to countries A and C (we use the same notion of overexposure introduced in the previous section, see footnote 11); we use oe_{bc} to denote the amount of portfolio investments by country B in country C exceeding the latter's share in aggregate portfolio investments. We use X_{bc} to indicate the portfolio investments in country C held by residents in country B, with $X_{b.}$ being the sum of all portfolio investments held by residents in country B, $X_{.c}$ the aggregate portfolio investments in country C, and $X_{..}$ the aggregate portfolio investments in the whole network.

$$oe_{bc} = [(X_{bc}/X_{b.}) - (X_{.c}/X_{..})] * X_{b.}$$

If a shock hits A, then B will reduce its over-investments (oe_{bc}) in country C by a country-specific factor Q_b given by its share of investments in country A multiplied by a parameter β capturing wealth effects and the sensitivity of investors to financial shocks:

$$\Delta X_{bc} = oe_{bc} * Q_b$$

$$Q_b = \frac{X_{ba}}{X_{b.}} * \beta$$

The parameter β may also be interpreted as a measure of the intensity of balance-sheet constraints causing investors to unwind positions in the presence of a negative shock that reduces the value of their portfolio investments. According to Goldstein et al, (2004), balance-sheet constraints are in fact equivalent to assuming that investors' risk aversion is decreasing in their net worth: when the overall value of their assets falls below a certain threshold, investors become more risk averse, as they anticipate that in the event of further losses they will have to reduce total assets or issue new capital.

The role of balance-sheet constraints as a financial accelerator has been extensively studied; with particular regard to contagion, Schinasi et al. (2001) develop a theoretical model with balance-sheet constraints, proving that portfolio rebalancing will trigger a contraction of investments by an amount that is a multiple of the losses borne by investors.[16] Kaminsky et al. (2003) claim that leveraged investors (such as international banks and hedge funds) represent one component of the 'unholy trinity' that characterizes 'fast and furious contagion episodes'; they argue that these episodes follow capital flow surges, which are reversed by single crisis events that are not anticipated by the markets and trigger an abrupt rise in risk aversion, inducing leveraged investors to rebalance their portfolios.

There are investors, e.g. open-ended funds, that are not exposed to solvency risk and on average are not highly leveraged.[17] Such investors, however, are subject to redemption risk as end-investors may redeem their shares at short notice; when redemption pressure rises, fund managers may be forced to sell assets to

[16] Up to 6 times for a leverage ratio equal to 3.

[17] It should be noted, however, that such financial intermediaries may still build up leverage through securities financing transactions and derivatives.

raise the liquidity needed to pay their obligations. In our model the coefficient β is meant to capture redemption risk for open-ended funds and forced sales as well.

Our model also accounts for the effects of liquidity market conditions on financial prices. Imagine that, as a result of an idiosyncratic shock hitting one economy, international investors rebalance their portfolios, reducing positions in another economy. The price impact will depend of the relative size of sales by foreign investors with respect to the liquidity of the domestic market. For example Baranova et al. (2017) estimate liquidity risk premia through a partial equilibrium model in which market makers require a price discount to accommodate sales by other investors; the liquidity risk premia will be higher, the lower the capacity of market makers to absorb sales by other investors. Along these lines, we expect a marked price correction when sales by foreign investors exceed the shock absorption capacity of market makers (imagine, for the sake of simplicity, domestic financial institutions). In our model we take into account this mechanism through the parameter α; the lower this parameter (say below 2, which is the value commonly used to identify a sudden stop), the more likely it is that the retrenchment by foreign investors will adversely affect financial prices in recipient economies, stoking contagion effects.

5. The outcomes of the simulation

The simulation is carried out using 2014 portfolio investment data (CPIS) for a sample of 53 countries;[18] the annex provides descriptive statistics on the sample data used. Three main aspects are worth stressing before analysing the simulation outcomes. First, the size of portfolio investments is considerable as, on average, the stock of liabilities is worth more than 60 per cent of GDP. Second, the ratio of portfolio liabilities to GDP is higher in advanced economies than in emerging ones, where the sources of portfolio investment are also more concentrated. Third, the volatility of portfolio inflows is also significant: during the period 2005-2014 the standard deviation computed on quarterly data was, on average, equivalent to about 5 per cent of the stock of portfolio liabilities in 2014 while the median was 2.6 per cent.

The outcomes are analysed in two stages: first, we define our base calibration through a sensitivity analysis; second, we focus on economies that may be considered systemic in the sense that if they underwent a financial shock, the subsequent contagion effect would spread throughout the network.

We assume that 12 countries,[19] defined as safe countries, are neither exposed to financial shocks nor affected by contagion; these countries include reserve currency issuers and countries with a triple A rating on sovereign debt (assigned by at least one international agency). This assumption captures the fact that international investors consider investments in these countries to be a safe haven in times of financial distress. Note also that some of them (the US and the UK, for example) are financial centres playing a crucial role in the network and may a priori be considered systemic. From this angle we aim to fill a gap in the literature on network effects in the global financial system by assessing the contagion risk associated with non-core countries.

In order to estimate the contagion effect, we run the simulation N times (equal to 41, i.e. the sample size minus the number of safe countries); each time, we assume that an idiosyncratic shock hits one economy in the sample (i=1, ..N) and simulate the portfolio rebalancing process illustrated in the previous section. Then we check whether any country is affected by contagion – that is, a country for which the reduction in portfolio investments by foreign investors exceeds its absorption capacity, as defined above – and we

[18] The sample of the simulation is larger than that used for network analysis as in the latter we included only the countries that contributed to the CPIS survey in all years from 2002 to 2015. For the simulation we used data relating to 2014 as Ireland did not contribute to the survey in 2015 (see footnote 9).

[19] These countries are United States, United Kingdom, Germany, Austria, Netherlands, Luxembourg, Switzerland, Canada, Australia, Japan, Hong Kong, and Singapore.

indicate with k the number of countries affected by contagion (with k=1, ..K). In this case the simulation is reiterated until no further country is affected by contagion. Finally, for each i-country, we compute a measure of the contagion effect (CEi) as the fraction of the sample (in terms of GDP, excluding the safe countries) represented by the k-countries. We also compute the average contagion effect (ACE) as the mean of the contagion effects of all simulations for a given set of parameters.

$$CE_i = \frac{\sum_k^K GDP_k}{\sum_j^N GDP_j}$$

$$ACE = \frac{1}{N}\sum_i^N CE_i$$

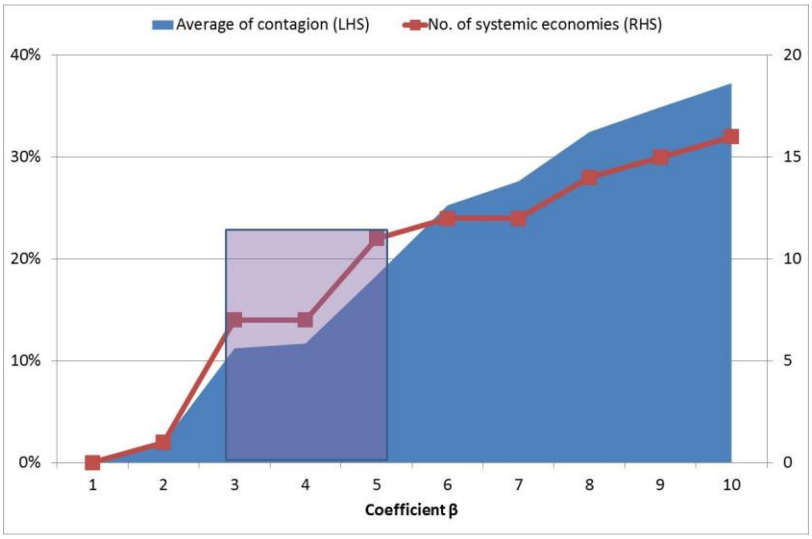
As mentioned above, there are two parameters to be calibrated: a) β determines the intensity of the portfolio rebalancing mechanism and hence the reduction in portfolio liabilities for each recipient economy to which the investor country is overexposed; b) α (which relates to the absorption capacity of the recipient economy) determines, once the portfolio adjustment process is complete, whether this economy is affected by contagion given the volatility of portfolio investment inflows at the country level. Note that a crucial assumption of the model is that an economy affected by contagion itself contributes to the propagation of the financial shock, reiterating the process of portfolio rebalancing.

Chart 8 shows that the size of the contagion effect depends crucially on the intensity of portfolio rebalancing. The average contagion effect varies from 0 to 37 per cent of the sample as a function of β, keeping α=2; likewise, the number of systemic economies, which we conventionally define as those that would lead to a contagion effect of over 10 per cent, varies from 0 to 16. Note that the number of systemic economies will be the same for any value of contagion effect from 5 to 25 per cent (see Chart 9).

In our base calibration we set β=4, which is a value consistent with a middle contagion scenario that is equivalent, on average, to 12 per cent of the sample (in terms of GDP). This corresponds to more than 7 times the sample average country GDP that can be considered the mean of idiosyncratic shocks.

Chart 8 Contagion effect conditional on β

(contagion effect as a percentage of aggregate GDP)

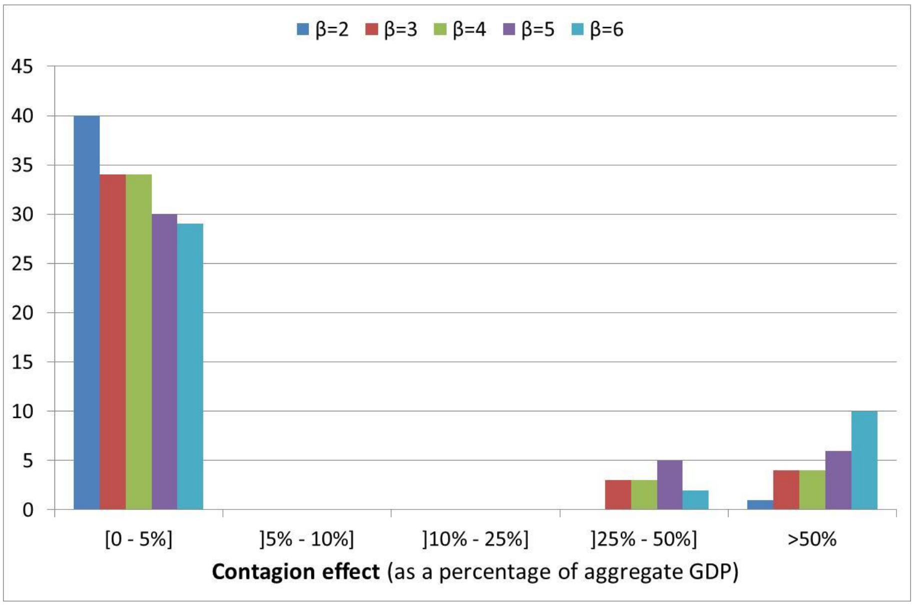


Notes: For α=2.

The shadow area indicates the values of β (from 3 to 5) used to identify the systemic economies; within this range, the average contagion effect varies from 11 to 20 per cent. We recall that these values are obtained as means of N simulations, assuming each time that an idiosyncratic shock hits one economy. Actually, contagion dynamics (that is, when the simulation loops) tend to occur only for a limited number of countries, but in these cases the contagion effect turns out to be large; the global portfolio network seems to exhibit the typical properties of robust-yet-fragile structures described in Section 3. In order to shed light on this aspect, Chart 9 illustrates how the contagion effect is distributed for different values of the parameter β. Using the base calibration (β=4) only 7 countries turn out to be systemic; the contagion effect is over 50 per cent for four countries, from 25 to 50 per cent for three countries and below 5 per cent for the others.

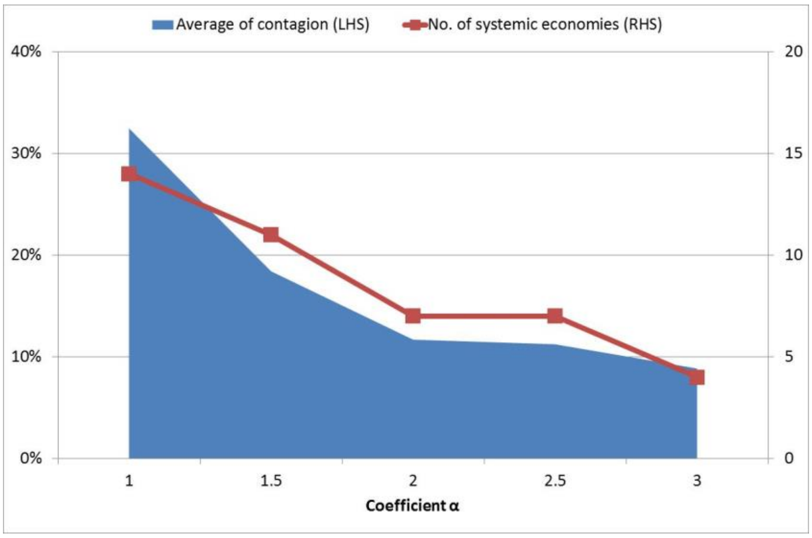
We repeat the same exercise for the parameter α. In the base calibration we set α=2, which is equivalent to assuming that a country is subject to contagion when negative inflows exceed twice the standard deviation of portfolio inflows from 2005 to 2014. Chart 10 shows the contagion effect conditional on α, keeping the other parameter constant (β=4); the number of systemic economies varies from 4 (with α=3) to 14 (with α=1), while the average contagion effect ranges from 8 to 32 per cent. Note also that, with the exception of the calibration with β=2, there are at least four systemic economies for which the contagion effect is over 50 per cent. The distribution of the contagion effect conditional on α (Chart 11) is similar to that conditional on β, confirming that when contagion risk materializes, its effect tends to be wide for a broad range of parameters.

Chart 9 Distribution of contagion effects conditional on β
(number of countries as potential sources of contagion)



Notes: For α=2.

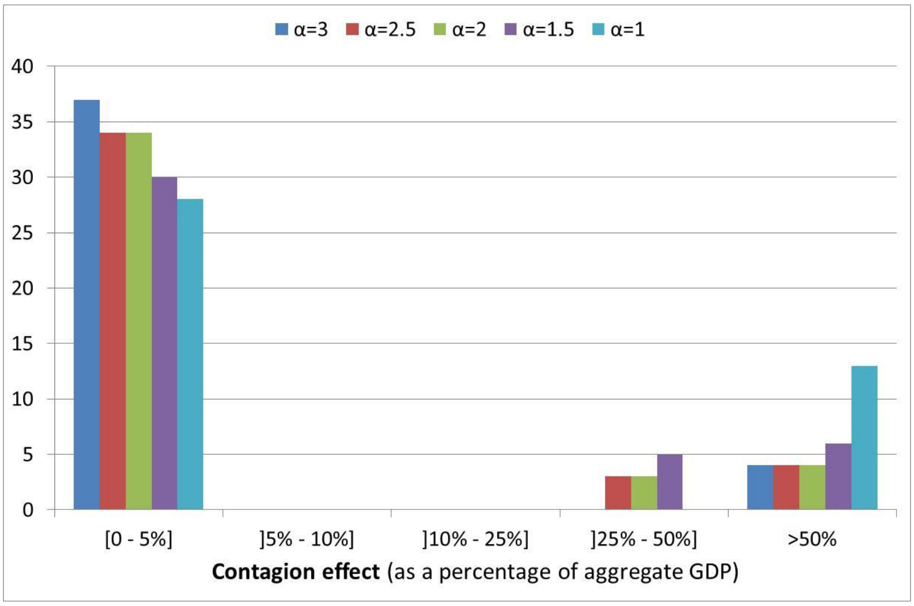
Chart 10 Contagion effect conditional on α
(contagion effect as a percentage of aggregate GDP)



Notes: For β=4.

As mentioned, the parameter α determines whether a country is affected by contagion: for any given level of negative inflows, a low (high) level of α implies a greater (lesser) contagion risk (Chart 10). Emerging economies are considered to be more prone to contagion as their domestic markets are small and relatively illiquid, and therefore domestic financial conditions are more sensitive to capital inflows. For these economies one can imagine that α is relatively low as even modest negative inflows may cause financial distress in domestic markets.

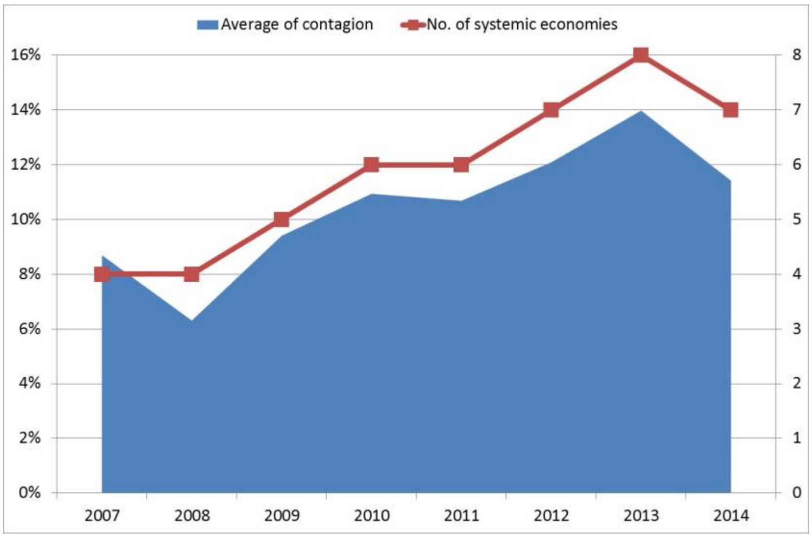
Chart 11 Distribution of contagion effects conditional on α
(number of countries as potential sources of contagion)



Notes: For β=4.

In order to assess whether the contagion effect varies over time, depending on the evolution of the network, we have repeated the simulation for all years starting with 2007, using the base calibration. We find that the contagion effect declined in the immediate aftermath of the global financial crisis, probably as a result of the reduction in global portfolio investments (Chart 12); thereafter, the contagion effect (as well as the number of systemic economies) increased again, reaching a new peak in 2013. This outcome suggests that financial interdependence rose again after the global financial crisis, reflecting the increasing role of global funds and the increased integration of the emerging economies (see IMF, 2016).

Chart 12 The average contagion effect since 2007
(contagion effect as a percentage of aggregate GDP)



Notes: For β=4 and α=2.

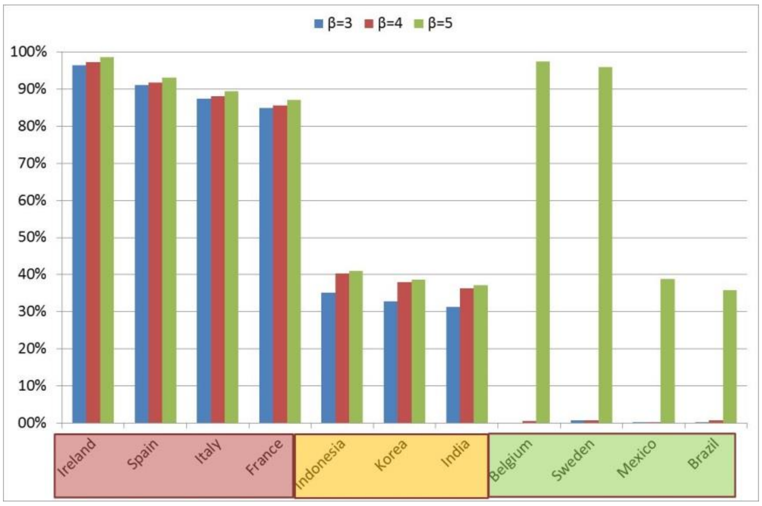
Taking into account the results of the sensitivity analysis, we use six different estimates to identify the systemic economies, varying each parameter (β and α) around its base calibration. The size of the contagion effect associated with each country is computed as the aggregate GDP of the countries affected by contagion over the aggregate GDP of the sample.

For β=4±1 we obtain that the number of systemic economies varies from four to eleven. Chart 13 highlights three country groups. The first group includes those economies (Ireland, Spain, France and Italy) for which contagion effects would also be widespread (that is, over 50 per cent) when β equals 3 (our lower bound). Note that in this group only Ireland and France rank among the first ten positions according to centrality indicators and may be considered central nodes (see Table 1a in the Annex). This outcome, along with the consideration that contagion effects tend to be substantial for a wide range of the parameters α and β, suggests that systemic economies need not be among the central nodes in the portfolio network.

The second group includes those economies (Indonesia, Korea and India) for which the contagion effect is between 30 and 40 per cent for any value of the parameter β from 3 to 5. Finally, in the third group (Belgium, Sweden, Mexico and Brazil) the contagion effect is conditional on the intensity of the portfolio rebalancing mechanism; if we set β=5 (corresponding to the upper bound), Belgium and Sweden would be in the first group while Mexico and Brazil in the second one.

Chart 13 Systemic economies (x axis) in 2014 conditional on β

(contagion effect as a percentage of aggregate GDP)



Notes: For α=2.

The sensitivity analysis for α=2±0.5 produces similar findings to those illustrated for parameter β, suggesting that the two parameters, although capturing different aspects of the contagion process, affect the simulation outcomes in a broadly similar way.

It is worth noting that while for advanced economies when the contagion effect is substantial it is always over 80 per cent, for the emerging economies classified as systemic the contagion effect is below 50 per cent. Moreover, it turns out that when the idiosyncratic shock hits a systemic emerging economy, advanced economies (with the exception of Sweden) are not subject to contagion. The fact that emerging economies are less resilient to contagion risk may depend on the higher concentration risk, as their funding sources tend to be less diversified (Chinazzi et al., 2017).

Network statistics support this hypothesis. The in-degree index for emerging economies is, on average, half that for advanced economies (see Chart 3), indicating that emerging economies rely financially on a smaller number of countries. Not surprisingly, the Herfindahl index for emerging economies turns out to be far higher than that for advanced economies (respectively 0.31 and 0.17 in 2014; see Table 3a in the Annex).

Several papers (e.g. Minoiu and Reyes, 2013) reach the same conclusion, i.e. that economies with more concentrated funding sources are more vulnerable to external shock. Along these lines, an IMF study (see footnote 5) finds that after the global financial crisis the recession was deeper in countries with a high Herfindahl index.

Financial integration – measured by a country's in-degree (as defined Section 3) – seems to work in two opposite directions. On the one hand, less integrated economies appear to be more vulnerable to contagion risk as they have a higher concentration risk. On the other hand, contagion risk is higher if the financial crisis originates in an economy that is more financially integrated, as the idiosyncratic shock may propagate through multiple linkages (in fact the in-degree index for systemic economies (21.7) is significantly higher than for the other economies (9.6)).

Another interesting finding is that contagion tends to spread across regions. It is worth noting that even in the case of an idiosyncratic shock hitting a systemic emerging economy, the overall exposure of international investors towards all economies affected by contagion would be significant (about 7 per cent of global portfolio investments). For the safe economies as defined above, the exposure to contagion would be even greater, in particular for Singapore, the United States, Hong Kong and Luxembourg (respectively 27, 15, 10 and 9 per cent).

We have already seen that our estimate of contagion effects changes over time. Using the base calibration and comparing the results for 2014 (Chart 13) and 2007 (Chart 1a in the Annex), it turns out that prior to the global financial crisis, only four countries – all advanced economies – could be considered systemic; by contrast, in recent years few emerging economies can also be deemed systemic as a result of their increasing financial integration.

6. Conclusions

In this paper we provide an estimate of contagion effects through the portfolio channel in the case of idiosyncratic shocks, using a simulation model based on the concept of financial interdependence. We use aggregate bilateral portfolio investment data for a sample of 53 countries, representing about 80 per cent of the world-wide stock of portfolio investments. In our model we assume that countries act as representative international investors, so that when an economy undergoes a financial shock, countries overexposed to it rebalance their portfolios, reducing investments in other economies they are overexposed to. We simulate contagion effects assuming that recipient economies are themselves subject to contagion if the reduction i portfolio liabilities as a result of the portfolio adjustment process exceeds a given threshold, computed taking into account the observed volatility of portfolio inflows.

The outcomes of the simulation show that a few additional economies, on top of those identified as central nodes using network indicators, may be considered systemic in the sense that if they undergo an idiosyncratic shock, contagion effects would be likely to spread throughout the network. There are two main implications: first, for contagion to occur, the financial crisis does not need to originate in a central node; second, when contagion risk materializes, its effects tend to spread throughout the network. The simulation estimates also suggest that contagion risk, which had declined in the immediate aftermath of the global financial crisis, has increased again more recently. The number of systemic economies has also increased, and contagion effects across different regions could now also be triggered by an idiosyncratic shock hitting an emerging economy.

The contagion effects depend on both the intensity of the portfolio rebalancing mechanism and the resilience of domestic markets. As these two aspects may vary according to circumstances, we calibrate the model making a range of alternative assumptions about the strength of the reaction of international investors to financial shocks and the severity of the repercussions on domestic markets. The sensitivity analysis shows that contagion risk is significant for a wide range of values of the parameters of the model.

The sensitivity analysis highlights two options for mitigating contagion risk; on the one hand, the economies whose capacity to absorb a sudden stop is limited should make their financial markets more liquid and resilient, notably by diversifying their sources of funding. On the other hand, regulators should aim to contain the risk of sudden stops, including by reducing the intensity of the portfolio rebalancing mechanism.

In this paper we discuss two main elements affecting the intensity of portfolio rebalancing, namely balance-sheet constraints and redemption risk. While the first aspect concerns mostly international banks, which are subject to strict regulation, the second aspect concerns mutual funds in particular, whose role in the intermediation of capital flows has increased significantly since the global financial crisis. Until the global financial crisis, the regulation of these financial intermediaries sought mainly to protect end-investors; more recently, increasing awareness of the systemic risks associated with forced sales by mutual funds has prompted international institutions[20] to develop a macroprudential approach that takes vulnerabilities into account, focusing on liquidity mismatch, redemption policies and pricing rules. From this perspective, tools designed to increase the resilience of mutual funds and reduce the frequency and intensity of forced sales would also have the effect of mitigating contagion risk.

Given the importance of the portfolio channel and the increasing role of the shadow banking system in the intermediation of capital movements, the authorities should address contagion risk by setting out policies in a comprehensive and consistent manner, filling loopholes in prudential regulation and targeting specific types of financial intermediaries. Coordination between regulators is also needed at the international level to internalize the spillover effects stemming from country-specific measures and to avoid undue externalities from regulatory arbitrage.

[20] See, for example, ‘Policy Recommendations to Address Structural Vulnerabilities from Asset Management Activities’, Financial Stability Board, January 2017; ‘Macroprudential policy beyond banking: an ESRB strategy paper’, European Systemic Risk Board, July, 2016.

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ANNEX

A1. Network analysis indicators

In this brief annex we provide a qualitative description of the indicators used in this paper. Network indicators can be classified into two broad categories, depending on whether they refer to single nodes (node-degree, eigenvalue, betweenness, etc.) or to the whole network (interconnectedness, centralization, etc.). The connections (or links) across the nodes in the network are represented through a square matrix A, whose order is given by the number of nodes. When two nodes (say *i* and *j*) are directly connected, we set $A_{ij} = 1$, otherwise $A_{ij} =0$. In our network the links are represented by the stock of portfolio investments between country pairs; $A_{ij} = 1$ if the value of portfolio investments in country j by residents in country *i* is greater than USD 1 billion. Clearly, links between countries are 'directed' in the sense that outward links denote portfolio investments from a given country, whereas inward links denote portfolio investments into a given country.

The node-degree indicator quantifies the number of links from (out-degree) and to (in-degree) a given node. Dividing these indicators over the number of nodes in the network, we obtain the corresponding centrality indicators.

$$ND_i^{out} = \sum_{j \neq i} A_{ij}$$

$$ND_j^{in} = \sum_{i \neq j} A_{ij}$$

Another indicator of the first type is the eigenvalue (or prestige), which is a measure of the influence of each node in the network and can be considered a weighted measure of centrality. It is based on the concept that connections to the most central nodes contribute more to the score of the node in question than do connections to peripheral nodes.

The shortest path length indicates the minimum number of nodes (separation degrees) between a pair of nodes. The average is often used to gauge the density of the network. A measure often used to identify the nodes that play the role of intermediaries within the network is the betweenness indicator, which measures the frequency a node is interposed between all the other nodes along their shortest paths.

Moving to the indicators referring to the entire network, the interconnectedness index measures the probability that any two nodes are directly linked, and is obtained as the number of existing links in the network over the number of all possible ones.

$$C = (\sum_{ij}^{N} A_{ij})/[(N*(N-1)]$$

The centralization index is a measure of the heterogeneity of the network and takes values from 0 (all nodes have the same index and the network is uniform) to 1 (all nodes but one are connected only with this one). It can be computed as the ratio of the sum of the differences between the in-degree index of the most central node and those of all other nodes in the network to the theoretically largest such sum of differences in any network of the same size.

A2. The interdependence index

The interdependence index (FI) is a measure of spillover effects between two countries (see Broner et al., 2006). Let X be a square matrix representing stocks of bilateral portfolio investment; rows represent investing countries (*i*) and columns stand for borrowing countries (*j*). Each element of the matrix (X_{ij}) denotes the investments of country *i* into country *j*. For each *i*-country we compute the investment share (I_{ij}) in the *j*-country; conversely for each *j*-country we compute the funding share (F_{ij}) from the *i*-country. We use $X_{i.}$ to indicate the sum of portfolio investments held by residents in country *i*, while $X_{.k}$ indicates the sum of portfolio investments in country *j* held by residents in all other countries, and $X_{..}$ to indicate the aggregate investments in the whole network.

$$I_{ij} = \frac{X_{ij}}{X_{i\cdot}} \qquad\qquad F_{ij} = \frac{X_{ij}}{X_{\cdot j}}$$

We say that the *i*-country is overexposed to the *j*-country if

$$I_{ij} > M_j = \frac{X_{.j}}{X_{..}}$$

Where M_j is the share of aggregate investments in the *j*-country.

We define the overexposure matrix OE, in which the generic element is given by

$$OE_{ij} = \max(I_{ij} - M_j; 0)$$

Multiplying the matrices F and OE, we obtain the interdependence matrix (FI).[21]

$$FI = F * OE'$$

The generic element FI_{jk} of the matrix FI will be equal to the summation (over *i*) of the country *j* funding shares from economies (*i*) that are overexposed to country *k*, each multiplied by the corresponding overexposure index OE_{ik}.

$$FI_{jk} = \Sigma \frac{X_{ij}}{X_{.j}} * \left(\frac{X_{ik}}{X_{i\cdot}} - \frac{X_{.k}}{X_{..}}\right)$$

In the special case in which only the *i*-country is overexposed to the *k*-country, the interdependence index between countries *j* and *k* will be given by a single term:

$$FI_{jk} = \frac{X_{ij}}{X_{.j}} * \left(\frac{X_{ik}}{X_{i\cdot}} - \frac{X_{.k}}{X_{..}}\right)$$

[21] As the interdependence index is defined for country pairs, we set the diagonal elements of the matrix FI equal to zero.

A3. Tables and charts

Table 1a Network centrality indicators (year 2014)

COUNTRY	Out-degree	In-degree	Eigencentrality	Betweeness	Relative share
United States	51	47	0.55	787.2	0.21
United Kingdom	42	35	0.36	150.3	0.10
Luxembourg	50	33	0.35	246.7	0.09
Ireland	42	31	0.26	95.3	0.05
Germany	44	28	0.25	83.7	0.07
Netherlands	39	29	0.19	73.5	0.05
France	35	28	0.23	64.0	0.07
Japan	37	22	0.36	24.3	0.06
Canada	36	23	0.18	27.4	0.03
Switzerland	36	21	0.13	27.9	0.03
Italy	27	22	0.12	20.2	0.04
Australia	24	25	0.07	24.6	0.02
Norway	38	19	0.11	21.6	0.02
Sweden	25	22	0.06	21.0	0.02
Belgium	24	21	0.07	12.0	0.02
Spain	20	23	0.04	11.9	0.02
Denmark	31	18	0.05	16.1	0.01
Hong Kong	20	20	0.05	10.2	0.01
Austria	24	19	0.03	10.7	0.01
Singapore	15	17	0.07	7.5	0.01
Korea	18	19	0.02	7.8	0.01
Finland	18	17	0.03	0.2	0.01
South Africa	6	15	0.02	5.4	0.00
Greece	11	11	0.01	4.4	0.00
Russia	7	15	0.00	12.2	0.00
Brazil	3	21	0.00	1.9	0.01
Portugal	13	14	0.01	0.7	0.00
Malaysia	7	15	0.01	0.1	0.00
Poland	6	17	0.00	2.1	0.00
Mexico	2	17	0.01	0.1	0.01
Chile	9	10	0.02	0.0	0.00
Thailand	7	13	0.00	0.4	0.00
Czech Republic	8	12	0.00	2.5	0.00
Indonesia	2	17	0.00	1.0	0.00
India	0	18	-	0.0	0.01
New Zealand	4	10	0.00	0.1	0.00
Turkey	0	17	-	0.0	0.00
Philippines	2	12	0.00	0.0	0.00

Note: The countries in this table represent a fraction of the sample used in the network analysis (see footnote 6).
Source: Calculations based on CPIS data.

Table 2a Correlation matrix between network centrality indicators

	Out-degree	In-degree	Eigencentrality	Betweenness
In-degree	0.83			
Eigencentrality	0.87	0.81		
Betweenness	0.56	0.65	0.78	
Relative share	0.78	0.81	0.95	0.91

Source: Calculations based on CPIS data.

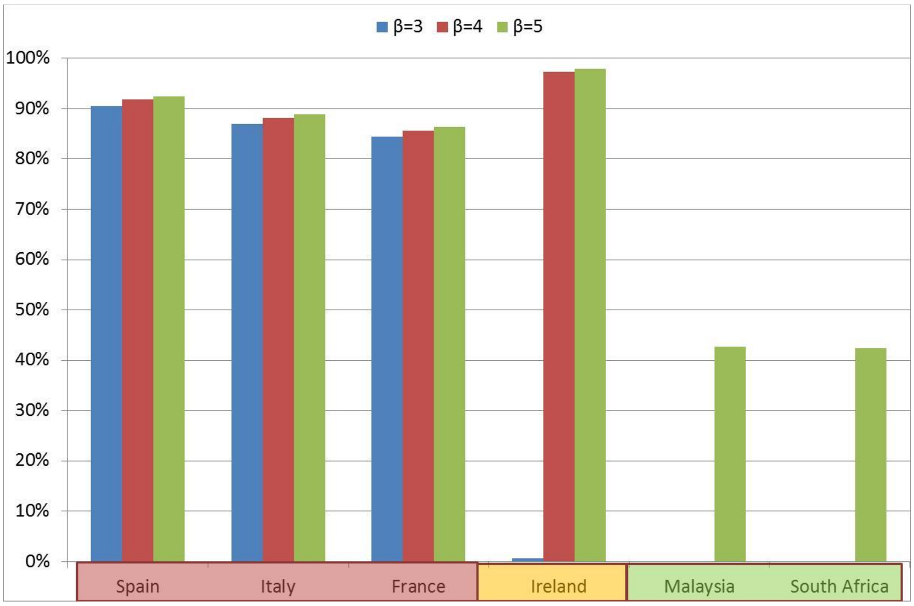
Table 3a Descriptive statistics on sample data used in the simulation

Statistics	Portfolio liabilities (% GDP)*	Concentration of portfolio liabilities (Herfindahl Index)	Standard deviation of portfolio inflows in percent of the amount of portfolio liabilities
p25	21.45	0.12	1.8%
median	34.05	0.19	2.6%
p75	78.84	0.28	5.0%
sample mean (53 countries)	63.69	0.24	5.4%
average of advanced economies (26 countries)	99.89	0.17	5.1%
average of emerging economies (27 countries)	32.66	0.31	5.6%

Note: Statistics in this table relate to 2014. The standard deviation is computed using quarterly data from 2005 to 2014. (*) Excluding Luxembourg.

Source: World Economic Outlook and calculations based on CPIS data.

Chart 1a Systemic economies (x axis) in 2007 conditional on β
(contagion effect as a percentage of aggregate GDP)



Notes: For α=2.