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The geographical composition of national external balance sheets: 1980–2005

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Abstract

This paper constructs a data set on stocks of bilateral external assets and liabilities for a group of 18 countries, including developed and emerging economies. The data set covers the years 1980 to 2005 and distinguishes between four asset classes: foreign direct investment, portfolio equity, debt, and foreign exchange reserves. A number of stylised facts emerge from it. There has been a remarkable increase in interconnectivity over the past two decades. Financial links have become larger and more frequent and countries have become more open. The global financial network is centred around a small number of nodes, which have many and large links. In addition, the network exhibits 'small-world' properties, such as high clustering and low average path length. The combination of high interconnectivity, a small number of hubs, and 'small-world' properties makes for a robust-yet-fragile system, in which disturbances to the key hubs would be rapidly and widely transmitted. The global financial network is centred around the United States and the United Kingdom, which have large links and are connected to most other countries. This contrasts with the global trade network, which is arranged in three clusters: a European cluster (centred on Germany), an Asian cluster (centred on China), and an American cluster (centred on the United States).

Key words: International financial networks, international investment, financial liberalisation.

JEL classification: F2, F3.

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The data set constructed in this paper can be requested by email to fgs22@cam.ac.uk.

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Summary

Financial globalisation has been one of the most striking phenomena happening in the world economy in the past two decades. Until recently, very little was known about the size and composition of countries' external financial assets and liabilities. This gap was partly narrowed by the work of Lane and Milesi-Ferretti, which provides estimates of the total external financial assets and liabilities of 145 countries, from 1970 to 2004. These data show that there has been a marked increase in the ratio of foreign assets and liabilities to GDP, particularly since the mid-1990s. This increase has been especially pronounced among industrial countries, where financial integration has exceeded trade integration. However, very little is known about the geographical composition of assets and liabilities. This paper contributes to a better understanding of the geographical composition of countries' external positions by constructing a data set of stocks of bilateral assets and liabilities for a group of 18 countries, covering the period from 1980 to 2005.

The data distinguish between four asset classes: foreign direct investment, portfolio equity, debt, and foreign exchange reserves. For the first three asset classes, missing data are constructed using gravity models, which have been extensively applied to explain cross-border trade and have been increasingly used to explain financial stocks and flows. These models explain bilateral assets by the geographical and historical proximity between the source and host countries, including variables such as distance, time difference, whether the source and host countries share a common border, a common language, or have colonial links. These models tend to have a large explanatory power, suggesting that financial markets are not frictionless, but are segmented by information asymmetries and familiarity effects. For reserves, a two-step procedure is adopted. First, data on the currency composition are collected and then are translated into geographical composition.

To give a flavour of the data set and identify the key stylised facts that emerge from it, a number of tools from network analysis are applied. The international financial system is represented as a network, where nodes represent countries and links represent bilateral financial assets. The evolution of the global financial network over time shows that there has been a remarkable increase in interconnectivity over the past two decades. Financial links have become larger and countries have become more open. Financial links are centred around a small number of nodes,

which have many and large links. In addition, the average path length of the global financial network has decreased over time and the clustering coefficient has increased. These are properties of 'small-world' networks which, from a stability perspective, are robust yet fragile. Because these networks are highly interconnected and some nodes have multiple and large links, they are susceptible to targeted attacks affecting the key financial hubs. Disturbances to the key hubs would be transmitted rapidly and widely throughout the network.

For comparison, the same type of analysis is applied to the global trade network. There are some common features with the financial network. In particular, the trade network also shows an increase in interconnectivity over time and is centred around some key hubs. However, there are important differences between the trade and financial networks. While the financial network is centred around the United States and the United Kingdom, which have large links and are connected to most other countries, the trade network shows strong intracontinental links and is arranged in three clusters: a European cluster (centred on Germany), an Asian cluster (centred on China), and an American cluster (centred on the United States).

This data set can be used for a number of applications. For example, it can be used to examine how financial links affect the international transmission of shocks. Other possible applications include an analysis of whether emerging markets have decoupled from advanced economies and whether business cycles in the G7 have become more synchronised.

1 Introduction

Financial globalisation has been one of the most striking phenomena happening in the world economy in the past two decades. Until recently, very little was known about the size and composition of countries' external financial assets and liabilities. This gap was partly narrowed by the work of Lane and Milesi-Ferretti (2001, 2007), which provides estimates of the total external financial assets and liabilities of 145 countries, from 1970 to 2004. These data show that there has been a marked increase in the ratio of foreign assets and liabilities to GDP, particularly since the mid-1990s. This increase has been especially pronounced among industrial countries, where financial integration has exceeded trade integration. However, very little is known about the geographical composition of assets and liabilities. This paper contributes to a better understanding of the geographical composition of countries' external positions by constructing a data set of stocks of bilateral assets and liabilities for a group of 18 countries, covering the period from 1980 to 2005.

The data are constructed separately for four asset classes: foreign direct investment (FDI), portfolio equity, debt and foreign exchange reserves. The methodology used to construct the data is similar for the first three asset classes and relies on the use of gravity models. For reserves we adopt a different procedure and start by constructing the currency composition, which is then translated into the geographical composition: if country i holds an amount X of reserves in US dollars, we take X as being the amount of reserve assets that country i holds in the United States.

For FDI, equity and debt we collect data from a variety of sources. For bilateral FDI assets, we use data from the OECD International Direct Investment by Country data set and from the United Nations Conference on Trade and Development (UNCTAD). Data on equity are from the IMF Coordinated Portfolio Investment Survey (CPIS). For debt, we use data from both the CPIS and the Locational Banking Statistics of the Bank for International Settlements (BIS).

Data gaps are filled in using gravity models, which are the workhorse models for trade in goods. They explain trade flows between countries i and j by their sizes (GDPs) and a variety of variables capturing the geographical and historical proximity between the two countries (distance, common language, common border, colonial links, etc). These models have more recently been applied to bilateral financial stocks and flows. Martin and Rey (2004) develop a theoretical framework that delivers an equilibrium relation between bilateral asset flows, the size of the home and host countries and transportation and information costs. Their model provides a theoretical foundation for gravity models applied to asset trade. Portes and Rey (2005) use a gravity model to explain bilateral cross-border equity flows between 14 economies in the period from 1989 to 1996. They find that the model performs at least as well as when applied to goods trade and there is a significant negative effect of distance on equity transactions. Lane and Milesi-Ferretti (2008) use a gravity model to explain stocks of bilateral portfolio equity in 2001 using data from the IMF CPIS. They find that bilateral equity holdings are strongly correlated with bilateral trade in goods and services and are also positively associated with measures of proximity. Daude and Stein (2007) focus on the determinants of FDI stocks in OECD countries in the late 1990s (they consider the average of FDI stocks for the period 1997-99) and find that differences in time zones have a negative and significant effect on the location of FDI.

Consistent with previous studies, we find gravity models to have very good explanatory power when applied to bilateral FDI, equity, and debt stocks. We find a significant effect of the standard gravity variables on financial stocks: countries that are less distant or share a common border or a common language have stronger financial linkages across all three asset classes. We also confirm the findings in Daude and Stein (2007) on the negative effect of time differences on FDI stocks and find that this is true for equity and debt holdings as well.

For reserves, we use the BIS Multilateral Surveillance Statistics, which contains data on the currency composition of reserves for countries in the G10. The remaining countries are covered by the IMF COFER (Currency Composition of Official Foreign Exchange Reserves) data set. This data set is confidential but has been used by some authors in previous studies (for example Dooley *et al* (1989) and Eichengreen and Mathieson (2000)). For these countries we estimate the currency composition using the coefficients reported in Eichengreen and Mathieson (2000), who had access to COFER.

After describing the data construction in detail, we apply a number of tools from network analysis to examine the key stylised facts that emerge from the data. The international financial system can be seen as a network, where nodes represent countries and links represent bilateral financial assets. By examining the evolution of the global financial network over time, we observe that there has been a remarkable increase in interconnectivity over the past two decades. Financial links have become larger and countries have become more open. The global financial network is centred around a small number of nodes, which have many and large links. The network also exhibits some ‘small-world’ properties, with a small number of degrees of separation between nodes and a high clustering coefficient. The combination of high interconnectivity, a small number of hubs, and ‘small-world’ properties makes for a robust-yet-fragile system, where a disturbance to one of the central countries would be transmitted rapidly and widely. These features of the global financial network are discussed in Haldane (2009).

The global trade network has some of the same features as the financial network and also shows an increase in interconnectivity over time. However, there are some important differences between the trade and financial networks. While the financial network is centred around the United States and the United Kingdom, which have large links and are connected to most other countries, the trade network shows strong intracontinental links and is arranged in three clusters: a European cluster (centred on Germany), an Asian cluster (centred on China), and an American cluster (centred on the United States).

2 Data construction

2.1 Country selection and treatment of financial centres

The data are constructed at annual frequency and include 18 countries, listed in Table A. The sample was selected to include countries located in different continents and include both emerging markets and developed economies. To measure the proportion of total external assets in the world that is accounted for by our sample, we use the data by Lane and Milesi-Ferretti and compute the share of total external assets in their sample of 145 countries that is accounted for by the 18 countries in our sample. Chart 1 shows how this share has changed over time for different asset classes. The 18 countries in our sample account for the majority of the world’s total external assets. Until the late 1990s, the share of the world’s total external assets accounted for by our sample was between 70% and 80%. This fraction dropped to around 60% in the 2000s.[1] Looking at the disaggregation by asset class, coverage is largest for FDI, followed by equity and debt. It is lowest for foreign exchange reserves, with our sample capturing between 50% and 60% of the world’s total reserves.

[1] The countries whose share of the world’s total external assets most increased in the 2000s were Luxembourg, Ireland and the Netherlands, which are not in our sample.

Some of the countries in the sample — the United Kingdom, the United States, Singapore and Hong Kong — are important financial centres and are both final destinations and intermediaries of foreign investment. Balance of payments statistics are constructed on the basis of the residence principle. For example, if a German resident invests in a Chinese company and directs the investment via a financial institution located in the United Kingdom, balance of payments data would register the transaction as an asset of Germany in the United Kingdom and an asset of the United Kingdom in China, even though the United Kingdom has only acted as an intermediary.

There can be significant differences between bilateral links built on the basis of the residence principle and ultimate exposures. Felettigh and Monti (2008) derive ultimate exposures from data based on the residence principle. They use data from the IMF CPIS, which are constructed following the residence principle. They focus on equity and debt assets held by France, Germany, Italy and Spain in Luxembourg and Ireland. These two destination countries are chosen because they have a large mutual funds industry. To illustrate the methodology used by Felettigh and Monti, suppose that we are looking at assets held by Italy in Ireland. To derive ultimate exposures, the authors first separate the share of assets that Irish mutual funds reinvest at home and the share that they reinvest abroad. They use the share reinvested at home to determine how much Italian investment stays in Ireland. The part that does not stay in Ireland is allocated to ultimate destinations using the geographical composition of foreign assets held by Ireland. Comparing bilateral exposures after this reallocation with data from the CPIS suggests that there is little difference between the two for debt assets, but there are sizable differences for equity assets. For example, the share of intra-Euro Area securities on total Italian equity assets falls by 33.5 percentage points after this correction. This exercise gives an indication of the large differences that may exist between bilateral links measured in terms of residence and ultimate exposures.

Most available data sets on bilateral financial links follow the residence principle. A notable exception is the BIS consolidated banking statistics, which contain information on cross-border assets held by banks and are based on the nationality of the reporting bank, netting out intragroup positions. This data set is described in detail in McGuire and Wooldridge (2005). The BIS also collects data based on residence (locational banking statistics). For a useful discussion of the differences between the two data sets see McGuire and Tarashev (2008). Which data are preferable depends on the question being addressed. Data based on residence provide an idea of broad trends in cross-border links and the structure and size of global financial links from a geographical perspective. Data based on nationality may be preferable for analysing the transmission of shocks between banks, but this depends on whether foreign subsidiaries and branches fund themselves locally or in their country of nationality. For example, suppose that Abbey in the United Kingdom (part of Santander, a Spanish group) borrows from households in the United Kingdom to lend to China. Consolidated data would treat this as an investment of Spain in China. This may be appropriate to study the effect of a shock in China on Santander as a group. However, it would not be appropriate to study the implications of a shock in the United Kingdom for cross-border capital flows. For this question locational data would be preferable.

Since neither residence nor nationality-based data are clearly preferable in all circumstances and residence-based data are more widely available, we follow the balance of payments methodology and construct the data set based on the residence principle.

2.2 General approach for FDI, equity, and debt

The data are disaggregated in four asset classes: FDI, equity, debt, and foreign exchange reserves. The methodology used to construct the data is somewhat different for each asset class. For the first three asset classes, missing data are estimated using gravity models, which have been used extensively in the trade literature. These models explain bilateral assets using a variety of variables, including standard gravity variables, such as distance, common language, common border, time difference, and colonial links; and additional regressors, such as bilateral trade, and exchange rate volatility. For foreign exchange reserves, we start by estimating their currency composition and then transform it into geographical composition. Because data on the currency composition of reserves are confidential, we base our estimations on the results reported in previous studies which had access to such data.

Because the construction of data for FDI, equity, and debt follows a similar approach, it is useful to describe the general approach before discussing the elements that are specific to each asset class. The construction of data for these three asset classes follows a six-step procedure:

- **Step 1**. Collect available data on bilateral assets from a variety of sources.
- **Step 2**. Compute geographical weights.

By dividing assets of country i in country j (A_{ijt}) by total external assets of country i (A_{it}), obtain the percentage of assets of country i which are held in country j (w_{ijt}):

$$w_{ijt} = \frac{A_{ijt}}{A_{it}}$$

Weights do not necessarily add up to 100, since the 18 countries in the sample do not account for a country's total external assets.

- **Step 3**. Estimation of gravity models for geographical weights.

  Missing data are estimated using gravity models, which are the workhorse models for trade in goods. They explain trade flows between countries i and j by the size of the two countries (measured by GDP) and a variety of variables capturing their geographical and historical proximity (such as distance, common language, common border, colonial links, etc). More recently, they have been applied to explain asset flows and stocks, and have been found to perform quite well, typically explaining more than 70% of the variation in cross-border flows and stocks of foreign assets.

  The idea that variables such as distance and cultural affinities may explain a large proportion of cross-border asset flows and stocks may seem surprising. Unlike goods, assets are not subject to transportation costs. Also, if investors wish to diversify their portfolios, they may choose to invest in more distant countries, where the business cycle has a low or negative correlation with their own country's business cycle. The fact that gravity variables perform at least as well in explaining financial positions as in explaining trade suggests that financial markets are not frictionless, but are segmented by information asymmetries and familiarity effects.

  We use the following specification for the gravity models:

$$\log\left(\frac{w_{ijt}}{1 - w_{ijt}}\right) = \phi_i + \phi_j + \phi_t + \alpha X_{ij} + \beta Z_{ijt} + \varepsilon_{ijt} \qquad \textbf{(1)}$$

  This is estimated separately for each asset class: FDI, equity, and debt. w_{ijt} is the proportion of assets of country i held in country j in year t. We choose to estimate the model on weights rather than stocks of foreign assets because stocks would be non-stationary, implying that the usual distributions for OLS estimates would be invalid. The dependent variable is the logit of weights. This is a standard transformation to deal with proportions data, transforming **(1)** into a linear model which can be estimated by OLS. The downside of this transformation is that taking logs eliminates observations for which the weights are zero. However, given the small proportion of zeros in the data (less than 10%), eliminating them should not have much influence on the results.[2]

[2]Eliminating zeros may be less problematic than estimating a model that fits over both zero and non-zero observations. This is because

ϕ_i and ϕ_j are dummy variables for each source and host country and ϕ_t are time dummies. The host country fixed effects control for characteristics that explain why some countries are more attractive to foreign investors than others. The source country fixed effects control for characteristics that explain why some countries invest larger shares abroad than others. In addition to these fixed effects, we include a set of bilateral variables, X_{ij}, which are standard in trade gravity models and measure the geographical and historical proximity between economies: common border, common language, colonial links, distance, and time difference. The colony dummy is asymmetric and is equal to 1 if country i is a former coloniser of country j. We construct this variable asymmetrically to reflect the fact that, while former colonisers may have preferential status when they invest in former colonies, former colonies may not have preferential status when investing in former colonisers. The time difference between countries i and j is included as a measure of information asymmetry and transaction costs. It has been found to be significant in previous studies (Daude and Stein (2007)). Z_{ijt} is a set of time-varying regressors.

- **Step 4**. Combine 'actual' with estimated weights.
  After estimating gravity models for geographical weights, we use the estimated coefficients to obtain out-of-sample predictions of weights for those years and country pairs for which data are missing. We then combine 'actual' weights with those predicted values to obtain a data set on asset weights with no missing observations ($\tilde{w}_{ijt}$).
- **Step 5**. Multiply geographical weights by total assets from the Lane and Milesi-Ferretti (2007) data set to obtain stocks of foreign assets.
  To transform geographical *weights* into *stocks* of foreign assets, we multiply the weights obtained in step 4 by total external assets of country i reported in the Lane and Milesi-Ferretti (2007) data set:

$$\widetilde{A}_{ijt} = \tilde{w}_{ijt} \times A_{it,LMF}$$

  This step ensures that bilateral stocks of foreign assets incorporate some adjustment for valuation effects arising from exchange rate movements and changes in asset prices. Lane and Milesi-Ferretti introduce this adjustment in their data. By multiplying bilateral weights by total external assets from their data, this adjustment will be incorporated into bilateral stocks.[3]

the determinants of whether a country has *any* financial linkages with another country may be different from the determinants of the *size* of the exposures given that countries are linked.

[3] A more accurate method to adjust for valuation effects would be to do it directly on bilateral stocks, taking into account changes in bilateral exchange rates and in stock market valuations in the host country. By taking the adjustment from Lane and Milesi-Ferretti we are applying the adjustment on total external assets to bilateral assets, rather than making it specific to each country pair.

This is potentially important, since valuation effects have been shown to be sizable (see Gourinchas and Rey (2007)).

- **Step 6** (symmetry). Construct liabilities from assets.

  The data set is constructed taking the assets perspective. The last step in the data construction explores the fact that assets and liabilities should be symmetric and constructs liabilities from assets:

  $$Liabilities_{ijt} = Assets_{jit}$$

  Liabilities of country i with country j at year t equal assets of country j in country i at year t.

2.3 FDI

2.3.1 Data

The main source of data on FDI assets is the OECD International Direct Investment by Country data set. This contains FDI data at book value reported by OECD members, starting in 1981. There are many missing values in the data. To the extent possible, missing observations are filled in with data from the United Nations Conference on Trade and Development (UNCTAD). The two data sets do not report exactly the same numbers when the data overlap, but the discrepancies are not large and they are broadly consistent. Even after combining the data sets, there are still gaps in the data. Table B lists the percentage of missing data for each source country. Coverage is better for developed economies, with no missing data for Germany and small percentages of missing data for Canada and the United States. On the other hand, there is a large fraction of missing data for Mexico, Argentina and India. Overall, approximately 44% of the data on bilateral FDI are missing and need to be estimated.

Because the OECD and UNCTAD report data on both assets and liabilities, it would, in principle, be possible to combine the two and reduce the percentage of data that need to be estimated. We could use liabilities reported by country j in country i to be equal to assets of country i in country j. However, there is a large asymmetry between reported FDI assets and liabilities. For example, we would expect the value of FDI assets reported by China in Hong Kong to be equal to the value of FDI liabilities reported by Hong Kong in China. However, the two are remarkably different: China reports a value of FDI assets in Hong Kong at US$24,632 million in 2003, while Hong Kong reports FDI liabilities in China at US$99,197 million, a value more than four times larger.

This discrepancy is due to the way FDI liabilities are reported, following the Ultimate Beneficiary Owner (UBO) principle, according to which the source of inward FDI is allocated to the country of ultimate ownership. The equivalent principle on the assets side would be the Country of Ultimate Destination (CUD) principle, according to which outward FDI would be allocated to the country of final destination. However, while the UBO principle is widely adopted in the production of FDI statistics, the CUD principle is not the norm, ie, liabilities are reported following the ultimate ownership principle and assets are reported following the residence principle adopted in the balance of payments statistics.

This difference in reporting principles generates large discrepancies between assets and liabilities. For illustration suppose that, in the example above, China channels part of its investment in Hong Kong through Taiwan. When reporting its FDI assets in Hong Kong, China includes only investment that goes directly to Hong Kong. Investment channelled through Taiwan is reported as a Chinese asset in Taiwan. Hong Kong, on the other hand, follows the UBO principle and reports its liabilities with China including investment that is channelled through Taiwan. Thus, Hong Kong's reported liabilities are much larger than China's reported assets. This confirms the findings of Felettigh and Monti (2008) that there can be large discrepancies between data based on the residence principle and data based on final destinations. Because of these discrepancies, it is not possible to mix data on FDI assets and liabilities. Since we choose to follow the balance of payments methodology, we focus only on assets and make no use of data on liabilities.

2.3.2 Estimation

FDI asset weights are estimated using model **(1)**. The gravity variables, X_{ij}, are obtained from the Distance Database compiled by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The set of time-varying regressors, Z_{ijt}, includes GDP per capita in countries i and j, and the degree of openness of country j to inward FDI. GDP per capita captures the degree of development and is obtained from the World Bank, World Development Indicators. It is measured at constant prices and is PPP-adjusted. The degree of openness of country j to inward FDI is measured as a time-varying index. For most countries, it is constructed from the tables in Kaminsky and Schmukler (2003), which report the chronology of stock market liberalisation and classify countries into three degrees of liberalisation over time:

- **No liberalisation:** foreign investors are not allowed to hold domestic equity and cannot repatriate capital, dividends, and interest until five years after the initial investment.
- **Partial liberalisation:** the country is open to foreign investment, but with some restrictions.
- **Full liberalisation:** foreign investors are allowed to hold domestic equity and to repatriate capital, dividends and interest without restrictions.

We transform this classification into a numerical variable which takes the value 0 if country j is not liberalised in year t, 1 if it is partially liberalised, and 2 if it is fully liberalised.

Some of the countries in our sample are not studied by Kaminsky and Schmukler (2003). For those countries, we use information on the timing of stock market liberalisation from other studies and code it according to the criteria used by Kaminsky and Schmukler (2003). For China, we use information in Bekaert, Harvey and Lundblad (2007), Prasad and Wei (2005) and OECD (2000), and for India, we use Ahluwalia (2002) and Reserve Bank of India (2006).

Table C reports the index on liberalisation to FDI investment for those countries that were not fully liberalised throughout the whole period.

As well as being used as a control in regression **(1)**, this index is used to fill in some of the missing data prior to estimation. Table D illustrates how this is done, using as an example FDI assets of the United Kingdom in China. Using the liberalisation index on inward FDI in China, we are able to fill in the missing values from 1980 to 1990. Because China was closed to inward FDI in those years, there would have been no inwards flows to China from the rest of the world. We know the stock of assets of the United Kingdom in China in 1991, while China was still closed. Because there would have been no inward flows to China during the period 1980 to 1990, the stock of assets in that period should equal the stock in 1991 adjusted for valuation effects due to changes in exchange rates and asset prices. To adjust for valuation effects, we assume that the bilateral stocks of the United Kingdom in China in the period from 1980 to 1990 grow at the same rate as total Chinese FDI liabilities. Therefore, we take the value in 1991 as the starting point and build stocks backwards using the growth rate of total Chinese liabilities.

Turning to the estimation results, we might expect the host country fixed effects to account for most of the explanatory power in regression **(1)**. To study this, we estimate a model where FDI asset weights are only explained by the host country fixed effects. The results are reported in column (1) of Table E. The predictive power is not negligible, with an R^2 of 41%. Column (2) adds source country fixed effects, with an improvement in the R^2 to 50%. This suggests that some source countries are more diversified than others, investing a smaller share in a larger number of countries. Including the standard gravity variables further increases the R^2 to 68%, which is remarkably high and is consistent with the results found in other empirical studies.

The standard gravity variables are significant and have the expected signs: FDI weights are larger for countries that share a common border or a common language and have colonial links. Distance and time difference have a significant negative effect on FDI weights. Time-varying controls are included in column (4). Countries with larger GDP per capita receive larger shares of FDI investment. This illustrates the paradox discussed in Lucas (1990) that capital tends to flow to rich countries even though the marginal product of capital is larger in poor countries, and is consistent with the findings in Papaioannou (2009). Countries whose markets are more liberalised to FDI also receive larger investment shares. However, the improvement in the R^2 from including these time-varying controls is only marginal. Most of the explanatory power comes from the source and host country fixed effects and standard gravity variables.

We also experimented with additional controls. One variable which has been found in previous studies to have a significant effect on bilateral asset holdings is bilateral trade. There are at least two reasons why this may be the case. First, bilateral trade may capture an additional familiarity effect, over and above the gravity variables. Second, countries may use financial investment to hedge against shocks in countries with which they trade. For example, if country A imports from country B, a potential hedge against output shocks in country B is to hold equity in that country: an increase in the domestic demand for imports from country B would be compensated by higher dividend yields from holding equity in country B. We extended the model to include trade weights, measured as the ratio of trade between countries i and j (exports plus imports), over total trade of country i, using data from the IMF Direction of Trade Statistics (DOTS). Trade weights were found to have a positive but insignificant effect in explaining FDI weights and were not included in the model used for prediction.[4]

Another variable we experimented with was the volatility in bilateral exchange rates, measured as the standard deviation in the rate of change of monthly bilateral exchange rates on a three-year

[4]Only variables with a p-value lower than 0.25 were kept in the model used for prediction.

rolling window. Exchange rates were obtained from the IMF International Financial Statistics. This is a common explanatory variable in gravity models for financial stocks and flows. The idea is that bilateral financial positions may be smaller when the bilateral exchange rate is more volatile, since there is more uncertainty about the returns. This variable turned out to have an insignificant effect on FDI asset weights and was excluded from the model used for prediction. The insignificant effect of bilateral exchange rates is consistent with the findings of previous studies. Portes and Rey (2005) use it to explain bilateral equity flows and find an insignificant effect. The same result arises in Lane and Milesi-Ferretti (2008) for equity stocks.

2.4 Equity

2.4.1 Data

Data on portfolio equity assets are collected from the IMF CPIS, which covers all countries in our sample except China, who did not participate in the survey. The time coverage though is quite limited: a pilot survey was conducted in 1997 and a regular annual survey was introduced in 2001 for an extended group of participating countries. Table B lists the proportion of missing data by source country. Given limited time coverage of the CPIS, over 60% of data are missing for all countries and need to be estimated. For China, this proportion is higher since it does not participate in the CPIS.

As for FDI, we only use data on assets and make no use of liabilities data. This is because, while countries who participate in the CPIS are required to report assets, liabilities are reported on a voluntary basis. The only countries in our sample that report liabilities are Australia, India, Japan, Portugal and Spain. For these countries, there is a big discrepancy between reported liabilities and liabilities derived from assets reported by creditor countries. Because of this discrepancy we decided to use only reported assets.

2.4.2 Estimation

Table F shows the results of estimating model **(1)** on equity weights. The host country fixed effects only explain 46% of the variation in equity weights. Introducing source country fixed effects increases the R^2 to 55%, indicating that some source countries are more diversified and invest smaller shares in a larger number of destinations. The standard gravity variables, X_{ij}, are the same as in the regression for FDI weights. The coefficients on these variables are significant and have the expected signs except for colonial links, which is negative. This suggests that investors may prefer to invest in countries with a similar degree of development as their home country, regardless of historical colonial links. The inclusion of these variables leads to a significant improvement in the R^2, which rises to 71%.

The set of time-varying controls, Z_{ijt}, includes GDP per capita in country j, bilateral exchange rate volatility, and the degree of openness of country j to inward equity investment. The results suggest that investors invest more in countries that are more open to inward equity investment and have a larger GDP per capita. They also invest more when the volatility of the bilateral exchange rate is smaller. However, these time-varying variables do not have a large explanatory power and lead to a very small improvement in the R^2.

The degree of openness of country j to inward equity investment was constructed in the same way as the one for FDI. In fact, FDI can be seen as a type of portfolio equity investment where the degree of ownership exceeds 10% of the firm's equity. However, countries may liberalize their stock markets to foreign portfolio equity investment and remain closed to FDI by introducing a ceiling on the percentage of total equity that can be owned by foreign residents. While this may be true for other countries, the only country in our sample where the index of liberalisation to equity investment differs from the one for FDI is Korea, where foreign portfolio equity investment was partially liberalised in 1991, while foreign FDI investment remained restricted. Both types of investment were then fully liberalised in 1998. For all other countries, the liberalisation index for equity coincides with the index for FDI reported in Table C.

As for FDI, the liberalisation index for equity is used to estimate missing data. However, while for FDI it was possible to take a data point when the host country was still closed and build the data backwards using the growth rate of its total liabilities — as illustrated in Table D — for equity the data start when all countries were already open to inward equity investment. Since it is not possible to build the data backwards in the same way as for FDI, we simply impose zero bilateral weights for the period when the host country was closed to inward equity investment. The only exception to this rule is equity investment of Hong Kong in China. China was closed to inward equity investment until 1992. However, given the strong political and administrative links between the two countries, we do not impose zeros for Hong Kong's equity investment in China pre-1992.

We also experimented with other control variables. To capture stock market returns and correlations in returns, we included averages, standard deviations, and the correlation coefficient of daily stock market indices in the host and source countries. These variables were insignificant and therefore were not included in the final regression. GDP per capita in country i, stock market capitalisation in country j, and trade weights were also insignificant.

2.5 Debt

2.5.1 Data

Data on portfolio debt assets are also collected from the IMF CPIS. In addition, we use data from the BIS Locational Banking Statistics, which reports debt assets and liabilities of banks for all countries in our sample, except Argentina, China, Hong Kong, Korea, and Singapore. The BIS data set has the advantage of having a much longer time coverage, going back to 1977 for most advanced countries. However, it has the limitation of only reporting debt assets held by banks, while the CPIS has a broader coverage, including not only banks but also other financial institutions, monetary authorities, the government, non-financial corporations, and households. Another difference between the two data sets is that, while the CPIS only covers portfolio debt, the BIS also covers loans and deposits.

To test whether it is sensible to combine data from the BIS and the CPIS, we computed the correlation coefficient between the asset weights generated by the two data sources. The correlation coefficient is quite large (80%), suggesting that it is appropriate to combine the two data sources. By default, we use asset weights computed from the BIS data, and complete it with weights computed from the CPIS data whenever possible. After combining the two data sets, approximately 43% of the data are missing. Looking at the proportion of missing data by source country in Table B, the gaps are especially pronounced for China, which is not covered by either data set, and for countries not covered by the BIS Locational Banking Statistics, for which we only have data after the CPIS was introduced in 1997.

As for the other asset classes we make no use of data on liabilities. For CPIS data we face the same problems as with equity: very few countries report liabilities in the CPIS and, when they do, there is a large difference between those reported liabilities and assets reported by creditors. For BIS data there is also a problem in using liabilities to build assets by symmetry. Because the

BIS reports assets and liabilities held by banks against both banks and non-banks, the data are not symmetric: banks in country i report assets held against *banks and non-banks* in country j, while *banks* in country j report liabilities against both banks and non-banks in country i. Because of this lack of symmetry it is not possible to derive assets from liabilities.

2.5.2 Estimation

Table G reports the results of estimating model **(1)** on debt weights. The model with only host country fixed effects explains 49% of the variation in debt weights. Adding source country fixed effects increases the R^2 to 57% and adding standard gravity variables further improves the R^2 to 69%. Border was excluded from the set of gravity variables because it had no significant effect on debt weights. The colony dummy has a negative sign, as in the model for equity. This is an interesting finding and suggests that, for types of investment which imply a larger degree of commitment, such as FDI, former colonisers tend to invest in former colonies. However, for equity and debt investment, they seem to prefer countries with a similar degree of development, regardless of colonial links.

Unlike for FDI and equity, the set of time-varying controls, Z_{ijt}, does not include the degree of liberalisation of the host country to inward debt investment. This is because we were unable to construct an index which captures restrictions only to *inward* investment. The closest measure we were able to find was a time-series index for capital account restrictions, based on the chronology in Kaminsky and Schmukler (2003). This index captures restrictions to borrowing abroad by banks and corporations (which could be interpreted as restrictions to debt capital *inflows*) as well as exchange rates and other restrictions to capital *outflows*. Because it confounds restrictions to inward and outward investment, we decided not to use it.

As for equity, the results suggest that investors tend to invest larger shares in more developed countries — the Lucas paradox — and in countries with lower exchange rate volatility with respect to the currency of the source country. In contrast with the result for FDI and equity, bilateral trade weights have a significant and positive effect on debt weights. This is consistent with the findings in Rose and Spiegel (2004). In their paper borrowers fear that defaulting on their debt may lead to a reduction in international trade. Therefore, creditors systematically lend more to countries with closer trade links to the source country.

We experimented with additional controls and estimated the model including bond market capitalisation and measures of bond returns, using the JP Morgan EMBI and Global Bond Index. These variables turned out insignificant and were not included in the model used for prediction.

The model captures the geographical composition of debt and abstracts from its currency composition. For FDI and equity, it is reasonable to assume that assets are denominated in the currency of the host country. For debt, however, this equivalence between currency and geographical composition is not so simple, since countries may issue bonds denominated in foreign currencies. Therefore, investors make a simultaneous decision about the *geographical* as well as the *currency* composition of their debt investments. This introduces a further complication, since we should model these two choices simultaneously. Here we simplify and focus solely on the geographical composition.

2.6 Reserves

The construction of the reserves data follows a different approach from the one used for the other three asset classes. While for FDI, equity and debt investors choose *where* to invest, for reserves they choose *in which currency* to invest. We follow a two-step procedure to obtain the geographical composition of reserves. First, we obtain the currency composition. Then, we translate it into the geographical composition: if country i holds an amount X of reserves in US dollars, we take X as being the amount of reserve assets that country i holds in the United States. For simplification, we focus on the four main reserve currencies: the US dollar, the euro, the pound, and the yen. These should capture the bulk of countries' foreign exchange reserves. Also for simplification, we treat reserves of country i denominated in euros as being assets of country i in Germany. For the period before the introduction of the euro, we use the Deutsche mark.[5]

An important limitation in constructing data on the currency composition of reserves is that, given its confidentiality, data are not readily available. The BIS Multilateral Surveillance Statistics contain data on the currency composition of reserves for the countries in the G10 since 1994. This gives us data for six counties in our sample: France, Germany, Italy, Japan, the United Kingdom, and the United States. Given the remarkable stability of currency weights over time, we assume that weights stay constant from 1980 to 1994. For the remaining countries, the IMF

[5] A more precise way of dealing with euro reserves would be to allocate them according to the relative GDP of each country in the euro area. Here we take a shortcut and allocate all euro reserves to Germany.

collects data in the COFER data set. Although the numbers are only released as aggregates across industrialised and developing countries, disaggregated data have been used in some previous studies. We follow the approach in Lane and Shambaugh (2007) and use the results reported in those studies to obtain estimates of the currency composition of reserves for the countries in our sample that are not members of the G10.

The studies we use are Eichengreen and Mathieson (2000) and Dooley *et al* (1989), who adopt the following specification to explain the currency composition of reserves:

$$\begin{aligned} share_{ict} &= c + \alpha_1 dollar\_peg_{ict} + \alpha_2 other\_peg_{ict} + \\ &\quad \beta share\_trade_{ijt} + \gamma share\_debt\_payments_{ict} + \varepsilon_{ict} \end{aligned} \qquad \textbf{(2)}$$

The dependent variable is the share of foreign exchange reserves held by country i in currency c at time t, obtained from COFER. The regression includes a constant term, dummy variables equal to 1 if country i pegs to the US dollar or to another currency, the share of trade between country i and country j at time t (where country j is the country that issues currency c), and the share of debt service payments of country i in currency c at time t. The share of trade is calculated as the sum of exports and imports between countries i and j divided by total exports plus imports plus debt service payments of country i. The share of debt payments in currency c is calculated as service payments of country i on debt denominated in currency c divided by total exports plus imports plus debt service payments of country i.

Eichengreen and Mathieson (2000) report the results of estimating this model for a sample of 84 emerging and transition economies for the period 1979-96. We collect data for the right-hand side variables and multiply by the estimated coefficients reported in their paper to obtain estimates of the currency composition of reserves.[6]

Data on exchange rate regimes are obtained from Levy-Yeyati and Sturzenegger (2005). They

[6]We use the coefficients reported in Table 3 of Eichengreen and Mathieson (2000).

report an index which classifies exchange rate regimes in three categories: floating, intermediate, and fixed. We transform this index into a binary variable, which takes the value 0 if the country has a floating regime and 1 if the country has an intermediate regime or a peg. We construct one indicator for US dollar pegs and another for other currency pegs. Data on trade are collected from the IMF Direction of Trade Statistics. Debt service payments are obtained by multiplying the six-month Euro currency deposit rates, obtained from Datastream, by the amount of debt outstanding, obtained from the World Bank, Global Development Finance.

This approach gives us estimates of the currency composition of reserves which seem sensible. While it is difficult to have a benchmark for comparison, countries occasionally report their reserve shares in announcements and media interviews. For example, China is reported to hold roughly 70% of its reserves in dollars, 20% in euros and 10% in other currencies. Our estimation gives 79% in dollars and 21% in euros.

3 A look at the data

The international financial system can be seen as a network, where nodes represent countries and links represent bilateral financial assets. Our data set provides information on the links and allows us to study how the global financial network has changed over time. In this section, we use network methods to give a flavour of the data set and show the key stylised facts that emerge from it. First, we look at the evolution of the financial network over time for all asset classes, looking at the configuration of the network in 1985, 1995, and 2005. We then focus on the composition of assets and represent the network in 2005 for each asset class: FDI, equity, debt, and reserves. Finally, we compare the financial network with the trade network.

3.1 Financial network — undirected

Chart 2 looks at the evolution of the global financial network and Table H provides some summary statistics, in particular measures of skewness and 'peakedness' of the distribution of links, average path length and clustering.[7] In each year t links are given by the sum of bilateral assets and liabilities divided by the sum of the GDP of the source and host countries:

[7]Definitions of these statistics are presented in the appendix. The network charts were done in Pajek (Program for Analysis and Visualization of Large Networks).

$$link_{ijt} = \frac{Assets_{ijt} + Liabilities_{ijt}}{GDP_{it} + GDP_{jt}}$$

Since assets and liabilities are symmetrical, the network is *undirected*, ie, the link from i to j is the same as the link from j to i. The network is also *weighted* because links represent the strength of the connections between nodes and not simply whether a connection exists or not. To simplify the diagrams, we impose a cut-off and represent only the strongest links (where the ratio defined above is higher than 0.3%). This cut-off is chosen in such a way that every node is linked to at least one other node. The thickness of the lines indicates the size of the links and the size of the nodes is proportional to the country's financial openness, measured by the sum of its total external assets and liabilities. Pairs of countries with stronger links are placed closer to each other.[8]

A few findings emerge:

- **The interconnectivity of the global financial network has increased significantly over the past two decades.** This can be seen from the increase in the size of the nodes and the increase in number and size of the links.
- **The distribution of financial links exhibits a long tail.** Measures of skewness and kurtosis show the asymmetry compared to the normal distribution. In particular, the global financial network is characterised by a large number of small links and a small number of large links.
- **The average path length of the global financial network has decreased over time.** Average path length measures the average of the shortest distance between all pairs of nodes. In 2005 there are less than 1.4 degrees of separation on average between any two nodes.[9]
- **The network has become more clustered over time.** The clustering coefficient measures the probability that, given that node i is linked to j and k, nodes j and k are also linked to each other. The increase in this coefficient is another symptom of the increase in interconnectivity.

[8] This is achieved using the Kamada-Kawai algorithm, which positions nodes in the space so that their geometric distance reflects the strength of the links between them.

[9] Note that average path length depends on the cut-off chosen for the links. Imposing a cut-off enables us to apply statistics developed for unweighted networks (such as average path length and clustering) to our network. Because the global financial network is complete, ie, all pairs of nodes are linked even if the size of financial assets and liabilities is very small, these statistics would be meaningless if we had not imposed a cut-off.

A long-tailed distribution of links is a property of 'scale-free' networks, whose robustness has been studied, for example, by Albert *et al* (2000). Their study shows that these networks are robust to random shocks: since the majority of the nodes have only a few small links, there is a higher probability that a random shock will hit a less connected node. However, they are very vulnerable to targeted attacks hitting the most interconnected nodes.

Low average path length and a high clustering coefficient are characteristics of the so-called 'small-world' networks described, for example, in Watts and Strogatz (1998). In contrast to 'scale-free' networks, these networks do not exhibit much variability in the number of links of each node. This suggests that they are not particularly vulnerable to targeted attacks. However, because these networks are characterised by a high degree of interconnectivity, once an attack occurs it will tend to spread more widely.

The global financial network exhibits characteristics of both 'scale-free' and 'small-world' networks. From a stability perspective, this makes for a robust-yet-fragile structure. Because the network has a small number of nodes with multiple and large links and is highly interconnected, it is susceptible to targeted attacks affecting the key financial hubs. Disturbances to those hubs spread rapidly throughout the network. These properties of the global financial network and its consequences for stability are discussed in Haldane (2009).

3.2 Financial network — directed

Chart 3 looks at the evolution of the global financial network from a different perspective. Links are now defined as the ratio of gross bilateral assets to GDP of the source country, including all asset classes — FDI, equity, debt, and foreign exchange reserves:

$$link_{ijt} = \frac{Assets_{ijt}}{GDP_{it}}$$

The network is now directed: an arrow pointing from county i to j represents the value of country i's assets in country j, scaled by country i's GDP. As before, the smallest links (with a ratio of assets to GDP below 1.7%) were deleted.

The directed network exhibits the same properties as the undirected network. There has been a remarkable increase in interconnectivity over time, as shown by the increase in the size of the nodes and the size and number of links. In addition, it allows us to analyse which countries are the main sources and destinations of international investment. Table I shows a number of measures of network centrality for each of the nodes. Detailed definitions for these measures are in the appendix and follow the ones used in von Peter (2007) to identify international banking centres.

The key findings that emerge from the network charts and the centrality measures are as follows:

- **The United States, the United Kingdom and Germany are the main recipients of foreign investment**. This can be seen by the number of arrows pointing to these nodes and by the high value of *in-degree centrality*, which measures the number of links that arrive at a node divided by the maximum number of links.
- **Financial centres — Hong Kong, Singapore and the United Kingdom — are the main originators of foreign investment**, as can be seen by the number of arrows pointing out and the high value of *out-degree centrality*, which measures the number of links that depart from a node divided by the maximum number of links.
- **The countries which are located closer to other nodes in the network are the United States, Germany, Hong Kong, Singapore, and the United Kingdom.** *Closeness centrality* is the inverse of the average distance between countries, where distance is measured by the number of links on the shortest path. A country which is directly connected to all other countries, such as the United States, has a closeness score equal to 1.
- **The United States and the United Kingdom are the main countries connecting other nodes.** This is captured by *betweenness centrality*, which measures the frequency with which a country lies on the shortest path between two other countries, and *intermediation centrality*, which captures the intensity of links by incorporating portfolio shares.
- **The United States and United Kingdom also score highest in terms of prestige centrality.** *Prestige centrality* (or eigenvector centrality) reflects the importance of the counterparties. A country with high prestige is one that is linked to others that have themselves high prestige. This is computed by assigning to each country the same initial score and adding a term involving the scores of the creditors, weighted by the portfolio shares. The prestige scores are simultaneously determined in a system of equations.

3.3 Financial network — asset composition

To analyse differences across asset classes, Chart 4 represents the networks with links given by the ratio of assets to GDP of the source country for each asset class in 2005.[10] Tables J to M, meanwhile, provide measures of network centrality for each of these networks. These results are broadly consistent with the findings for the average across asset classes. In particular, the United States and the United Kingdom emerge as the main recipients of foreign investment for FDI, equity and debt, as can be seen by their high score for in-degree centrality. Singapore and Hong Kong score low as recipients of foreign investment, but score high as originators.

There are some interesting differences across asset classes. The equity network is less dense than for other asset classes, with some countries (China, Korea, and India) being unconnected. The United States scores high as originator of FDI and equity investment, but scores low as originator of debt investment. For reserves, the network is less dense because we only measure reserve holdings in four currencies: dollars, euros, pounds and yen. Among these currencies, the dollar is clearly dominant, with much higher values for in-degree, closeness and prestige centrality.

3.4 Comparison with the trade network

To compare the financial network with the trade network Table N reports the same summary statistics as Table H for the global trade network and Chart 5 represents the undirected trade network. Links are given by the sum of bilateral exports and imports divided by the sum of the GDP of the source and host countries:

$$link_{ijt} = \frac{Exports_{ijt} + Imports_{ijt}}{GDP_{it} + GDP_{jt}}$$

Data on bilateral trade are from the IMF Direction of Trade Statistics (DOTS). As before, a cut-off is imposed so that only the largest links (for which the ratio above is higher than 0.21%) are shown. This cut-off is set so that every node is linked to at least one other node. The thickness of the lines is proportional to the size of the links and the size of the nodes is proportional to the country's trade openness, measured by the sum of total exports and imports.

[10] The cut-off for deletion of the smallest links is 0.3% for FDI and equity and 1% for debt. No cut-off is imposed for reserves.

Countries are placed more centrally in the network if they are more interconnected and pairs of countries with strong links are placed closer to each other.

A few findings emerge:

- Just as for the global financial network, **the interconnectivity of the global trade network increased over the past two decades**. This can be seen from the increase in the size of the nodes and the increase in the size and number of links.
- **The distribution of trade links also exhibits a long tail**, with a small number of countries having large links.
- **The global trade network has 'small-world' properties**, with a short average path length and a high clustering coefficient, even though these are less strong than in the financial network.

To distinguish between sources and destinations of international trade, Chart 6 looks at the directed trade network, where links are given by the ratio of bilateral exports to GDP of the source country:

$$link_{ijt} = \frac{Exports_{ijt}}{GDP_{it}}$$

An arrow pointing from i to j is proportional to the value of country i's exports to country j, divided by the GDP of country i. Links for which this ratio is below 1.3% are not shown in the chart. Measures of centrality associated with this network in 2005 are given in Table O.

The directed trade network confirms the increased interconnectivity found in the undirected network. It also highlights some additional facts:

- **In all years, the trade network exhibits strong intracontinental links, with three clusters**: an American cluster (United States, Canada and Mexico), an Asian cluster (Singapore, Hong Kong, China, Korea, and Japan), and a European cluster (United Kingdom, Germany, France, Spain, Italy, and Portugal). This pattern contrasts with the one found for financial links, where the United Kingdom and the United States were clearly at the centre of the network, linking to almost all other nodes.

- **Germany, China and France are important trade centres** and score highly both as exporters and as importers. **The United States is the main importer, but scores low as an exporter. The opposite is true for Singapore, which is the main exporter, but scores low as an importer**.
- **Germany appears to be the centre of the European cluster and China appears to be the centre of the Asian cluster.** These countries play an important role connecting other nodes, as can be seen by their high scores for betweenness and intermediation centrality.
- **The United Kingdom occupies a much less central position in the trade network than in the financial network**.

4 Conclusions

This paper contributes to the study of financial globalisation by constructing a data set on bilateral financial links for a group of 18 countries, from 1980 to 2005. Network tools are used to identify the key stylised facts that emerge from the data. We find a remarkable increase in interconnectivity over the past two decades, with an increase in the number and size of financial links. In addition, the distribution of financial links has a long tail, with a small number of countries having large and numerous links. The network also exhibits some 'small-world' properties, with a very small number of degrees of separation between nodes and a high clustering coefficient. The combination of high interconnectivity, long-tails, and 'small-world' properties makes for a robust-yet-fragile system, where disturbances to one of the central hubs would be transmitted widely and rapidly.

The trade network also reveals an increase in interconnectivity over time. However, unlike the financial network, where the United States and the United Kingdom are at the centre and intracontinental links are not particularly strong, the trade network exhibits much stronger links within continents. In particular, there is a European cluster, centred around Germany; an Asian cluster, centred around China; and an American cluster, centred around the United States. The United Kingdom plays a much less central role in the trade network than in the financial network.

In addition to giving an idea of the structure and evolution of the global financial network over time, the data set can be applied to many other questions. For example, it can be used to understand how financial links contribute to the transmission of shocks across countries. There is a literature on whether business cycle comovement among developed countries has increased. The consensus is that comovement among developed countries rose sharply after the collapse of Bretton Woods and remained high since then. However, while in the 1970s and early 1980s comovement was mainly due to common shocks, the key drivers from the late 1980s onwards are likely to have been spillovers of country-specific shocks through trade and financial links. A robust finding in the empirical literature is that pairs of countries that trade more with each other exhibit a higher degree of output comovement (eg Baxter and Kouparitsas (2005)). Our data set allows this type of exercise to be done taking into account financial links.

There has also been an intense debate in recent years on whether comovement between emerging market economies (EMEs) and advanced economies has decreased — the decoupling hypothesis. Kose, Otrok and Prasad (2008) look at this question by decomposing output, investment and consumption fluctuations for a group of 106 countries into four factors: a global factor, three group specific factors (for industrial countries, emerging markets, and developing countries), country factors, and idiosyncratic factors specific to each time series. They find that during the period of globalisation (1985-2005) there has been an increase in business cycle convergence *within* the group of industrial countries and *within* the group of EMEs, but there has been divergence (or decoupling) *between* them. However, in a short chapter on this subject, Claessens and Kose (2008) make an important qualification. They note that the existing evidence in favour of the decoupling hypothesis has mainly focused on real economic links, but has left out financial links. Therefore, the evidence does not speak to the possibility of financial decoupling (or lack thereof). Though we do not pursue this here, our data set provides some information that could be used to analyse this question by looking at cross-country financial links.

Finally, the data set can be applied to another heated policy debate — the reform of IMF surveillance. The IMF has been under a gradual reform process for several years. An important aspect of this process is the shift in the perspective of surveillance from the country level to a multilateral level, taking into account cross-border spillovers. Having a better understanding of which countries are more closely linked by spillovers is an important step in the development of a framework for multilateral surveillance.

Appendix. Statistical definitions

Skewness is a measure of the asymmetry of a distribution and is defined as $\frac{E(X-\mu)^3}{(E(X-\mu)^2)^{3/2}}$. A normal distribution is symmetric and has a skewness of zero. A positive value for skewness indicates that the distribution has a long tail on the right, ie, there are many observations with small values of X and few observations with large values of X.

Kurtosis is a measure of the 'peakedness' of a distribution and is defined as $\frac{E(X-\mu)^4}{(E(X-\mu)^2)^2} - 3$. A normal distribution has a kurtosis of zero. A large value for kurtosis indicates that the distribution has 'fat tails'.

Network definitions

The network can be expressed in matrix form, where the typical element A_{ij} records the value of financial assets held by country i in country j. The matrix has dimension equal to the number of countries, n, and can be read in two directions: rows of A represent assets of country i in country j and columns of A represent liabilities of j in i. All diagonal elements are zero. Off-diagonal elements are zero for country pairs that have no links or whose links are below the cut-off, defined in such a way that each country is linked to at least one other country (either as a creditor or as a debtor). The network is directed and weighted, hence A is not symmetric and its entries reflect the size of financial assets.

Two perspectives can be taken when analysing weighted networks. One perspective looks at whether a link exists or not, regardless of the value of the link, ie it looks at the indicator $N_{ij} = 1$ if $A_{ij} > 0$, and 0 otherwise. Another perspective takes into account the size of the links A_{ij}.

Average path length is the average of the shortest paths between all pairs of nodes in the network. For example, if node i is directly linked to node k, the shortest path between the two nodes has length one. If node i is linked to k via j, the shortest path between i and k has length two. Average path length is the average of this measure for all pairs of nodes.

Clustering measures the probability that, given that node i is directly linked to nodes j and k, node j is also directly linked to k. The clustering coefficient is given by $\frac{\sum_{i,j\neq i,k\neq j,k\neq i} N_{ij} N_{ik} N_{jk}}{\sum_{i,j\neq i,k\neq j,k\neq i} N_{ij} N_{ik}}$.

Measures of network centrality

The definitions of the centrality measures used in the paper follow closely the box in von Peter (2007) and focus on the directed financial network. Similar definitions hold for the trade network.

The centrality measures apply to each node and describe how that node relates to the network, taking different perspectives. Degree, closeness and betweenness centrality are based on whether a link exists or not, regardless of the value of the link, ie, they are based on the indicator N_{ij}. Intermediation and prestige centrality take into account the size of the links and rely on the portfolio shares $P_{ij} = A_{ij}/\sum_k A_{ik}$ for all i.

In-degree is the number of links that point to a node, ie, it is given by the sum $\sum_j N_{ji}$. The measure of in-degree centrality reported in the tables scales this sum by the total possible number of links, $n-1$. Out-degree is the number of links departing from a node, ie, $\sum_j N_{ij}$. This is divided by $n-1$ to obtain the numbers reported in the tables.

Closeness is the inverse of the average distance from node i to all other nodes. The distance between i and j, δ_{ij}, equals the length of the shortest path. The average distance from i to all other nodes is given by $\sum_j \delta_{ij}/(n-1)$. Closeness is the inverse of this measure.

Betweenness focuses on the nodes that the shortest path goes through. Let g_{jk} denote the number of shortest paths between j and k, and $g_{jk}(i)$ denote the number of such paths that go through node i. The probability that node i is on the shortest path from j to k is given by $g_{jk}(i)/g_{jk}$. Betweenness of node i is the sum of these probabilities over all nodes excluding i, divided by the maximum that the sum can attain: $(\sum_{j\neq i}\sum_{k\neq i} g_{jk}(i)/g_{jk})/(n-1)(n-2)$.

Intermediation extends the betweenness measure taking into account the value of the links. The probability that a dollar sent by i reaches j in two steps is given by $\sum_k P_{ik}P_{kj}$. The probability that a dollar sent by i reaches j through k is given by $P_{ik}P_{kj}/\sum_k P_{ik}P_{kj}$. The intermediation measure for node k is obtained by summing these probabilities for all pairs (i, j), divided by the total number of pairs $n(n-1)$.

Prestige (or eigenvector centrality) considers the identity of the counterparties. The prestige of country i (v_i) is obtained by taking the prestige of its creditors, weighted by their portfolio shares with i, ie, $v_i = \sum_j P_{ji} v_j$. This defines a linear system $v = P'v$, where P is the matrix of portfolio shares. The solution to this system is the eigenvector associated with the unit eigenvalue. Following von Peter (2007), we solve the alternative system $v = \frac{1}{2}P'v + e \Rightarrow v = (I - \frac{1}{2}P')^{-1}e$, where e is the unit vector. This avoids countries with a zero score contributing nothing to the centrality of others.

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Table A. Country coverage

Developed countries	Emerging Markets
Australia	Argentina
Canada	Brazil
France	Mexico
Germany	China
Italy	Hong Kong
Japan	India
Portugal	Korea
Spain	Singapore
United Kingdom	
United States	

Table B. Proportion of missing data

Source country	FDI	Equity	Debt
Argentina	84%	63%	76%
Australia	40%	68%	62%
Brazil	67%	68%	78%
Canada	3%	63%	0%
China	76%	89%	94%
France	19%	63%	0%
Germany	0%	67%	0%
Hong Kong	77%	72%	79%
India	84%	84%	76%
Italy	26%	63%	0%
Japan	15%	63%	0%
Korea	15%	68%	78%
Mexico	86%	85%	86%
Portugal	52%	65%	62%
Singapore	54%	64%	77%
Spain	76%	64%	11%
United Kingdom	16%	64%	0%
United States	6%	63%	0%
Full Sample	**44%**	**69%**	**43%**

NOTE: Proportions are computed after filling in missing values using the index of stock market liberalisation.
For equity, the CPIS only reports data for 1997 and the period from 2001 to 2005. Data for all other years are missing.
For debt, data for Argentina, China, Hong Kong, Korea, and Singapore are from the IMF CPIS only. Therefore, data are missing for all years except 1997 and 2001 to 2005.

Table C. Liberalisation index on inward FDI

	Argentina	Brazil	China	India	Japan	Korea	Mexico	Portugal
1980	1	1	0	0	1	0	0	1
1981	1	1	0	0	1	0	0	1
1982	0	1	0	0	1	0	0	1
1983	0	1	0	0	1	0	0	1
1984	0	1	0	0	1	0	0	1
1985	0	1	0	0	2	0	0	1
1986	0	1	0	0	2	0	0	2
1987	0	1	0	0	2	0	0	2
1988	0	1	0	0	2	0	0	2
1989	2	1	0	0	2	0	1	2
1990	2	1	0	0	2	0	1	2
1991	2	1	0	1	2	0	2	2
1992	2	2	1	1	2	0	2	2
1993	2	2	1	1	2	0	2	2
1994	2	2	1	1	2	0	2	2
1995	2	2	1	1	2	0	2	2
1996	2	2	1	1	2	0	2	2
1997	2	2	1	1	2	0	2	2
1998	2	2	1	1	2	2	2	2
1999	2	2	1	1	2	2	2	2
2000	2	2	1	1	2	2	2	2
2001	2	2	1	1	2	2	2	2
2002	2	2	1	1	2	2	2	2
2003	2	2	1	1	2	2	2	2
2004	2	2	1	1	2	2	2	2
2005	2	2	1	1	2	2	2	2

NOTE: 0 denoted no liberalisation; 1 denoted partial liberalisation; and 2 denoted full liberalisation. Countries in our sample that are not shown in this table are fully liberalised through the period 1980-2005.

SOURCES: Kaminsky and Schmukler (2003), Table 1, Appendix Table 1, and Annex Table 1. For China: Bekaert, Harvey and Lundblad (2007), Prasad and Wei (2005) and OECD (2000). For India, Ahluwalia (2002) and Reserve Bank of India (2006).

Table D. Using the liberalisation index on inward FDI to fill in missing data

Year	FDI assets of UK in China	Liberalisation index on inward FDI in China
1980	8	0
1981	8	0
1982	10	0
1983	13	0
1984	19	0
1985	30	0
1986	44	0
1987	60	0
1988	77	0
1989	100	0
1990	124	0
1991	150	0
1992	157	1
1993	271	1
1994	184	1
1995	270	1
1996	778	1
1997	776	1
1998	566	1
1999	2027	1
2000	2246	1
2001	3055	1
2002	5177	1
2003	3229	1
2004	3645	1
2005	5364	1

NOTE: Highlighted values are filled in using the liberalisation index.
SOURCES: OECD and UNCTAD, values in millions of US dollars.

Table E. Estimation results for FDI weights

	(1) Host country FE	(2) Host and source country FE	(3) Gravity variables	(4) Model for prediction
Border			0.394***	0.340***
			(0.119)	(0.113)
Language			1.585***	1.598***
			(0.095)	(0.094)
Colony			0.507***	0.481***
			(0.092)	(0.096)
Log(Distance)			-0.681***	-0.681***
			(0.043)	(0.040)
Time difference			-0.054***	-0.054***
			(0.010)	(0.009)
Log($GDPpc_{it}$)				0.750***
				(0.295)
Log($GDPpc_{jt}$)				1.817***
				(0.137)
Index Liberalisation FDI_{jt}				0.379***
				(0.054)
N	3810	3810	3810	3810
R^2	0.41	0.50	0.68	0.71
Marginal R^2 of gravity variables			0.36	
Marginal R^2 of time-varying variables				0.04

NOTE: Robust standard errors in parentheses.* significant at the 10% level, ** at the 5% level, *** at the 1% level. Regression (4) includes time dummies. The marginal R^2 of the gravity variables indicates the percentage improvement in the R^2 from including these variables, over and above the model with only host and source country fixed effects. The marginal R^2 of time-varying variables indicates the percentage improvement in the R^2 from the time-varying variables (including time dummies) over and above the model with fixed effects and the gravity variables.

Table F. Estimation results for Equity weights

	(1)	(2)	(3)	(4)
	Host country FE	Host and source country FE	Gravity variables	Model for prediction
Border			0.820***	0.820***
			(0.185)	(0.187)
Language			1.729***	1.736***
			(0.143)	(0.141)
Colony			-0.792***	-0.805***
			(0.203)	(0.192)
Log(Distance)			-0.453***	-0.433***
			(0.074)	(0.072)
Time difference			-0.107***	-0.110***
			(0.017)	(0.017)
Log($GDPpc_{jt}$)				4.063***
				(0.769)
Exchange rate volatility				-0.003**
				(0.001)
Index Liberalisation $Equity_{jt}$				2.452***
				(0.603)
N	1341	1341	1341	1341
R^2	0.46	0.55	0.71	0.72
Marginal R^2 of gravity variables			0.29	
Marginal R^2 of time-varying variables				0.01

NOTE: Robust standard errors in parentheses.* significant at the 10% level, ** at the 5% level, *** at the 1% level. Regression (4) includes time dummies. The marginal R^2 of the gravity variables indicates the percentage improvement in the R^2 from including these variables, over and above the model with only host and source country fixed effects. The marginal R^2 of time-varying variables indicates the percentage improvement in the R^2 from the time-varying variables (including time dummies) over and above the model with fixed effects and the gravity variables.

Table G. Estimation results for Debt weights

	(1) Host country FE	(2) Host and source country FE	(3) Gravity variables	(4) Model for prediction
Language			1.081***	1.001***
			(0.077)	(0.081)
Colony			-0.261***	-0.170**
			(0.078)	(0.082)
Log(Distance)			-0.423***	-0.367***
			(0.042)	(0.044)
Time difference			-0.119***	-0.114***
			(0.010)	(0.010)
Log($GDPpc_{jt}$)				0.892***
				(0.120)
Trade $weights_{ijt}$				1.160***
				(0.449)
Exchange rate $volatility_{ijt}$				-0.003***
				(0.001)
N	4187	4187	4187	4187
R^2	0.49	0.57	0.69	0.70
Marginal R^2 of gravity variables			0.21	
Marginal R^2 of time-varying variables				0.01

NOTE: Robust standard errors in parentheses.* significant at the 10% level, ** at the 5% level, *** at the 1% level. Regression (4) includes time dummies. The marginal R^2 of the gravity variables indicates the percentage improvement in the R^2 from including these variables, over and above the model with only host and source country fixed effects. The marginal R^2 of time-varying variables indicates the percentage improvement in the R^2 from the time-varying variables (including time dummies) over and above the model with fixed effects and the gravity variables.

Table H. Summary statistics on the international financial network

	1985	**1995**	**2005**
Skewness	7.62	7.96	3.25
Kurtosis	75.07	80.63	15.11
Average path length	1.55	1.44	1.37
Clustering coefficient	0.71	0.83	0.84

Table I. Measures of network centrality – Finance, 2005

	In-degree	Out-degree	Closeness	Betweenness	Intermediation	Prestige
United States	100.00 (1)	35.29 (7)	1.00 (1)	24.67 (1)	49.89 (1)	7.41 (1)
Germany	82.35 (2)	35.29 (8)	0.85 (2)	11.18 (4)	9.28 (3)	2.68 (3)
Hong Kong	23.53 (9)	76.47 (1)	0.81 (3)	7.34 (6)	2.35 (7)	1.30 (11)
Singapore	23.53 (10)	76.47 (2)	0.81 (4)	6.70 (7)	1.16 (9)	1.22 (14)
United Kingdom	64.71 (3)	70.59 (3)	0.77 (5)	21.82 (2)	15.46 (2)	4.33 (2)
Spain	41.18 (6)	52.94 (5)	0.74 (6)	16.46 (3)	5.60 (4)	1.72 (6)
France	58.82 (4)	52.94 (4)	0.71 (7)	9.21 (5)	5.26 (5)	2.31 (4)
Italy	41.18 (7)	29.41 (10)	0.65 (8)	0.00	2.35 (8)	1.70 (7)
Japan	47.06 (5)	35.29 (9)	0.65 (9)	4.90 (8)	2.57 (6)	2.03 (5)
Canada	29.41 (8)	29.41 (11)	0.63 (10)	0.00 (13)	1.14 (11)	1.59 (8)
Portugal	17.65 (12)	41.18 (6)	0.63 (11)	1.18 (9)	0.68 (14)	1.17 (16)
Australia	23.53 (11)	23.53 (12)	0.61 (12)	0.00	1.15 (10)	1.42 (9)
Korea	17.65 (13)	17.65 (13)	0.61 (13)	0.90 (10)	0.61 (15)	1.22 (13)
China	17.65 (14)	17.65 (14)	0.59 (14)	0.79 (11)	0.89 (13)	1.32 (10)
Argentina	5.88 (17)	17.65 (15)	0.57 (15)	0.00	0.22 (16)	1.07 (17)
Brazil	17.65 (15)	5.88 (16)	0.57 (16)	0.00	1.10 (12)	1.23 (12)
India	11.76 (16)	5.88 (17)	0.55 (17)	0.00	0.11 (18)	1.07 (18)
Mexico	5.88 (18)	5.88 (18)	0.53 (18)	0.00	0.18 (17)	1.19 (15)

Note: Numbers in parenthesis indicate the ranking. In-degree, betweenness and intermediation are expressed in per cent.

Table J. Measures of network centrality – FDI, 2005

	In-degree	Out-degree	Closeness	Betweenness	Intermediation	Prestige
United States	82.35 (1)	64.71 (2)	0.89 (1)	22.74 (1)	40.99 (1)	6.36 (1)
United Kingdom	64.71 (2)	70.59 (1)	0.81 (2)	10.87 (2)	13.14 (2)	3.35 (2)
France	41.18 (6)	58.82 (4)	0.74 (3)	3.62 (5)	3.62 (8)	1.78 (8)
Germany	47.06 (4)	52.94 (6)	0.74 (4)	3.64 (4)	4.04 (7)	1.81 (7)
Singapore	23.53 (12)	64.71 (3)	0.74 (5)	1.58 (8)	1.99 (11)	1.35 (14)
Canada	41.18 (7)	47.06 (8)	0.71 (6)	2.76 (6)	1.67 (14)	1.87 (5)
Hong Kong	29.41 (10)	58.82 (5)	0.71 (7)	2.69 (7)	5.77 (4)	2.62 (3)
Brazil	52.94 (3)	11.76 (14)	0.68 (8)	0.18 (11)	5.13 (5)	1.70 (10)
Spain	47.06 (5)	47.06 (7)	0.68 (9)	6.74 (3)	6.96 (3)	1.75 (9)
Japan	41.18 (8)	17.65 (12)	0.65 (10)	0.77 (9)	2.08 (10)	1.43 (11)
Australia	35.29 (9)	35.29 (9)	0.63 (11)	0.54 (10)	2.31 (9)	1.82 (6)
Italy	23.53 (13)	29.41 (10)	0.59 (12)	0.00	1.68 (13)	1.34 (15)
Korea	17.65 (14)	17.65 (13)	0.57 (13)	0.11 (12)	1.48 (15)	1.18 (17)
Portugal	11.76 (15)	23.53 (11)	0.57 (14)	0.00	1.05 (17)	1.20 (16)
China	29.41 (11)	0.00 (16)	0.52 (15)	0.00	4.49 (6)	2.57 (4)
India	0.00 (18)	5.88 (15)	0.49 (16)	0.00	0.37 (18)	1.08 (18)
Mexico	5.88 (17)	0.00	0.49 (17)	0.00	1.25 (16)	1.42 (12)
Argentina	11.76 (16)	0.00	0.47 (18)	0.00	1.99 (12)	1.38 (13)

Note: Numbers in parenthesis indicate the ranking. In-degree, betweenness and intermediation are expressed in per cent.

Table K. Measures of network centrality – Equity, 2005

	In-degree	Out-degree	Closeness	Betweenness	Intermediation	Prestige
United States	82.35 (1)	58.82 (1)	0.83 (1)	20.36 (1)	47.59 (1)	6.96 (1)
Germany	58.82 (3)	35.29 (6)	0.69 (2)	0.81 (6)	3.90 (6)	2.13 (5)
United Kingdom	64.71 (2)	52.94 (2)	0.69 (3)	7.13 (2)	13.62 (2)	3.62 (2)
France	58.82 (4)	35.29 (7)	0.65 (4)	0.85 (5)	5.77 (4)	2.48 (4)
Canada	11.76 (10)	52.94 (4)	0.61 (5)	0.07 (10)	0.80 (15)	1.50 (9)
Hong Kong	23.53 (9)	52.94 (3)	0.61 (6)	1.30 (3)	3.92 (5)	1.80 (6)
Italy	47.06 (6)	29.41 (9)	0.61 (7)	0.15 (8)	2.66 (9)	1.66 (7)
Japan	52.94 (5)	17.65 (12)	0.61 (8)	0.09 (9)	6.22 (3)	3.07 (3)
Singapore	11.76 (11)	47.06 (5)	0.58 (9)	0.37 (7)	1.71 (12)	1.24 (13)
Spain	41.18 (7)	29.41 (10)	0.58 (10)	0.86 (4)	3.67 (7)	1.60 (8)
Australia	29.41 (8)	23.53 (11)	0.56 (11)	0.00	0.87 (14)	1.39 (12)
Portugal	0.00	35.29 (8)	0.53 (12)	0.00	0.59 (16)	1.12 (17)
Argentina	0.00	11.76 (13)	0.45 (13)	0.00	0.15 (18)	1.03 (18)
Brazil	11.76 (12)	5.88 (14)	0.45 (14)	0.00	3.27 (8)	1.23 (14)
Mexico	0.00	5.88 (15)	0.43 (15)	0.00	0.17 (17)	1.14 (16)
China	0.00	0.00	0.00	0.00	1.85 (11)	1.42 (11)
India	0.00	0.00	0.00	0.00	1.33 (13)	1.21 (15)
Korea	0.00	0.00	0.00	0.00	1.91 (10)	1.42 (10)

Note: Numbers in parenthesis indicate the ranking. In-degree, betweenness and intermediation are expressed in per cent.

Table L. Measures of network centrality – Debt, 2005

	In-degree	Out-degree	Closeness	Betweenness	Intermediation	Prestige
United States	88.24 (1)	23.53 (10)	0.89 (1)	24.20 (2)	36.02 (1)	6.15 (1)
Singapore	23.53 (8)	76.47 (1)	0.81 (2)	9.82 (4)	2.76 (9)	1.36 (10)
United Kingdom	64.71 (2)	70.59 (2)	0.77 (3)	27.44 (1)	23.51 (2)	5.54 (2)
Hong Kong	17.65 (12)	64.71 (3)	0.74 (4)	4.20 (7)	3.32 (7)	1.35 (11)
France	52.94 (3)	52.94 (4)	0.71 (5)	10.39 (3)	7.85 (3)	2.64 (3)
Germany	47.06 (4)	41.18 (5)	0.68 (6)	1.18 (9)	7.55 (4)	2.53 (4)
Italy	41.18 (5)	29.41 (9)	0.65 (7)	0.15 (10)	2.81 (8)	1.86 (6)
Spain	35.29 (6)	41.18 (6)	0.65 (8)	5.40 (5)	4.54 (5)	1.83 (7)
Japan	35.29 (7)	41.18 (7)	0.63 (9)	5.15 (6)	4.29 (6)	2.02 (5)
Australia	23.53 (9)	11.76 (11)	0.59 (10)	0.00	1.83 (10)	1.39 (9)
Portugal	23.53 (10)	41.18 (8)	0.59 (11)	2.50 (8)	0.83 (14)	1.21 (12)
Canada	23.53 (11)	11.76 (12)	0.57 (12)	0.00	1.26 (11)	1.45 (8)
Korea	17.65 (13)	5.88 (14)	0.57 (13)	0.00	0.60 (15)	1.21 (13)
Brazil	17.65 (14)	5.88 (15)	0.55 (14)	0.00	1.08 (13)	1.14 (14)
Argentina	0.00 (18)	11.76 (13)	0.50 (15)	0.00	0.07 (18)	1.03 (18)
Mexico	5.88 (16)	5.88 (16)	0.50 (16)	0.00	0.21 (17)	1.11 (16)
China	11.76 (15)	0.00	0.49 (17)	0.00	1.24 (12)	1.13 (15)
India	5.88 (17)	0.00	0.46 (18)	0.00	0.23 (16)	1.05 (17)

Note: Numbers in parenthesis indicate the ranking. In-degree, betweenness and intermediation are expressed in per cent.

Table M. Measures of network centrality – Reserves, 2005

	In-degree	Closeness	Prestige
United States	94.12 (1)	0.94 (1)	11.19 (1)
Germany	58.82 (2)	0.71 (2)	5.84 (2)
United Kingdom	52.94 (3)	0.71 (3)	1.40 (4)
Japan	35.29 (4)	0.61 (4)	3.57 (3)

Note: Numbers in parenthesis indicate the ranking. In-degree is expressed in per cent.

Table N. Summary statistics on the international trade network

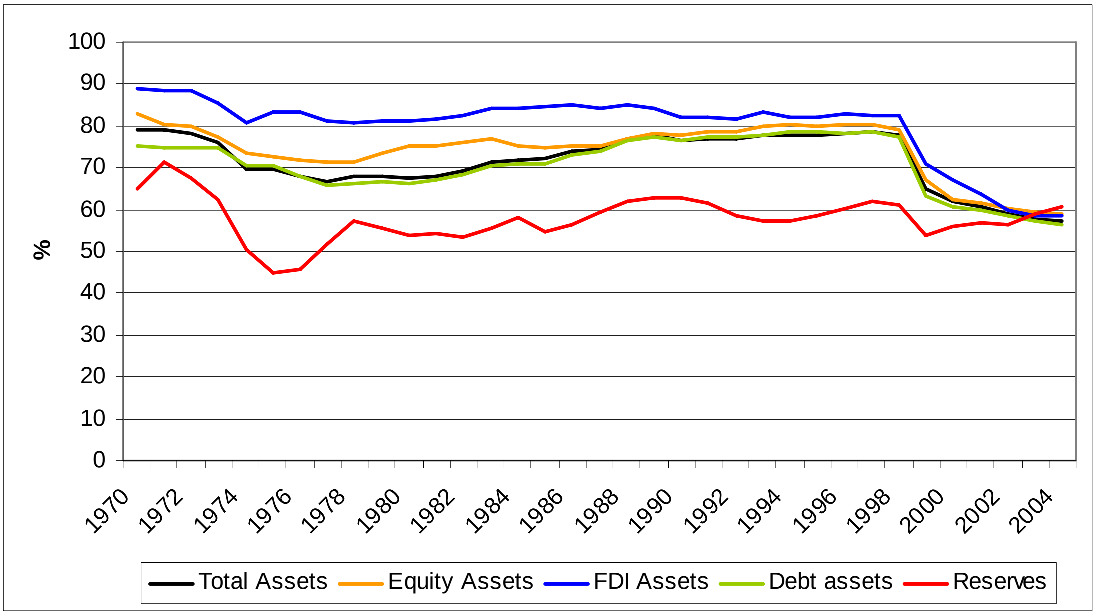
	1985	1995	2005
Skewness	3.44	5.91	3.78
Kurtosis	15.5	46.37	21.24
Average path length	1.70	1.59	1.44
Clustering coefficient	0.60	0.76	0.78

Table O. Measures of network centrality – Trade, 2005

	In-degree	Out-degree	Closeness	Betweenness	Intermediation	Prestige
United States	88.24 (1)	5.88 (15)	0.89 (1)	5.33 (5)	28.55 (1)	5.42 (1)
Singapore	5.88 (12)	64.71 (1)	0.74 (2)	6.74 (4)	2.60 (12)	1.42 (13)
Germany	52.94 (2)	29.41 (2)	0.71 (3)	10.99 (2)	10.03 (2)	2.64 (3)
China	35.29 (3)	29.41 (3)	0.65 (4)	11.64 (1)	9.93 (3)	2.67 (2)
France	35.29 (4)	29.41 (4)	0.63 (5)	1.50 (8)	6.73 (5)	2.25 (5)
Korea	17.65 (8)	29.41 (6)	0.63 (6)	2.08 (7)	3.00 (11)	1.59 (12)
United Kingdom	35.29 (5)	17.65 (10)	0.63 (7)	0.27 (9)	7.29 (4)	2.25 (4)
Hong Kong	17.65 (9)	29.41 (7)	0.61 (8)	7.90 (3)	3.52 (9)	1.69 (11)
Japan	23.53 (6)	11.76 (13)	0.57 (9)	0.25 (10)	5.66 (7)	2.10 (7)
Portugal	5.88 (13)	29.41 (8)	0.57 (10)	0.15 (12)	0.91 (18)	1.23 (17)
Italy	17.65 (10)	23.53 (9)	0.55 (11)	0.15 (13)	4.36 (8)	1.82 (10)
Argentina	0.00 (18)	17.65 (12)	0.53 (12)	0.00	0.97 (17)	1.13 (18)
Mexico	5.88 (14)	11.76 (14)	0.53 (13)	0.18 (11)	1.50 (16)	1.85 (9)
India	5.88 (15)	5.88 (17)	0.52 (14)	0.00	1.58 (14)	1.25 (16)
Brazil	5.88 (16)	5.88 (18)	0.50 (15)	0.00	3.47 (10)	1.35 (14)
Canada	11.76 (11)	5.88 (16)	0.50 (16)	0.00	1.54 (15)	2.12 (6)
Australia	5.88 (17)	17.65 (11)	0.49 (17)	0.00	2.16 (13)	1.35 (15)
Spain	23.53 (7)	29.41 (5)	0.47 (18)	4.29 (6)	6.21 (6)	1.90 (8)

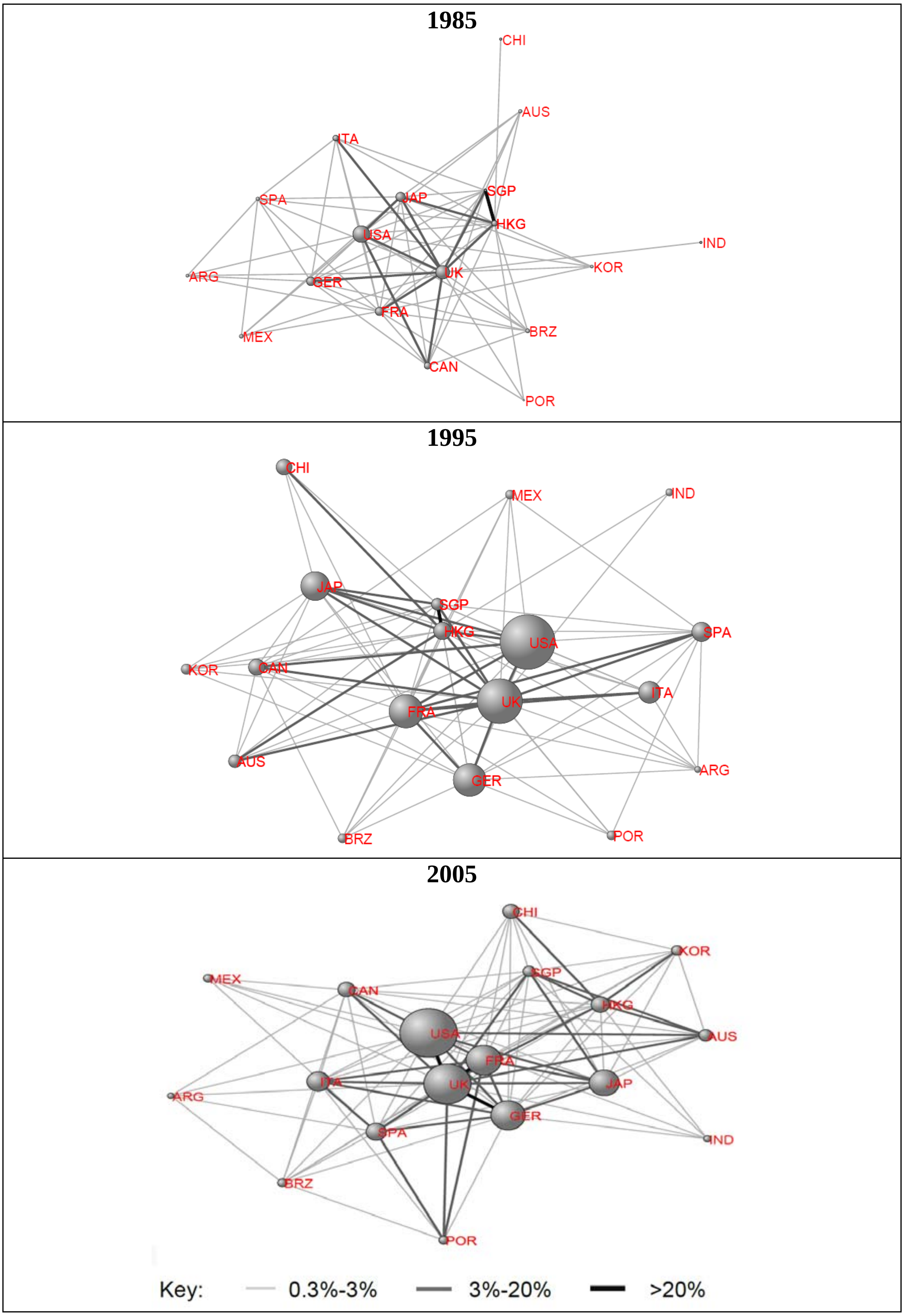
Note: Numbers in parenthesis indicate the ranking. In-degree, betweenness and intermediation are expressed in per cent.

Chart 1. Percentage of world's total assets accounted for by the 18 countries in our sample



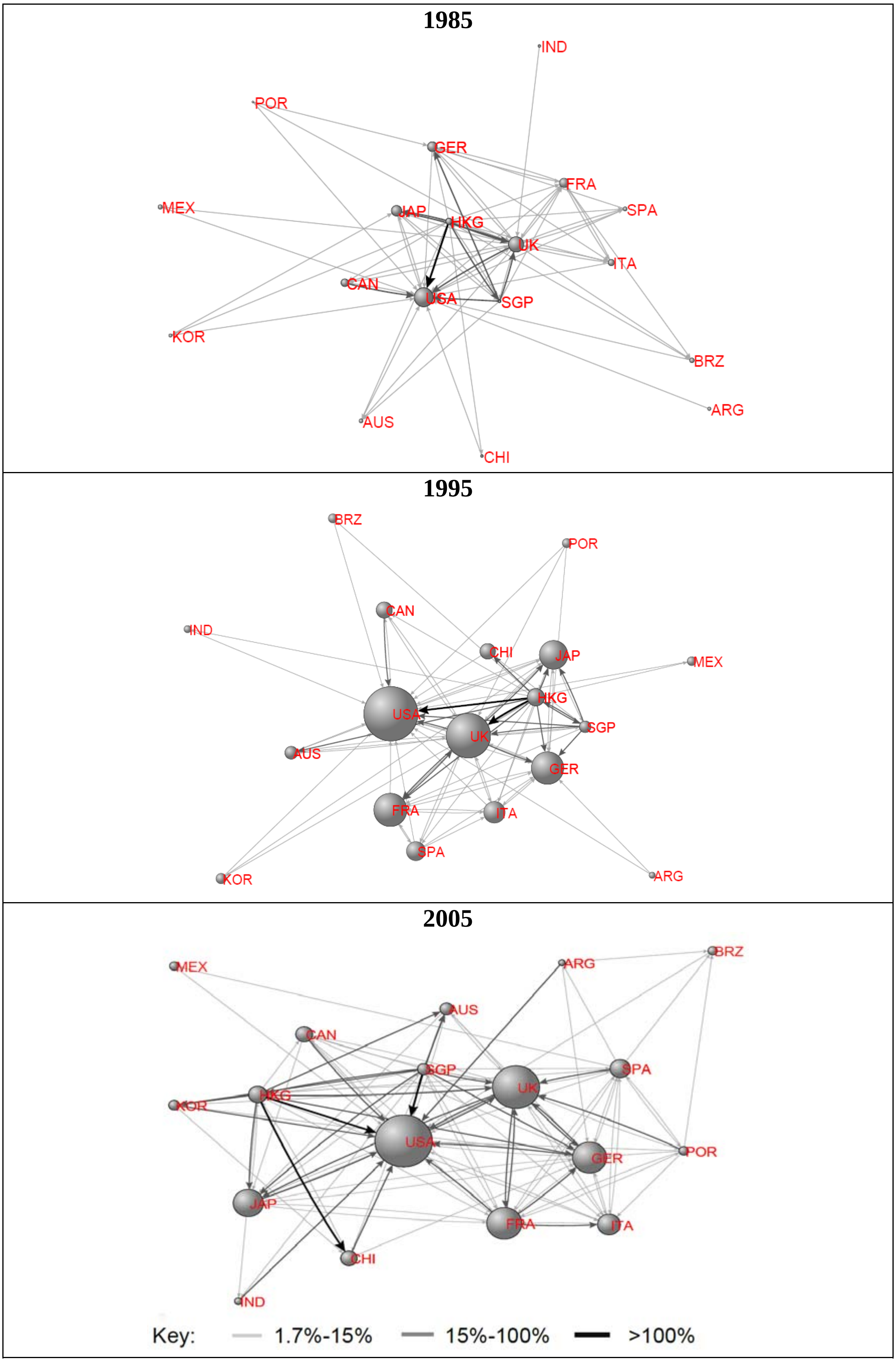
SOURCE: Lane and Milesi-Ferretti (2001, 2007) data set.

Chart 2. International financial network – undirected



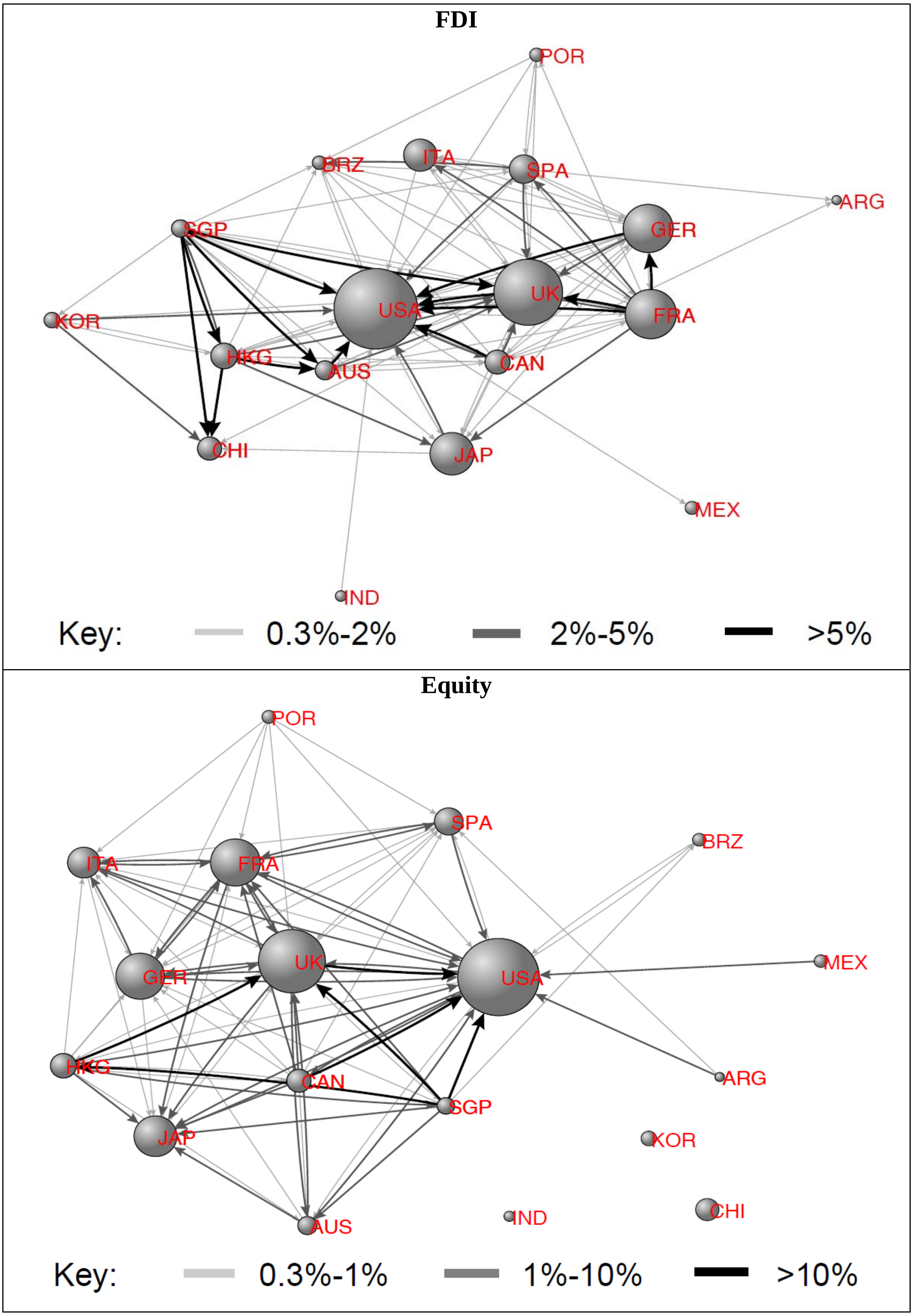
NOTE: Links are given by the sum of bilateral assets and liabilities divided by the sum of the GDPs of the source and host countries. The size of the nodes is proportional to the country's financial openness, measured by the sum of its total external assets and liabilities. More interconnected countries are placed more centrally in the network and pairs of countries with stronger links are placed closer to each other. Figures are drawn in Pajek (Program for Analysis and Visualization of Large Networks).

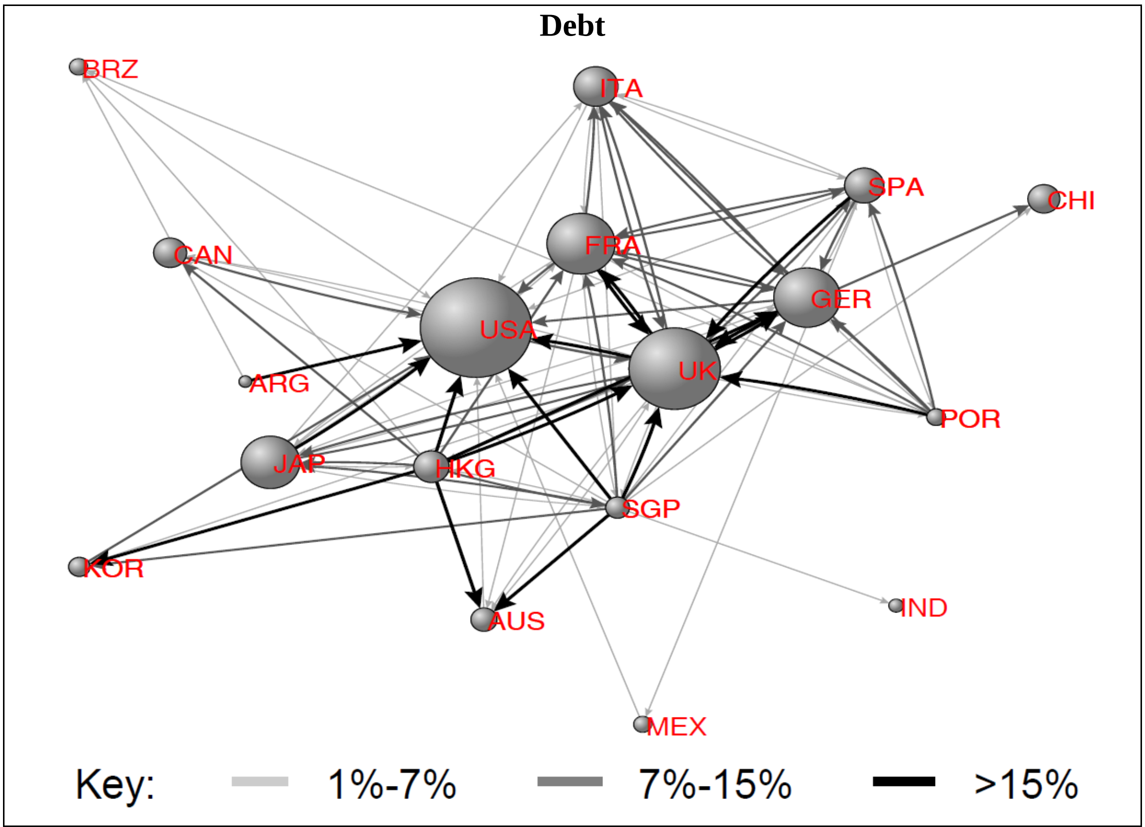
Chart 3. International financial network – directed

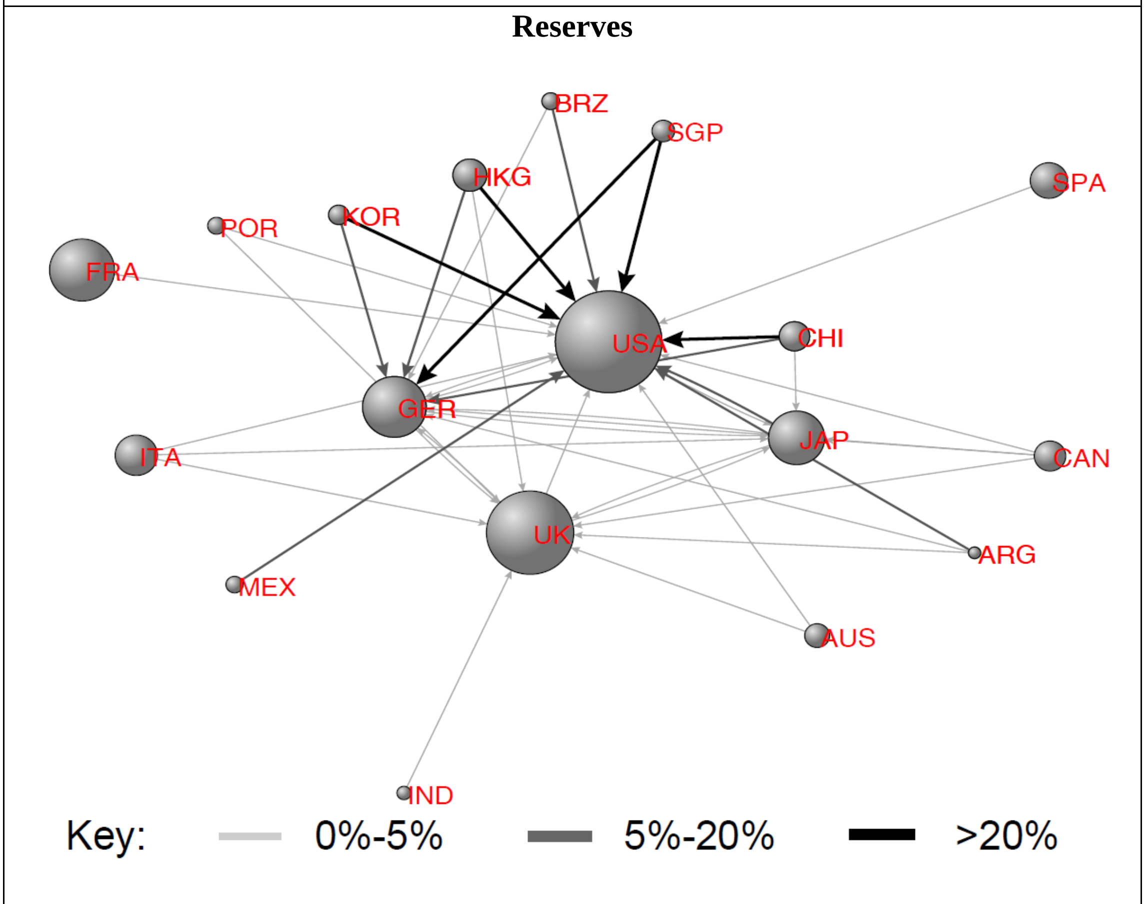


NOTE: Links are given by the ratio of bilateral assets to GDP of the source country. The size of the nodes is proportional to the country's financial openness, measured by the sum of its total external assets and liabilities.

Chart 4. International financial network – directed, by asset class, 2005

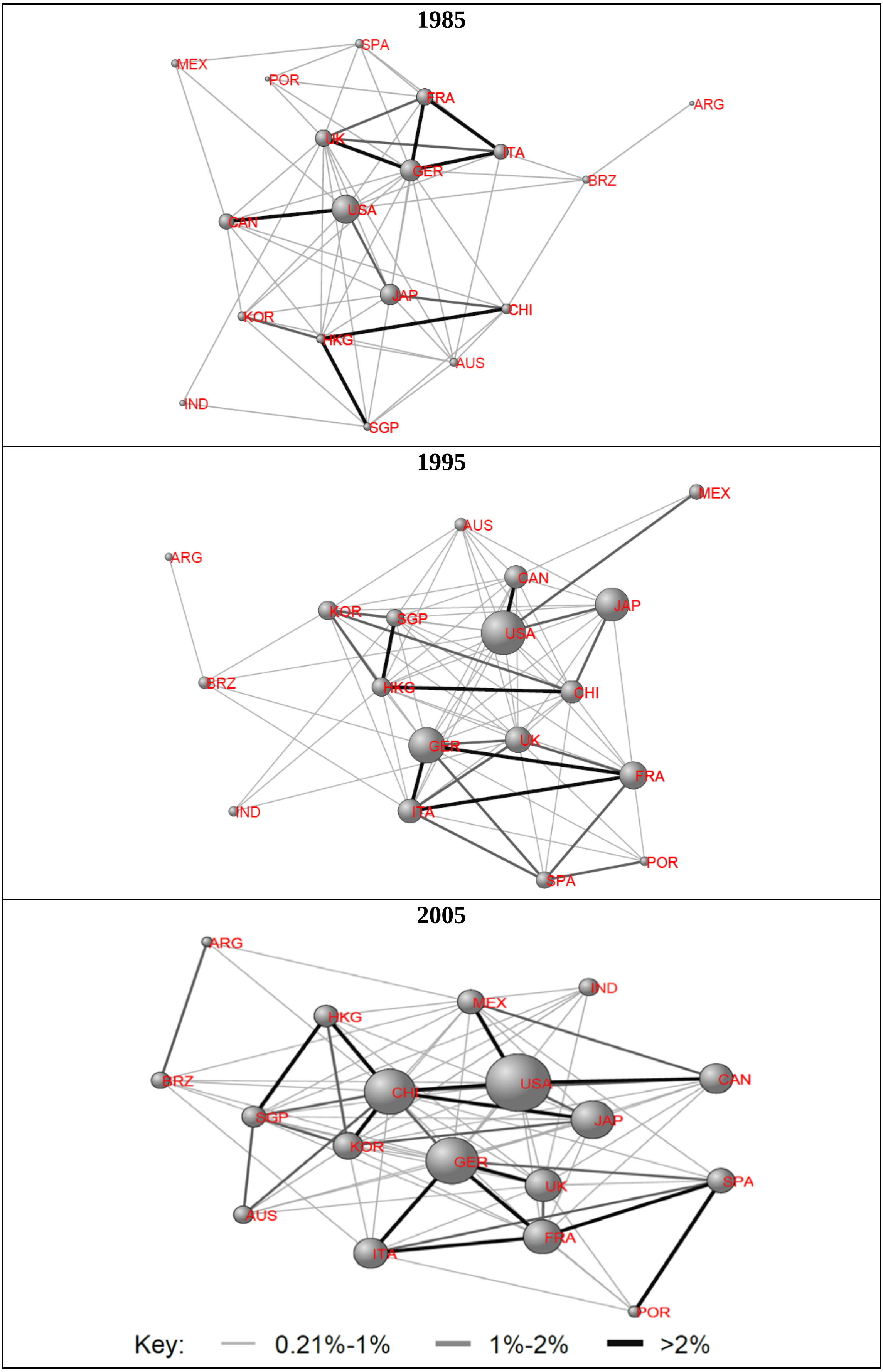






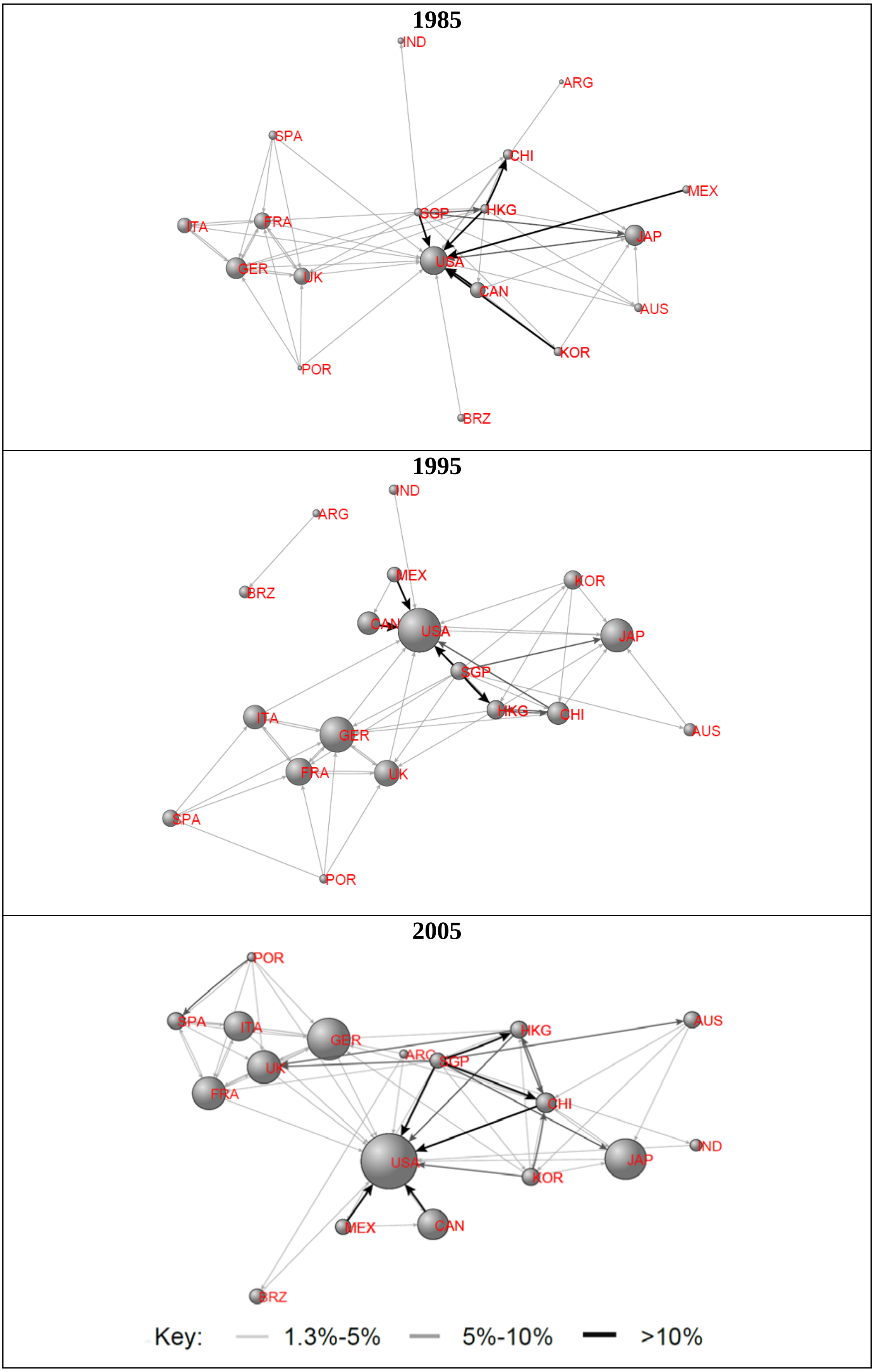
NOTE: Links are given by the ratio of bilateral assets to GDP of the source country for each asset class. The size of the nodes is proportional to the country's financial openness, measured by the sum of its total external assets and liabilities.

Chart 5. International trade network – undirected



NOTE: Links are given by the sum of bilateral exports and imports divided by the sum of the GDPs of the source and host countries. The size of the nodes is proportional to the country's trade openness, measured by the sum of its total exports and imports.

Chart 6. International trade network – directed



NOTE: Links are given by the ratio of bilateral exports to GDP of the source country. The size of the nodes is proportional to the country's trade openness, measured by the sum of its total exports and imports.