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Uncertainty Shocks and the Cross-Border Funding of Banks: Unmasking Heterogeneity

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Uncertainty Shocks and the Cross-Border Funding of Banks: Unmasking Heterogeneity.*

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Abstract

This paper looks at the relation between uncertainty shocks and cross-border funding of banks through the lens of a new dataset. Our key innovation is to study the impact of uncertainty measures based on volatility, newspapers, and professional forecast surveys. We provide a comprehensive assessment of how cross-border liabilities in different banking systems respond to the uncertainty type, funding sector, country, and period. We show that the contraction of bank funding can be large and quite different along these dimensions. Volatility-based uncertainty and non-bank funding display the strongest results, with news-based uncertainty mattering most outside the Global Financial Crisis.

Keywords: uncertainty, international capital flows, BIS Locational Banking Statistics, retrenchment, flight-to-safety

JEL: F21, F32, F42

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1 Introduction

How does country-specific uncertainty explain variations in the cross-border funding of banks? Uncertainty is as important in explaining credit growth as monetary policy (Valencia, 2017). Studying the link between uncertainty and international finance is also practically relevant given the increasing reliance on international borrowing in the advent of financial globalization and the international banking transmission mechanisms of the Global Financial Crisis (GFC). Despite the burgeoning research on uncertainty since the coining of the Great Moderation (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2002), the few investigations on the relation between uncertainty and the cross-border funding of banks focus on a specific type of uncertainty and aggregate flows (Cerutti *et al.*, 2017; Choi and Furceri, 2019). Our paper, in contrast, decomposes different types of funding sources and uncertainty shocks.

We look at the relation between uncertainty and cross-border funding of banks through the lens of a newly compiled dataset with uncertainty measures based on volatility, newspapers, and professional forecast surveys. Our contribution to the literature is a comprehensive study of how cross-border liabilities of banks from a diverse panel of countries respond to uncertainty shocks when heterogeneity across the following four key dimensions is explicitly accounted for; uncertainty shocks, funding sectors, countries, and periods.

Uncertainty reduces cross-border borrowing. Our innovations, moreover, allow us to unmask key heterogeneities. We provide evidence of a wide range of results departing from the industry-standard panel-based approach. Volatility-based uncertainty does not affect international bank funding in tranquil times, but news-based uncertainty, the only type of uncertainty that rose since the GFC, dampened funding even after the GFC.

We split our empirical analysis into two parts. First, we investigate the dynamic properties of our banking and uncertainty data. Second, we estimate the relations between banking and uncertainty measures using bivariate and multivariate analysis.

Cross-border funding has grown over the past two decades, especially in the years preceding the GFC. Growth in non-bank funding, particularly during and after the crisis, dominates growth in other sectors of funding. Non-bank is also more volatile than bank funding, which is more volatile than overall. Sub-components of funding are therefore unlikely to share time-series properties of aggregate funding. Moments of uncertainty mostly display n-shaped patterns, other than news-based measures of uncertainty. Uncertainty shocks are short lived. We find similar heterogeneities across uncertainty measures as we find across funding sectors, thus we also conclude that different measures of uncertainty are unlikely to share homogeneous time-series properties.

In the second part of our analysis, we estimate bivariate and multivariate models and explore multiple sources of heterogeneities including time, country, uncertainty measure, and borrowing source. Both our bivariate and multivariate regressions reflect conservative, parsimonious choices. Funding declines with uncertainty are sizable, but heterogeneous. Funding falls most for non-banking sectors and least for aggregate. Volatility-based uncertainty measures display the largest elasticities, followed by news-based uncertainty measures. Results are not only statistically significant, but also economically relevant. A one standard deviation shock to uncertainty typically reduces aggregate funding by between \$573 billion and \$889 billion. Country specific regressions yield similar, though more often insignificant, results than panel regressions. Outside of the GFC, only news-based uncertainty matters. News-based uncertainty dampened funding particularly for European countries because, unlike other uncertainty measures, news-based uncertainty measures have risen since the GFC.

Our work makes a number of contributions to the literature on banking and uncertainty.

Our first contribution is to provide more detail on the decomposition of international banking, specifically cross-border liabilities, the sum of loans and debt securities. Using the BIS's Locational Banking Statistics (LBS), we decompose liabilities from the aggregate into bank and non-bank flows.[1] The use of *decomposed* bank funding data represents a key innovation relative to the existing literature. This innovation allows us to unmask several heterogeneous results as contributions.

Our second contribution is to compile a comprehensive dataset on multiple types of uncertainty. Rather than argue the merits of relying solely on one type of uncertainty, we hedge by benchmarking uncertainty to the following classes: volatility-based, newspaper-based, and survey/forecast-based. Within each class, we examine several variants of uncertainty. For volatility-based measures, while realized volatility is backwards looking, implied volatility is forwards looking. We construct implied volatilities on national stock market aggregates at various maturities. The usefulness of implied volatility depends on the liquidity of option markets, and so, we also look at other measures of uncertainty. For newspaper-based uncertainty, Economic Policy Uncertainty (EPU) reflects policy-driven uncertainty. Country coverage restricts the usefulness of EPU, and differences in international construction complicate cross-country comparisons. We avoid both limitations by also including the World Uncertainty Index (WUI), which uses identical methods across countries and is available for most countries. Unlike EPU, WUI relates to general uncertainty. That is, WUI is constructed by newspaper mentions of uncertainty rather than policy-based economic uncertainty (combinations of words that signify policy, the economy, and uncertainty). Lastly, examining forecast errors and forecaster disagreement, we include forecast-based uncertainty.[2] GDP growth forecasts mitigate international comparability issues.

[1]In preliminary investigations, we explored intragroup, financial, and non-financial flows, but insufficient data is available to conduct regression analysis using these sub-components of the aggregate flow data.

[2]Publicly available historical international forecast data at quarterly frequency is limited. For example,

In addition to the heterogeneous sub-components of banking and measures of uncertainty, we expand the country coverage in our dataset as much as possible to allow for a third dimension of heterogeneity.[3] The geographically diverse sample includes countries with heterogeneous global banking systems as classified by Bénétrix *et al.* (2017). That is, we include home countries such as Australia, Spain, Sweden, and Switzerland with large local and cross-border foreign claims that go over and beyond the size of their cross-border banks; we include host countries like Brazil, India, and Turkey with heavy local presence of foreign banks; and we include financial centres such as Ireland, Singapore, and the UK with large balance sheets.

To place our paper in context of the literature, ours is closest in spirit to that of Choi and Furceri (2019). The authors uncover a negative relation between banking flows and uncertainty. Although incorporating assets as well as liabilities, their paper focuses on realized volatility and EPU as well as bilateral data and aggregate banking flows. We provide, in contrast, analysis decomposing banking flow data into sub-components and exploring a wide variety of types of uncertainty. By examining a breadth of uncertainty measures, we mitigate the issues of relying solely upon backward-looking uncertainty (realized volatility) and uncertainty that is compromized by variations in method of creation across country (EPU). We are therefore able, through diverse uncertainty types and sub-components of banking data, to uncover a novel set of heterogeneous results.

Papers that are similar to ours concentrate on a specific type of uncertainty and its impact on aggregate capital flows. Few studies use uncertainty to explain cross-border bank flows (Cerutti *et al.*, 2017; Choi and Furceri, 2019), most seeking to explain general international capital flows. One takeaway from Cerutti *et al.* (2017) relevant to our paper is

the IMF's WEO provides semi-annual forecasts, but the IMF forbids staff to share quarterly forecasts.

[3]Another source of heterogeneity relates to our including calm and volatile episodes. Spanning 2003Q1–2018Q4, we conduct sub-sample analysis for the turbulent GFC and European Sovereign Debt Crisis.

that cross-border flows decline when US VIX increases. The literature relating uncertainty with international capital flows finds, among other results, that global risk accompanies extreme capital flow episodes (Forbes and Warnock, 2012), that emerging market equity flows increase and debt flows decrease following uncertainty shocks (Gauvin *et al.*, 2013), and that volatility forecasts political risk and hence flows (Gourio *et al.*, 2015).[4]

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 reports preliminary data investigations to uncover time-series properties of uncertainty measures and sub-components of funding. Section 4 presents the results of our empirical analysis. Section 5 concludes.

2 Data

2.1 International Bank Funding

We measure international bank funding by taking cross-border liabilities (loans plus debt securities) of different banking system reporting to the Bank for International Settlement's Locational Banking Statistics (BIS LBS).[5] Our work makes different contributions to the literature of international bank flows and how this relates to uncertainty. In relation to the bank data, we do not stop at the aggregate liability level. Instead, we decompose liabilities into the sectoral composition of the counterparty as uncertainty can have a different impact on cross-border access to funding from banks or non-banks (other financial and non-financial institutions). This decomposition, in turn, is one of the key differentiating dimensions with

[4]As risk rises, inflows decrease and outflows increase, potentially due to expropriation risk (Gourio *et al.*, 2015). That is, modelling expropriation risk as more prevalent for foreign than for local investors generates counter-cyclical home bias. Other notable studies include Ahmed and Zlate (2014), who show that global risk appetite is a relevant for net private inflows to emerging market economies, and Benhima and Cordonier (2020), who examine the effects of news and investor sentiment shocks on international capital flows.

[5]We are less concerned with purely idiosyncratic shocks abroad affecting only the source or counterparty country or sector and, therefore, we use 'multilateral' data, i.e., cross-border liabilities vis-à-vis the rest of the world.

respect to article by Choi and Furceri (2019) looking at *aggregate* bank flows and using *realized volatility* as its main uncertainty measure.

We examine a sub-sample of the reporter countries list that excludes small states or small islands or financial centers, almost entirely driven by global shocks. We also omit countries where data coverage is short due to lack of data or late membership to the set of BIS reporter countries, such as Russia or China.

Figures 1–4 present the time series plots of liability data for each of the 24 countries individually.[6] To ensure comparability and because we are interested in the time series properties of the data, we plot the logarithms of index numbers that take the value of 100 in 2002Q1, instead of plotting the levels of bank funding in US dollars.[7] In addition, we plot vertical lines to indicate the start and the end of the contiguous GFC and European Debt Crisis in 2008Q3 and 2012Q2. The start date relates to when the TED Spread broke its record and Lehman Brothers collapsed and the end date relates to when Margio Draghi delivered his "Whatever it takes" speech.

A common feature of these data is the positive trend in bank borrowing for advanced countries and some emerging market economies from the early 2000s, a stylized fact extensively documented in the literature led by the seminal work of Lane and Milesi-Ferretti (2007). The crisis period and the aftermath are characterized by a halt or by international deleveraging of most banking systems, in particular European banks (McCauley *et al.*, 2019) and most notably within our sample in Belgium, Ireland, Italy, and Portugal. Exceptions

[6]These 24 core countries are listed in Table 1. BIS shows that the full set of 48 reporters accounted for 94% of global coverage of cross-border claims of banks in 2017. The full set of reporting countries is the following: Australia, Austria, Bahamas, Bahrain, Belgium, Bermuda, Brazil, Canada, Cayman Islands, Chile, China, Curaçao, Cyprus, Denmark, Finland, France, Germany, Greece, Guernsey, Hong Kong, India, Indonesia, Ireland, Isle of Man, Italy, Japan, Jersey, Luxembourg, Macao, Malaysia, Mexico, Netherlands, Norway, Panama, Philippines, Portugal, Russia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Turkey, UK, and USA.

[7]However, the regression analysis presented below is conducted with data starting in 2003Q1 to ensure a balanced sample.

are Canada, Australia, Japan, Norway, and Singapore. Most emerging market economies continued with the pre-crisis trend after the end of the crisis. All in all, cross-border liabilities in our sample present a variety of dynamics across different countries, in the overall time period, before, during, and after the GFC.

One relevant innovation of our paper is to go beyond the aggregate data and also study the sectoral breakdown of the counterparties. Figures 5–8 present the same set of log indices as before but for cross-border liabilities vis-à-vis other banks and "non-banks" that include other financial and non-financial institutions, such as firms or sovereigns. The public version of the BIS LBS provides the decomposition. Some initial data are missing, however, for liabilities vis-à-vis banks. Fortunately, the BIS reports the aggregate data for these periods and countries that allow us to have an estimate of the missing liabilities vis-à-vis bank data. We do this by taking the difference between liabilities vis-à-vis all sectors and the liabilities vis-à-vis non-banks. While these data are not reported by the BIS, maybe due to an allocation to sector issue or confidentiality, we think that the impact of this estimation is minimal for our analysis.

One important take-away of this section is the heterogeneity in the time series properties of these data depending on the counterparty sector. For instance, while for many European countries the deleverage process following the crisis predominantly took part vis-à-vis other banks (e.g. Austria, Belgium, Italy, the Netherlands), this was not the case for Germany or Spain, where the reduction was relatively more important in liabilities vis-à-vis the non-banking sector. For some countries, moreover, liabilities vis-à-vis non-banks grew after the crisis, while those vis-à-vis bank continued falling like in the French case.

Below, we present a more comprehensive assessment of the time series properties of these data in preparation for the study of the relation between uncertainty shocks, captured by different indicators, and cross-border funding.

2.2 Uncertainty Measures

One of main contributions of this paper is constructing a comprehensive dataset with four types of uncertainty measures and extending the country and period coverage as much as possible. By examining several measures, we hope to ameliorate the limitations of using one type of uncertainty. Financial measures such as realized volatility are backwards looking, yet forward looking implied volatility is less informative when option markets are less liquid (Black and Scholes, 1973; Merton, 1973). News search measures of uncertainty suffer from international variation both in the credibility of news sources and in the noise-to-signal ratios from the press (Baker *et al.*, 2016). Forecast-based measures are typically less comparable across countries. While our study includes forecasts of GDP, appropriate for international comparisons, accessible quarterly frequency forecasts on a wide sample of countries are limited. It is also not possible to automate through scripting when extracting the underlying data for calculating our implied volatility and forecast-based measure.[8] By collating data on several measures from various sources, we therefore build a dataset that we hope can illuminate the relation between uncertainty shocks and bank flows. We next describe each uncertainty measure in turn.

The first measure of uncertainty is implied volatility, based on at the money call options. This is constructed by looking at snapshots of implied volatility for call options on national stock market indices using Bloomberg's OVM function.[9] As with the VIX and VIX3M global risk proxies, we take one and three months as the expiration horizons. A key feature of implied volatility uncertainty indicators is the explicit account of expectations on the future, as these are forward looking measures.

[8]We thank our research assistants Joseph Carmody, Jesse Pound, and Alexandra Vasquez for helping us manually acquire this data over one month.

[9]More precisely, we take the last value in each quarter in Bloomberg's OVM function using the national stock market indexes reported in Table 1. As noted earlier, this function could not be automated for periods or countries, providing only a default snapshot that requires manual adjustment for each observation.

Our second measure of uncertainty is realized volatility, the most popular indicator used in the literature. This is a backward looking indicator used in papers like Choi and Furceri (2019). By construction, it does not include information on expectations as it is based on past data. To construct this variable, we source the national stock price index from Bloomberg as reported in Table 1. We take daily closing prices (US Dollar currencies) and transform these nominal prices into real prices by dividing by the US CPI. We multiply the sum of the squared real returns by $\#Year/\#Q$, where $\#Year$ denotes the number of trading days in the year and $\#Q$ denotes the number of trading days in quarter Q.[10] Quarterly annualized realized volatility is the square root of this quantity.[11]

Our third measure of uncertainty is derived from news search. We employ Economic Policy Uncertainty (EPU) and the World Uncertainty Index (WUI). EPU and WUI are sourced from `policyuncertainty.com`. The alternative WUI index is based on frequency counts of the word 'uncertainty' and its variants in quarterly Economic Intelligence Unit country reports. EPU and WUI are a mixture of a backward looking component and a forward looking component. They reflect current uncertainty and expectations of future uncertainty.[12]

Our fourth uncertainty variable is built from survey data on forecasts of quarterly GDP growth as in related research including Bachmann *et al.* (2013) and Morikawa (2016). More precisely, we source quarterly real GDP growth forecasts by multiple forecasters from Bloomberg's ECFC function.[13] As forecast-based measures are not comparable across coun-

[10]We deviate from the convention of using $\#Year = 252$ typical trading days in the US because total annual trading days differ for many reporters. $\#Year/\#Q$ allows for heterogeneity across countries and over time.

[11]In an earlier version of the paper, to obtain a measure of idiosyncratic stock market volatility, we purge realized volatility and implied volatility of each country by a proxy for global uncertainty, VIX. Results are similar. As we use multilateral data, the counterparty is the rest of the world.

[12]These indicators behave similarly and are positively correlated. Pearson and Spearman correlations are significantly positive across our sample with a median of about 0.25.

[13]Similar to the OVM function, automating through scripting when creating panel data from the ECFC function is not possible; therefore, procuring forecast data involved another labor intensive data collection

tries, we compute three statistics to avoid this limitation. First, we look at forecast dispersion defined as the standard deviation of forecasts across the forecasters. Second, we look at the standard deviation of the forecast error across the forecasters, where we define the forecast error as the distance between realized GDP and the forecast of GDP. Third, we take the mean of the absolute values of the forecast error across the forecasters. A nice property of this measure is that it treats deviations linearly rather than non-linearly (standard deviation) as is true for the previous two measures. As results are similar across forecast measures and in the interest of space, we report findings for the first statistic, forecast dispersion.

We argue that our forecast measures are superior to that published by the IMF on its World Economic Outlook not only due to its public availability at higher frequency, but also because these forecasts represent a wider sample of professional forecasting companies within each country. We are unaware of other studies that have employed forecast-based uncertainty measures building on this international dataset.

3 Preliminary Data Analysis

Before conducting the empirical analysis addressing the relationship between cross-border bank funding and uncertainty, we report some interesting time series features of these key variables. Our goal in this section is to have a broad overview of their dynamic behavior by computing country-specific statistics and studying their distributions at different points in time.

and preparation task for several research assistants over one month.

3.1 International Bank Funding

In assessing bank funding, we look at three statistics computed for the quarter-on-quarter growth rate of cross-border liabilities. First, we compare the average growth rates. Second, we look the volatility of these growth rates by reporting their standard deviation. Finally, we study their persistence by looking at their autoregressive coefficient, taken from regression models of growth rates on their first lag and a constant. We also account for different sub-periods in our analysis. That is, we report statistics for the period before, during, and after the GFC (2008Q3–2012Q2).

3.1.1 Average Growth Rates

Figure 9 reports the cumulative distributions for average growth rates of total cross-border liabilities as well as liabilities vis-à-vis banks and non-baking sector. The horizontal axes show the value of the country-specific average growth rate while the vertical axes show the proportion of countries with at least a given value for that statistic. The full, pre-crisis, crisis, and post-crisis periods are reported in panels (a), (b), (c), and (d).

An inspection of panel (a) in Figure 9 shows that the period 2002Q1–2018Q4 was characterized by a strong increase in cross-border liabilities in our sample. For all countries, except Portugal, total liabilities grew over the full period. The cross-country average quarter-on-quarter growth rate was 1.7% with a standard deviation of 1.1. The same pattern is found in the main sectoral breakdown of liabilities. Liabilities vis-à-vis banks and vis-à-vis non-banks grew for most countries too. Again, only Portugal showed a negative average growth rate in liabilities vis-à-vis banks. For liabilities vis-à-vis non-banks, negative average growth rates are found for Spain, Belgium, and Germany. For the full distributions, a clear pattern emerges in relation to the growth rates of the different counterparty sectors. The full period is characterized by a stronger growth in liabilities vis-à-vis non-banks, as its distribution dominates that for liabilities vis-à-vis banks for growth rates greater than 0.5%. This means that this was a common pattern and not the result of specific countries driving average results. In addition, the cross-country average of liabilities vis-à-vis non-banks is 2.2% versus 1.3% for liabilities vis-à-vis banks. Moreover, when we focus on the difference between the growth rates for each country instead of full distribution, we find that liabilities vis-à-vis non-bank grew faster than liabilities vis-à-vis banks in 75% of the countries in our sample.

Panels (b), (c), and (d) report these distributions for average growth rates computed before, during, and after the crisis. A key takeaway of this split is the importance of pre-crisis large and positive growth rates for liabilities from banks and non-banks, supporting Kleimeier *et al.* (2013) showing that the increase in cross-border banking took place in the interbank as well as in retail markets. The cross-country average growth rate was 4.6% for total liabilities On the other hand, the periods that followed are characterized by a close to 50-50 split between positive and negative growth rates in the overall distribution for total liabilities.

Counterparty sectors show that growth rates were mostly higher (or less negative) for liabilities vis-à-vis non-banks during and after the crisis. Before 2008 liabilities vis-à-vis non-banks did not seem to be very different from liabilities vis-à-vis banks. During the crisis, however, the growth rate of liabilities vis-à-vis non-banks is greater for at least 80% of the cases. In the post-crisis period, this is true for at least 70% of the cases.

Another way of studying the differences between growth rates for bank and non-bank sector funding is to look at the country-specific differences between the two sectors, instead of the relative location of the distributions for both sectors as before. That is, we compute the difference between growth rates in liabilities vis-à-vis bank and non-bank and look at the proportion of countries with this difference being positive or negative. This complementary approach is useful in explaining country-specific differences instead of broad patterns of the data, as we are looking at the position and "stochastic dominance" of the distributions. This analysis also points in the direction of liabilities vis-à-vis non-banks growing faster than vis-à-vis banks for most countries in our sample in the different sub-periods. For the full period, as reported above, non-bank funding grows faster than bank funding for 75% of the countries. For the pre-, during, and post-crisis periods, these proportions are 54%, 75%, and 75%.

3.1.2 Volatility

Following the previous approach, we also report the distributions for country specific standard deviation computed for quarter-on-quarter growth rates in Figure 10. We do this for the full sample and different sub-periods and for total liabilities vis-à-vis all sectors, banks, and non-banks.

For the full period, in panel (a), we find that the aggregate of cross-border liabilities vis-à-vis all sectors is the least volatile. At the extremes, we find Singapore and Finland with standard deviations of 4.1 and 21. The cross-country average volatility for the full 2002Q1–2018Q4 period was 8.2. The breakdown of these into bank and non-bank counterparties show that these two subcomponents were more volatile than the aggregate. Liabilities vis-à-vis non-banks were the most volatile of the three categories with a cross-county average of 14.9. The average for those vis-à-vis banks was 10.2. The finding of more volatile non-bank liabilities is also present in the sub-sample analysis, reported in panels (b), (c), and (d) of Figure 10. As before, we also looked at the differences between bank and non-bank within countries. Here, we find that for the full period between 2002 and 2018 at least 83% of countries exhibited liabilities vis-à-vis non-banks being more volatile.

3.1.3 Persistence

In addition to the first and second moments for the growth rates of cross-border liabilities, we also study their degree of persistence to shed light on potential useful patterns that will help with interpreting the findings of Section 4. To this end, we show the cumulative distribution of the point estimate coefficients of linear autoregression models estimated for each country individually. More precisely, we report the cumulative distribution of country-specific ρ coefficients obtained from the following regression model: $gBL^{j}_{i,t} = \alpha + \rho gBL^{j}_{i,t-1} + \epsilon_t$, where gBL is the growth rate of bank liabilities, i are the different countries, and j the counterparty sector (all, banks, and non-banks). We do this for the same periods and counterparty sector split as before.

Figure 11 shows that 64% of countries show positive autocorrelation coefficients in aggregate liabilities for the full period. However, around 60% of countries show negative autocorrelation for the two subcomponents. The period split shows that there is no apparent difference in terms of persistent and positive or negative autocorrelation coefficients between aggregate liabilities and liabilities vis-à-vis bank and non-banks. There are, however, differences in terms of the proportion of countries exhibiting positive or negative autocorrelation coefficients in the different sub-periods and the full sample. For aggregate liabilities, all sub-periods show a larger proportion of countries with negative autocorrelation coefficients. For the pre-crisis period, this proportion is the greatest with close to 80% of our sample exhibiting negative autocorrelations.[14]

[14] As these are estimated coefficients, the small differences reported across counterparty sectors may not be relevant in the statistical sense as coefficients may not be precisely estimated. We acknowledge other caveats to our procedure. Choosing an AR(1) is simplifying and likely fails to capture the dynamics, especially if nonlinearities, or structural breaks are present.

3.1.4 Moments

We compare the means, median, standard deviation, skewness, and kurtosis of banking flows and uncertainty measures over countries and time. With respect to the banking flow data, we again analyze overall flows, bank flows, and non-bank flows of liabilities. Our three periods once more are pre-2008Q3, 2008Q3–2012Q2 ('crisis'), and post-2012Q2 (2012Q3–2018Q4). Comparing the post-2012Q2 period with the 2008Q3–2012Q2 period, we use the Welch test for group differences between means and the Mood's test for group differences between medians. Table 2 presents our results.[15]

Means and medians of banking flow variables display u-shape patterns, being positive, negative, and positive, before, during, and after the crisis period – similar to their counter-cyclical skewness – while their standard deviations display n-shape patterns. Differences in group mean and median kurtosis over time are insignificant.

Overall, our preliminary screening of the banking data suggests that the different components of aggregate liabilities are unlikely to share the same time series properties of its aggregate measure. Most notably, we report stronger growth rates and larger volatility for cross-border bank funding from the non-banking sector as well heterogeneity in the pace, volatility, and persistence of bank liabilities across different time periods.

3.2 Uncertainty Measures

Following the same strategy presented before, we move on to the assessment of the dynamic properties of our uncertainty measures.[16] As the nature of this variable relates more to second and higher moments, we do not put too much emphasis on the averages as before.

[15]Table S1 of Section S2 in the online appendix displays results for cross-border flows of assets.

[16]To ensure consistency across uncertainty measures throughout the analysis, we use $\ln(\text{EPU}+1)$ for EPU. Similarly, denoting WUI and the forecast-based measures by x, we transform x to $\ln(100x+1)$.

We report, instead, some useful statistics related to higher moments of the data, a crucial dimension of uncertainty measures.

3.2.1 Moments

For our uncertainty data, Table 3 reports moments and significance of group differences using the same procedures as in Section 3.1.4. Realized volatility and implied volatility display n-shape patterns for group means, medians, standard deviations, skewness, and kurtoses over time. Group standard deviations are n-shaped over-time, except for EPU. Interestingly, the rise in the mean and median of EPU and WUI contrasts sharply with the n-shaped patterns of other measures of uncertainty that are unrelated to these policy-driven, news-based indices. That is, while other measures of uncertainty rose during the crisis and fell afterward, policy-driven, news-based uncertainty rose during and since the crisis. Later, when studying the impact of different types of uncertainty on cross-border funding in sub-sample analysis, we will return to the fact that, in contrast to other measures of uncertainty that spiked only during the crisis, news-based uncertainty has been rising since the crisis. Skewness and kurtosis for EPU display u-shaped patterns. For WUI, skewness decreases and kurtosis increases over time. Forecast-based uncertainty measures have group means and medians that are the same before and during the crisis period, but that weakly decline thereafter, while their standard deviations and skewness display n-shape patterns and their kurtoses rise weakly over time.

3.2.2 Dispersion and Turbulence

Data on uncertainty are characterized by time-varying differences in distributions. To explore changes in the distributions over time in more depth, we plot quantiles and serial correlation of countries' rankings over time. Time-varying dispersion through quantile plots allow us to visualize the evolution of inequalities in our measures across countries. Changes in serial correlation of countries' rankings permits us to visualize the evolution of turbulence in our measures across countries. Uncertainty is the focus of this section, but for illustration, we include comparisons with banking data.

We plot the 99$^{\text{th}}$, 95$^{\text{th}}$, 90$^{\text{th}}$, 75$^{\text{th}}$, 50$^{\text{th}}$, 25$^{\text{th}}$, 10$^{\text{th}}$, 5$^{\text{th}}$, and 1$^{\text{st}}$ quantiles over countries at each point in time for our uncertainty and banking flow measures in Figures 13–14.[17] This not only allows us to visually assess the time-varying cross-country dispersion, but also examine how various quantiles evolve and play a role in driving the cross-country dispersion. Realized volatility becomes less dispersed across countries during the crisis, but returns to being more so thereafter. Both the lower and upper quantiles rise to compress during the crisis and fall to expand afterward. Implied volatility displays similar patterns and evolutions of the quantiles. In contrast, most bank flows become more dispersed across countries during the crisis, but less so thereafter. The lower quantiles decline, while the upper quantiles rise during the crisis and fall afterward. That is, while volatility-based uncertainty exhibit u-shaped dispersion patterns, n-shaped dispersion patterns are characteristic of liabilities for overall flows, bank flows, and non-bank flows, though non-bank flows display high dispersion in the early 2000s. Dispersion in EPU rises over time. Dispersion in WUI falls marginally during the crisis, but rises afterward to a higher level than before the crisis. Forecast-based measures of uncertainty display higher dispersion in the early 2000s before declining to a lower level for a few years before the crisis, rising during the crisis, and falling afterward. Unlike financial measures of uncertainty (realized volatility and implied volatility) and banking flow measures, the increases and decreases in dispersion for news-based uncertainty and forecast-based measures of uncertainty are driven by the upper quantiles.

[17] Figure S2 of Section S3 in the online appendix plots dispersion for cross-border flows of assets.

As a measure of turbulence for each variable, we plot the correlation of countries' rank in the cross-country distribution of uncertainty across the current and prior period and superimpose the cross-country average at each point in time in Figures 15–17.[18] Low correlations imply churning in the rank ordering across countries, while higher correlations suggest the ordering of countries is more persistent. Turbulence is negatively correlated with averages for measures of realized volatility, EPU, WUI, and bank flows of liabilities. That is, there is little turbulence when these variables are high. In contrast, turbulence is strong when the following variables are high: implied volatility, forecast dispersion, and overall and non-bank flows of liabilities. Sub-samples display heterogeneity. Serial correlation of countries' rank is positive (low turbulence) with large differences over time for realized volatility, implied volatility, and WUI. Turbulence for realized volatility and implied volatility displays a modest increase during the crisis, while turbulence marginally decreases over time for WUI. Turbulence displays no discernible patterns being roughly constant with small changes for EPU and forecast-based measures of uncertainty. With banking flows, large changes occur in the serial correlation of countries' rank over time. For overall and non-bank flows of liabilities, serial correlation of countries' rank is weakly positive (some turbulence), with large, regular, seesaw-like oscillations over time akin to white noise. For bank flows of liabilities, this rank order correlation becomes negative (strong turbulence) from the crisis onward.

3.2.3 Persistence

We examine persistence of our uncertainty measures assuming they each follow the AR(1) process as in Section 3.1.3: $\Delta UNC_t = \alpha + \rho UNC_{t-1} + \epsilon_t$, where UNC_t denotes the uncertainty variable. Figure 12 plots the cumulative distribution functions of the AR(1) coefficients. Clear patterns emerge with S-curve relations, irrespective of whether we examine AR(1)

[18]Figure S3 of Section S3 in the online appendix plots turbulence for cross-border flows of assets.

coefficients or half-lives.[19] The uncertainty variables are ordered from least to most persistent as follows: forecast-based measures, WUI, EPU, implied volatility at one-month maturity, realized volatility, and implied volatility at the three-month maturity. Despite this heterogeneity, we can expect uncertainty to last about one quarter.[20]

Our measures of uncertainty and banking flows are short-lived. Furthermore, we can be confident that the procedures we employ are conservative in presenting an upper bound on our estimates of persistence (Curran and Velic, 2019). We can, therefore, see how banking flows may be influenced by uncertainty shocks. With short-term deviations from trend, banking flows can be subjected to temporary uncertainty shocks.

4 The Impact of Uncertainty Shocks

We study the relation between uncertainty shocks and cross-border funding by following a comprehensive empirical strategy that accounts for several sources of heterogeneity. At the same time, we keep the empirical strategy as simple as possible.

4.1 Heterogeneity

One dimension of heterogeneity corresponds to different measures of uncertainty.[21] The industry standard in the international capital flows literature is the use of realized volatility (Gourio *et al.*, 2015; Choi and Furceri, 2019) or EPU (Bloom, 2009; Choi and Furceri,

[19] Results on persistence are robust to the inclusion of the constant term. We also look at the first-order autoregressive coefficient, ρ, and obtain an estimate of the half-life, $\hat{h}$, from $\hat{h} = \frac{ln(0.5)}{ln(\hat{\gamma})}$, where $\hat{\gamma} = 1 + \hat{\rho} > 0$ is a complete scalar measure of persistence. Under mean-reversion a proportion $\hat{\gamma}^n$ of any shock will remain after n periods. Figure S1 of Section S1 in the online appendix plots cumulative distribution functions of the half-lives.

[20] Half-lives in Section S1 of the online appendix are about one quarter with most estimates below one quarter and only a few at around two quarters.

[21] Cross-border funding also depends upon country-specific characteristics such as economic growth, stock market growth, monetary policy rates, exchange rate growth, inflation, credit growth, and the level of debt-to-GDP. We control for these potential drivers of funding by accounting for them in multivariate analysis.

2019). Individual uncertainty measures have different advantages and disadvantages. For instance, realized volatility lacks the forward-looking, expectation component; news-based uncertainty relies on word frequencies resulting in indices that may be noisy signals of true uncertainty; some survey-based measures are incomparable across countries; and the practical relevance of implied volatility depends on option market liquidity. We hedge against relying solely upon one type of uncertainty by taking different measures of uncertainty that we categorize into four broad groups: backward-looking based measures based on volatility, forward-looking measures based on option price implied volatility, news-based measures, and survey- or forecast-based measures, as described in Section 2.2.

A second source of heterogeneity relates to the counterparty type of cross-border funding. The significance of differentiating the counterparty type is that uncertainty shocks may affect cross-border funding differently depending on which sector provides funding. In contrast to the related literature, we contribute by going beyond looking at aggregate liabilities, studying how uncertainty shocks affect cross-border funding from banks and non-banks, e.g., other financial institutions, sovereigns, firms, and households.

A third dimension for heterogeneity relates to differences across countries in our sample. Our dataset is formed by a mix of 24 advanced and emerging market economies with different structures in their banking systems and reliance on cross-border funding. This includes euro area countries, other western European countries, financial centres, large advanced economies with well developed financial markets, and emerging countries.

A fourth source of heterogeneity is in the time domain. Our periods of coverage include tranquil and turbulent times such as the GFC and the European Sovereign debt crisis. We conduct sub-sample analysis where we analyze pre-crisis (2003Q1–2008Q2), crisis (2008Q3–2012Q2), and post-crisis (2012Q3–2018Q4) periods.

4.2 Bivariate Models

Our first step to study the impact of uncertainty on international bank funding is to estimate dynamic panel regression models with country fixed effects, which allows us to account for unobserved cross-country heterogeneity captured by the different intercepts. We estimate

$$\ln(L_{i,t}) = \alpha_i + \beta \ln(UNC_{i,t}) + \rho \ln(L_{i,t-1}) + \epsilon_{i,t} \tag{1}$$

where $\ln(L_{i,t})$ is the natural logarithm of country i banking system's dollar value of cross-border liabilities vis-à-vis the rest of the world at time t, $UNC_{i,t}$ is the measure of uncertainty, and α_i is the country fixed effect. Our coefficient of interest is β.[22] By using logarithms of uncertainty and bank liabilities, we can interpret the β coefficient as an elasticity. We conservatively cluster standard errors by source country. Then, we present models estimated using Pesaran and Smith (1995)'s mean-group (MG) estimator as well as country-specific regression models to illustrate the extent of cross-country heterogeneity in the slope coefficients.[23]

[22]To mitigate issues of reverse causality, by following Bruno and Shin (2015b), we present bivariate and multivariate models in Section S4 of the online appendix where our uncertainty variables are lagged one period. Choosing a one-period lag of uncertainty produced similar results to contemporaneous uncertainty.

[23]The MG estimator is applicable for our study, with roughly equivalent sizes in the country N and time T dimensions, where T is sufficiently large to estimate sensible regressions for each country. The MG estimator conducts regressions for each group and averages the coefficients over the groups. This procedure produces consistent and unbiased estimates of the coefficient means – the consistency issue differs from the standard Nickell bias in panel models with small T and large N (Nickell, 1981). Methods that apply to datasets characterized by small T and large N usually involve fixed-effects estimators or combining fixed-effects and instrumental-variables estimators like GMM (Arellano and Bond, 1991). These methods allow only the intercepts to differ across groups and fix the slope coefficients and the error variance. The literature on large N, large T data often finds that slope parameters are heterogeneous. In addition, with larger T, nonstationarity is a concern. The MG estimator permits estimation of nonstationary dynamic panels allowing for parameters (intercepts, slope coefficients, and error variances) to be heterogeneous across groups. Nonstationarity is less of a concern with our variables, mostly growth rates. The key difference between the MG estimator and its cousin, the PMG (Pesaran *et al.*, 1997, 1999) estimator, is that PMG combines pooling and averaging to produce an intermediate estimator allowing the intercept, short-run coefficients, and error variances to differ across groups like MG, but restricts the long-run coefficients to be the same across groups like the fixed-effects estimator. We appeal to the literature on large T, large N suggesting that the slope coefficients are often heterogeneous and assert that we do not want to restrict other coefficients such as the error variances.

4.2.1 Bivariate Panel Analysis

Our baseline results are found in Table 4. Specifically, column (1) reports the βs for aggregate cross-border bank liabilities and different types of uncertainty indicators. Columns (2) and (3) show βs for liabilities of banks vis-à-vis other banks and vis-à-vis non-banks. In addition, Panel B shows slope coefficients obtained from implementing the MG estimator.

As it was impossible to collect all uncertainty variables for each of the 24 countries and periods, Table 4's outputs are useful only to assess the role of a given uncertainty indicator on different types of cross-border liabilities. To study the differences between alternative uncertainty indicators on a given liability type, we present estimates using a balanced subsample in Table 5.

All models produce negative coefficients, as expected, for most liability and uncertainty measures.[24] Consistent with the literature, uncertainty is associated with less borrowing from abroad. The effects of uncertainty, furthermore, can be sizable. For instance, a 1% increase in the three-month implied volatility indicator can contract bank cross-border borrowing by up to 4.1%. The magnitude of the funding response to uncertainty is also heterogeneneous. Comparable because they are available for the same sample, a 1% increase in implied or realized volatility shrinks cross-border funding by between 1.5% and 4.1%, depending on the volatility measure, counterparty sector, and the estimation strategy.

News-based indices contract cross-border funding too with quantitative results between different counterparty sectors differing across panel and MG models. The strongest effect occurs in funding from banks with up to a 2.9% contraction as reported in the panel model for EPU. Variations in non-bank funding are not associated with EPU shocks. Compared to the panel estimator, the MG estimator yields lower EPU elasticities of aggregate fund-

[24] The exceptions are three statistically insignificant β coefficients based on the forecast dispersion uncertainty measure for overall and bank counterparties in the panel model and for bank counterparties in the MG model.

ing. For the breakdown between bank and non-banks in MG, the coefficients on EPU are statistically insignificant. Examining WUI, we find statistically significant coefficients with funding contraction ranging from 0.5% for aggregate funding to 0.8% for funding from non-banks. Panel and MG models produce results of similar magnitudes for WUI. The largest effect is vis-à-vis non-banks, followed by banks and finally by overall flows. Forecast dispersion is statistically insignificant, except for funding from non-banks in the MG model, where the cross-border funding elasticity to uncertainty is 3.9%.

Ranking the sectoral borrowing source contraction from uncertainty shocks, the greatest is from non-banks and the weakest is from the aggregate. These relative magnitudes suggest some degree of a 'substitution effect' between funding from banks and non-banks in response to the uncertainty shock. Bank and non-bank funding contractions partially compensate each other, making the aggregate funding response proportionally less.

Our dataset is balanced across the bank liability components, but it is unbalanced across the uncertainty measures.[25] Unbalanced coverage for uncertainty measures limits comparisons to the effect of a change in a given uncertainty measure on the different sectoral sources of cross-border funding, instead of different types of uncertainty shocks on a given funding type. Following the previous strategy, Table 5 compares the effects of the uncertainty measures on cross-border borrowing overall, from banks, and from non-banks. To ensure a balanced panel, Table 5 restricts the sample to 13 countries.[26]

Similar negative relations emerge, except that forecast dispersion is significantly positive for bank funding in the MG model. Results are sizable with coefficients on implied volatility of up to 3.9%. Results are heterogeneous with coefficients on implied volatility and realized

[25]Of the 24 core countries, data coverage for the uncertainty measures is the following: 24/24 (realized volatility, implied volatility, and WUI), 16/24 (EPU), and 15/24 (forecast-based uncertainty).

[26]The 13 countries are the following: Australia, Brazil, Canada, Chile, France, Germany, India, Italy, Netherlands, Singapore, Spain, Sweden, and the United Kingdom.

volatility lying between 1.7% and 3.9%. For non-bank flows and in the panel model for bank flows, the largest declines are associated with three-month maturity implied volatility.[27] For overall flows and in the MG model for bank flows, realized volatility is the strongest. For news-based measures, EPU is strongest for overall flows with magnitudes of up to 2.5%, though EPU is insignificant for non-banks. Unlike Table 4, EPU is stronger for overall flows in the MG model than in the panel model. WUI is insignificant. Forecast dispersion is insignificant except for banks in the MG model, where forecast dispersion is positively significant (0.7%). Concluding our 13-country sub-sample analysis, mirroring our results from Table 4, we find our strongest magnitudes for non-bank flows, followed by bank flows, with our smallest magnitudes for overall flows.[28]

Beyond statistical significance, the finding that funding declines with uncertainty is *economically* significant. Consider the range of coefficients for implied volatility and realized volatility from Table 4, as these uncertainty measures are based on the same sample. Implied volatilities have standard deviations of 42.2% and 46.3%, and one percent rises or even one standard deviation rises in volatility are likely to occur from inspecting histograms and time-series. The average aggregate funding is $820 billion and the average non-bank funding is $223 billion. The magnitudes of elasticities are greatest for three-month maturity implied volatility and non-bank funding and weakest for one-month maturity implied volatility and aggregate funding. We thus interpret the minimum and the maximum quantitative effect. A one percent (standard deviation) rise in one-month implied volatility is associated with at least a $12 ($573) billion decline in aggregate funding and a $5 ($227) billion decline in non-bank funding. One-month maturity implied volatility is a conservative choice for

[27]Three-month maturity implied volatility is stronger than one-month implied volatility. One-month maturity implied volatility is insignificant for non-banks in the MG model.

[28]The exception to this relative order of magnitude is realized volatility in the MG model, where uncertainty shocks have strongest effects for banks, followed by non-banks, followed by overall flows.

a volatility-based measure of uncertainty. On the other extreme, a one percent (standard deviation) rise in three-month implied volatility is associated with up to a \$21 (\$889) billion decline in aggregate funding and a \$9 (\$386) billion decline in non-bank funding. Other uncertainty measures, such as EPU and sources of funding, e.g., bank, exhibit intermediate magnitudes of quantitative effects.[29] Our results are therefore both statistically and *economically* significant.

4.2.2 Country-by-Country Analysis

In addition to the panel models, we estimate equation (1) country-by-country and present the point estimates for the βs together with those from models in Table 4 in graphical form. We do this for liabilities vis-à-vis all sectors, banks, and non-banks, taking the full 2003Q1–2018Q4 period as before.

Figures 18–23 present these point estimates for the six versions of uncertainty. The size of these coefficients is measured on the x-axis, while the vertical axis captures the proportion. The proportion provides a sense of how uncertainty affects bank funding in the majority of countries and the models. We distinguish between point estimates being statistically significant (at the 10% level) by reporting these with filled markers. Hollowed markers denote coefficients statistically indistinguishable from zero. As in the rest of the paper, estimates related to liabilities vis-à-vis all sectors are reported in **black**, while those vis-à-vis banks and non-banks are reported in **blue** and **green**. We also organise this information by country in Table 6 to study if and by how much uncertainty affects cross-border funding of different banking systems.

In the country-specific models, our choices are conservative. Including the lagged-value

[29] Although elasticities for WUI are smaller, its standard deviation is larger at 131.8%. A one percent (standard deviation) rise in WUI is associated with a \$4 (\$573) billion decline in aggregate funding.

of cross-border funding accounts for much of the variation in cross-border funding and leaves less for the uncertainty measures to explain. It is expected, therefore, that most of these coefficients will be statistically zero. Coefficients are unlikely to be biased, given the large explanatory power of lagged funding, ameliorating the omitted variable problem.

Exploring the country-specific results, uncertainty reduces funding in most cases. Ignoring statistical significance, the range of variation of the elasticities changes between measures. The range of elasticities is most compressed for WUI, with a maximum contraction of 4%, occurring in cross-border funding from banks for Austria. The greatest country-specific elasticity is with forecast dispersion in Brazil for liabilities vis-à-vis non-banks. We next discuss the country results for each uncertainty measure in turn.

For three-month implied volatility, country-specific elasticities range from −14.1 to 11.5% across all counterparty sectors. Table 4 shows that panel and MG coefficients are negative and statistically significant for aggregate funding and for funding from banks and non-banks. For aggregate funding, Figure 18 illustrates that five out of the 24 countries exhibit non-negative elasticities, while for funding from banks and non-banks, we find positive elasticities for six and four countries. All non-negative elasticities are statistically insignificant. Although the majority of countries show a negative response of cross-border funding to an increase in three-month implied volatility, few show statistically significant elasticities. For overall funding, six countries exhibit statistical significance. For bank and non-bank funding, seven and four countries display statistical significance. One-month implied volatility presents similar patterns in terms of the range of variation of coefficients, number of countries with negative elasticities, and negative point estimates statistically relevant. Quantitative differences include a marginally more compressed range of variation than the three-month version from −11.4 to 10.3 across all funding sectors.

Relative to implied volatility, realized volatility presents a larger range of variation for the elasticities: the minimum and maximum elasticity values are −18.7 and 14 across funding sources. Although the majority of countries present negative elasticities, realized volatility yields some positive and statistically significant estimates. In particular, Japan displays a significantly positive elasticity of 4.7 for overall and Finland displays significant elasticities of 13.6 and 13.9 for overall and bank sources. Finding significant positive elasticities could be related with the limitations of this measure being backward looking.

As for the news-based measures, our country-by-country analysis shows again that most countries exhibit a negative response of cross-border funding to uncertainty shocks. Due to data limitations for EPU, we limit our analysis to a 16 country sample for EPU. As with all uncertainty measures, the majority of the estimates are statistically insignificant. News-based uncertainty elasticities present a different range of variation. Elasticities for EPU range from −11.2 to 20.9 across all funding measures. The WUI index, however, presents more compressed responses from −4 to 2.7. Contrary to the expected negative association, the EPU index yields positive and statistically significant coefficients for Japan in aggregate and bank funding and for Brazil in non-banks. The WUI shows a positive elasticity for India. In contrast to the previous volatility-based measures, news-based models show panel elasticities that are not always statistically significant.

The final measure, based on professional forecast dispersion, yields the weakest results. Due to data availability, the country sample is reduced further to 15 countries. As Table 4 shows, except for the MG model, panel models display statistically insignificant coefficients. Funding from non-banks is statistically negative. The cross-country range of variation for elasticity is from −30.7 to 4.4. Excluding Brazil shrinks this interval to range from −8.2 to 4.4. Elasticities are negative and statistically significant in the four following cases: the UK for liabilities from all sectors and Brazil, Italy, and the UK for funding from non-banks.

In addition to looking at the differences in the impact of uncertainty indicators across countries, with the help of cumulative distributions functions, we re-organise the previous data by country. This is helpful for getting a sense of how banking systems in different countries respond to uncertainty broadly defined.

Table 6 shows all available elasticities by country and funding sector. One takeaway is the considerable variation in the direction and magnitude banking systems' funding responds to uncertainty shocks. On the one hand, countries like Singapore show negative elasticities for most measures and funding sources without any of them being statistically significant. This is also true for Norway, where many elasticities are statistically insignificant with some showing positive signs too, or Switzerland with cross-border funding unaffected by uncertainty, possibly related to the scale of international operations by Credit Suisse and UBS banks and its safe haven status. On the other hand, uncertainty shocks can matter for international funding. One example is the French banking system with cross-border funding from banks strongly responding to most uncertainty indicators. Other cases include banks in Ireland with reductions in funding from non-banks in response to volatility-based and EPU uncertainty. Banks in Portugal exhibit negative and statistically significant elasticities for all measures of uncertainty and counterparty sectors, while those in Spain and Belgium strongly reduce funding from banks in response to volatility-based uncertainty or EPU, or volatility-based uncertainty, respectively. The country-specific assessment also reveals some responses going in the opposite direction. For instance, Finland and Japan exhibit increases in bank borrowing to volatility-based and news-based uncertainty shocks.

This section presented evidence of a negative link between uncertainty shocks, measured by six indicators, and cross-border funding. The negative relation is similar in the related literature taking one uncertainty measure, a panel approach, and an aggregate measure of capital inflows. We contribute to the literature by reporting the heterogeneities associated with the uncertainty indicator, counterparty sector, and borrowing country. In Section 4.4, we also study heterogeneities along the time dimension by explicitly focusing on the financial crisis period. We conclude that the uncertainty indicator and funding sector matter for understanding how cross-border banking responds to uncertainty shocks. A single uncertainty measure does not fit all, as banking systems across countries differ in their structures, ownership, cross-border activity, size, and exposure to the local economy.

4.3 Multivariate Models

The next stage in our approach introduces relevant conditioning factors to study the link between international funding of banks and uncertainty. To this end, again using panel data models with fixed effects and the MG estimator, we estimate

$$\ln\left(L_{i,t}\right) = \alpha_i + \beta \ln\left(UNC_{i,t}\right) + \gamma X_{i,t-1} + \rho \ln\left(L_{i,t-1}\right) + \epsilon_{i,t} \tag{2}$$

where $X_{i,t-1}$ is a vector of conditioning factors, lagged one quarter to mitigate potential issues of reverse causality as raised by Bruno and Shin (2015b). These conditioning factors include macroeconomic and macro-financial variables sourced from the related literature on uncertainty and international capital flows such as Choi and Furceri (2019). The list of additional regressors include real GDP growth, stock market growth, inflation rates, monetary policy rates, exchange rate growth, credit growth, and external debt-to-GDP.

In line with the literature on the determinants of capital flows, we expect cross-border borrowing by banks to be positively associated with economic growth, the stock market, and higher policy rates (Lane and McQuade, 2014; Bruno and Shin, 2015a; Correa *et al.*, 2018). GDP growth is not only associated with larger bank funding needs to serve local demand for credit, but GDP growth also affects current and expected returns, making it more attractive to international investors to fund local banks. Strong economic development promotes cross-border flows (Lane and Milesi-Ferretti, 2008; Lane and McQuade, 2014).

To disentangle level shocks from volatility shocks, especially with many of our uncertainty measures relating to the stock market, we include stock market returns following Bloom (2009). Financial development boosts cross-border flows (Lane and Milesi-Ferretti, 2008). Although developed domestic financial systems may diminish the role of foreign borrowing, domestic development may be improved by foreign borrowing or be the gateway for more access to international markets for finance.

Examining the relation between domestic credit growth and international capital flows, Lane and McQuade (2014) investigate how countries fund domestic institutions through borrowing from abroad. We therefore expect a positive relation between private bank credit growth and cross-border flows

Changes in the exchange rate matter directly for cross-border funding, if loans are denominated in foreign currency. A stronger domestic currency makes it more affordable to borrow in other currencies and across the border for many countries. That is, dollar-denominated lending increases when the dollar weakens (Avdjiev *et al.*, 2019; Bénétrix *et al.*, 2020). The risk-taking channel of Bruno and Shin (2015a) shows that depreciation can reduce cross-border bank lending. While for many countries in our study the dominating currency for international banking (dollar or euro) is also their domestic currency, we expect this relation to be weak in our 24-country sample.

The policy rate captures the bank lending channel of monetary policy globally (Bruno and Shin, 2015b; Rey, 2015; Correa *et al.*, 2018), and thus, we expect a positive relation between the policy rate and cross-border funding. Higher local rates makes it more attractive for banks to look for funding across the border.

Inflation associated with depreciation of the local currency can be linked with a reduction in cross-border borrowing, the negative relation depending on the funding being mostly denominated in foreign currency. In the other direction, increasing price levels could also be associated with strong economic performance and a strong currency, raising cross-border borrowing. Theory is thus ambiguous on the sign linking inflation and bank funding, leaving the direction of the relation open to empirical investigation.

External debt is measured by using the International debt statistics from the BIS. As this measure is the amount of outstanding debt securities issued in international markets, external debt could be a substitute for bank funding, and thus, be negatively associated with funding. The degree of substitutability will depend on the loans-to-debt composition of banks' cross-border funding. On the other hand, large outstanding positions in international markets may proxy well-developed financial markets that, in turn, could positively affect the extent of cross-border borrowing by local banks.

Tables 7 and 8 present regression outputs for panel and MG models following the specification in equation (2). These tables show that the conditioning factors exhibit coefficients consistent with expectations.

Consistent with the evidence reported before, uncertainty covaries negatively with cross-border funding. The multivariate approach produces elasticities of similar sizes and signs to those reported in the bivariate model. To be specific, panel regression models in Table 7 show that uncertainty captured by volatility measures and the EPU index are associated with a contraction in cross-border aggregate funding and bank counterparties, with elasticities ranging from −2.2% to −1.1%. Panel models yield a significant result for funding from non-banks only for WUI (−0.7) and the forecast-based measure (−1.0%). Coefficient sizes are mostly systematically lower in absolute value (less negative) in panel models with the conditioning factors than without the conditioning factors for all uncertainty indicators (excluding FD uncertainty), albeit some of them are statistically insignificant. The range of variation for the elasticities across these models narrows. Coefficients for uncertainty measures in the bivariate model range from −4.1% to 0.3%, while those in the multivariate model range from −2.2% to 0.5%.

MG models also yield negative elasticities in most cases. As expected, the introduction of conditioning factors reduces the precision of these estimates, with more coefficients being statistically insignificant than before. Abstracting from these larger standard errors, multivariate MG models yield less negative responses to most uncertainty shocks than bivariate MG models. This is true for aggregate funding, for funding from banks, and for funding from non-banks in IV1 and WUI measures only.

In contrast to the panel model with fixed effects, the min-max rage of variation for the point estimates in the multivariate MG model does not differ much from the bivariate counterpart. Coefficients on uncertainty for the multivariate MG model lie between −4.3% and 0.4% while those for the bivariate MG model lie between −4.0% and 0.5%.

As in the previous section, we also conducted a country-by-country analysis. Here, the min-max range for country-specific coefficients from multivariate models is greater than in the bivariate analysis for most uncertainty measures and counterparty sectors. The only case where the cross-country variation in uncertainty elasticities is more compressed for multilateral models is total funding changes in response to FD uncertainty shocks. The inclusion of conditioning factors does not homogeneously change the bivariate point estimates of the elasticities.

Similar to Section 4.2.2, Table 9 reports country-specific point estimates for regressions models including the conditioning factors. Reductions in cross-border funding based on country-specific regressions for countries like Portugal, Ireland, and France are robust to the inclusion of the additional regressors. As expected, many previous coefficients lose statistical significance in the country-level regressions too. Interestingly, the inclusion of additional controls reinforces the previous evidence on Finland borrowing more when uncertainty increases and reveals the case of banks in Australia borrowing more from banks because of increases in implied volatility.

In summary, results from the bivariate analysis are robust to multivariate analysis – the inclusion of these reasonable conditioning factors does not change the overall message. Cross-border bank funding responds negatively to uncertainty, with the magnitude of this effect changing across uncertainty indicators, countries, and counterparty sectors.

4.4 Heterogeneity across Time

We have thus far shed light on how heterogeneity in the response of cross-border bank funding to uncertainty shocks arises across uncertainty measures, countries, and funding sectors. The natural next dimension to complete our overview is time. Here, the obvious candidate is the potential structural break happening during the unfolding of the GFC as global banks were at the centre of the international transmission of shocks. Openness to global funding through other channels played no major role. Together with the reduction in local lending by foreign and local banks, loan supply declined from the contraction in cross-border lending by foreign banks (Cetorelli and Goldberg, 2011). Taking an international investment position perspective, Lane and Milesi-Ferretti (2018) show that the halt in international globalization was dominated by cross-border banking, and not so much by changes in other investment types. This contraction was mostly related to de-leverage by European banks (McCauley *et al.*, 2019).

In line with the empirical approach of this paper stressing the key role of heterogeneity, the Great Retrenchment in international capital flows was quite diverse across types, geography, and time (Milesi-Ferretti and Tille, 2011). Taking a more disaggregated perspective for cross-border bank lending, Cerutti *et al.* (2015) show that syndicated loans increased during the crisis years, due to the large credit lines extended before the crisis. Looking at heterogeneity from the point of view of residence, Broner *et al.* (2013) report a positive correlation between position changes of foreign and domestic investors during the GFC.

To examine different episodes, we modify our baseline empirical model by including a time dummy variable for the crisis periods and interaction effects with the different uncertainty measures. We follow both strategies already presented: a bivariate and a multivariate approach. To be precise, we estimate the following model

$$\ln\left(L_{i,t}\right) = \alpha_i + \beta \ln\left(UNC_{i,t}\right) + \psi \ln\left(UNC_{i,t}\right) * GFC_t + \delta GFC_t + \gamma X_{i,t-1} + \rho \ln\left(L_{i,t-1}\right) + \epsilon_{i,t} \quad (3)$$

where GFC_t is a dummy variable taking value one in the period 2008Q3–2012Q12 and zero otherwise and $UNC_{i,t} * GFC_t$ is the interaction term between the crisis dummy and the uncertainty measure being used. As we concentrate on subperiods rather than cross-country heterogeneity in this section, we do not present MG models.

Tables 10 and 11 present two versions of the models without and with the set of conditioning factors in $X_{i,t-1}$. In addition, Tables 12 and 13 present versions of models in equations (1) and (2) estimated with data before and after the crisis. This approach is equivalent to assuming a break for all variables in the model after the crisis years.

The crisis period dummy is associated with more cross-border funding from all sectors using volatility-based uncertainty indicators and from aggregate and bank sectors using EPU. The crisis dummy shows a negative coefficient for aggregate and bank funding sectors using the WUI. For forecast dispersion, the crisis dummy is insignificant. As expected, the interaction term between uncertainty and the crisis period is strongly negative and significant for all volatility-based uncertainty indicators in each funding sector. The interaction term is also negative and significant for aggregate and bank sector funding sources using EPU. Interestingly, most direct relations are insignificant, except for realized volatility exhibiting a positive association for aggregate funding in the multivariate model and for the news-based measures exhibiting a negative association for aggregate and bank sector funding. Taken together, our results suggest the following: (i) borrowing declined with uncertainty during the crisis; and (ii) volatility-based uncertainty only matters during the crisis.

The alternative approach of shifting the analysis to periods before and after the GFC shows that most uncertainty measures are insignificant, except EPU and WUI, which have negative coefficients. As emphasized in Section 3.2.1, news-based policy-driven uncertainty measures are the only measures whose first and second moments have risen since the GFC, with all other measures calming before and after the crisis. Looking across country groups, news-based uncertainty has a notable effect for European countries, particularly the EU15 and euro area countries, with some effects for advanced and G7 nations, but no effect for non-European and emerging markets.

To conclude, the message from this section is that uncertainty matters during the crisis years. Outside the crisis years, and especially for European countries, news-based uncertainty has a negative effect likely because news-based uncertainty has risen since the crisis, unlike other uncertainty measures.

5 Conclusion

We examine a sectoral breakdown of cross-border funding and how it responds to various uncertainty measures over time and across countries. Sub-components of funding are unlikely to share time-series properties of aggregate funding. Similar heterogeneities apply to uncertainty measures, which are short-lived, though we identify that news-based uncertainty has risen over time unlike other uncertainty measures that are usually pro-cyclical. Making conservative modeling choices, we find that funding declines in response to uncertainty and that the effects are statistically and economically significant. The non-banking sector displays the largest effects as do volatility-based uncertainty measures. Results are robust to country specific versus panel regressions and the addition of conditioning factors in multivariate analysis. Uncertainty mattered most during the GFC and European Sovereign Debt Crisis. Outside of the GFC, news-based uncertainty dampened funding particularly for European countries because news-based uncertainty measures have risen since the GFC, unlike other uncertainty measures.

This paper illuminates the heterogeneities inherent in a sectoral decomposition of aggregate cross-border funding of banks, across multiple types of uncertainty, between a diverse set of countries internationally with differing banking systems, and over different periods and historical episodes. The dataset we compile allows us to shed light on many of these idiosyncracies, but may be used to explore extra dimensions in future research such as dynamic structural econometric analysis. It is first necessary to understand the underlying data and relations prior to conducting a more structural approach, and thus, this paper aims to provide the groundwork for such analysis. If sufficient data was made available, researchers could explore further avenues such as the decomposition into intragroup borrowing between the branches of the same firm internationally and also split borrowing into financial and non-financial. It is likely that information networks within offices of the same firm located in different countries might suggest results that differ from those we find. Policymakers may also take note of the sizable and unique effect that news-based uncertainty has had on dampening cross-border flows since the Great Recession. Together with the data on multiple measures of uncertainty, the heterogeneities unmasked in this paper should encourage further work towards understanding the relation between uncertainty and cross-border bank flows.

References

Ahmed, S. and Zlate, A. (2014). Capital Flows to Emerging Market Economies: A Brave New World? *Journal of International Money and Finance*, **48** (PB), 221–248.

Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, **58** (2), 277–297.

Avdjiev, S., Du, W., Koch, C. and Shin, H. S. (2019). The Dollar, Bank Leverage, and Deviations from Covered Interest Parity. *American Economic Review: Insights*, **1** (2), 193–208.

Bachmann, R., Elstner, S. and Sims, E. R. (2013). Uncertainty and Economic Activity: Evidence from Business Survey Data. *American Economic Journal: Macroeconomics*, **5** (2), 217–49.

Baker, S. R., Bloom, N. and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, **131** (4), 1593–1636.

Bénétrix, A., Honohan, P. and Schmitz, M. (2020). *Euro-Dollar Exposures in Global Banking: the Role of Geography*. Tech. rep., Trinity College Dublin mimeo.

Bénétrix, A. S., McCauley, R. N., McGuire, P. M. and von Peter, G. (2017). *The Consolidated Wealth of Nations: a First Step Using BIS Data*. Tech. rep., Trinity College Dublin, mimeo.

Benhima, K. and Cordonier, R. (2020). *News, Sentiment and Capital Flows*. Working Papers 2020-04, Swiss National Bank.

Black, F. and Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, **81** (3), 637–654.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, **77** (3), 623–685.

Broner, F., Didier, T., Erce, A. and Schmukler, S. L. (2013). Gross Capital Flows: Dynamics and Crises. *Journal of Monetary Economics*, **60** (1), 113–133.

Bruno, V. and Shin, H. S. (2015a). Capital Flows and the Risk-Taking Channel of Monetary Policy. *Journal of Monetary Economics*, **71**, 119–132.

— and — (2015b). Cross-Border Banking and Global Liquidity. *The Review of Economic Studies*, **82** (2), 535–564.

Cerutti, E., Claessens, S. and Ratnovski, L. (2017). Global Liquidity and Cross-Border Bank Flows. *Economic Policy*, **32** (89), 81–125.

—, Hale, G. and Minoiu, C. (2015). Financial Crises and the Composition of Cross-Border Lending. *Journal of International Money and Finance*, **52**, 60–81.

Cetorelli, N. and Goldberg, L. S. (2011). Global Banks and International Shock Transmission: Evidence from the Crisis. *IMF Economic Review*, **59** (1), 41–76.

Choi, S. and Furceri, D. (2019). Uncertainty and Cross-Border Banking Flows. *Journal of International Money and Finance*.

Correa, R., Paligorova, T., Sapriza, H. and Zlate, A. (2018). *Cross-Border Bank*

Flows and Monetary Policy. Tech. Rep. 1241, FRB International Finance Discussion Paper.

Curran, M. and Velic, A. (2019). Real Exchange Rate Persistence and Country Characteristics: A Global Analysis. *Journal of International Money and Finance*, **97**, 35 – 56.

Forbes, K. J. and Warnock, F. E. (2012). Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. *Journal of International Economics*, **88** (2), 235–251.

Gauvin, L., McLoughlin, C. and Reinhardt, D. (2013). *Policy Uncertainty Spillovers to Emerging Markets - Evidence from Capital Flows*. Tech. rep.

Gourio, F., Siemer, M. and Verdelhan, A. (2015). *Uncertainty and International Capital Flows*. Tech. rep., SSRN 2626635.

Kim, C.-J. and Nelson, C. R. (1999). Has the US Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle. *Review of Economics and Statistics*, **81** (4), 608–616.

Kleimeier, S., Sander, H. and Heuchemer, S. (2013). Financial Crises and Cross-Border Banking: New Evidence. *Journal of International Money and Finance*, **32** (C), 884–915.

Lane, P. R. and McQuade, P. (2014). Domestic Credit Growth and International Capital Flows. *The Scandinavian Journal of Economics*, **116** (1), 218–252.

— and Milesi-Ferretti, G. M. (2007). The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970–2004. *Journal of International Economics*, **73** (2), 223–250.

— and — (2008). The Drivers of Financial Globalization. *American Economic Review*, **98** (2), 327–32.

— and — (2018). The External Wealth of Nations Revisited: International Financial Integration in the Aftermath of the Global Financial Crisis. *IMF Economic Review*, **66** (1), 189–222.

McCauley, R. N., Bénétrix, A. S., McGuire, P. M. and von Peter, G. (2019). Financial Deglobalisation in Banking? *Journal of International Money and Finance*, **94**, 116–131.

McConnell, M. M. and Perez-Quiros, G. (2000). Output Fluctuations in the United States: What has Changed Since the Early 1980's? *American Economic Review*, **90** (5), 1464–1476.

Merton, R. C. (1973). Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science*, pp. 141–183.

Milesi-Ferretti, G. M. and Tille, C. (2011). The Great Retrenchment: International Capital Flows During the Global Financial Crisis. *Economic Policy*, **26** (66), 285–342.

Morikawa, M. (2016). Business Uncertainty and Investment: Evidence from Japanese Companies. *Journal of Macroeconomics*, **49**, 224–236.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica: Journal of the Econometric Society*, pp. 1417–1426.

Pesaran, M. H., Shin, Y. and Smith, R. P. (1997). Estimating Long-run Relationships in Dynamic Heterogeneous Panels, DAE Working Papers Amalgamated Series 9721.

—, — and — (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association*, **94** (446), 621–634.

— and Smith, R. (1995). Estimating Long-Run Relationships from Dynamic Heterogeneous Panels. *Journal of Econometrics*, **68** (1), 79–113.

Rey, H. (2015). *Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence*. Tech. rep., National Bureau of Economic Research.

Stock, J. H. and Watson, M. W. (2002). Has the Business Cycle Changed and Why? *NBER Macroeconomics Annual*, **17**, 159–218.

Valencia, F. (2017). Aggregate Uncertainty and the Supply of Credit. *Journal of Banking & Finance*, **81**, 150–165.

Table 1: Stock Market Indexes For 24 Core Countries

Reporter	BBG Index	Reporter	BBG Index	Reporter	BBG Index
Australia	AS52	France	CAC	Portugal	BVLX
Austria	ATX	Germany	DAX	Singapore	STI
Belgium	BELPRC	India	SENSEX	Spain	IBEX
Brazil	IBOV	Ireland	ISEQ	Sweden	OMX
Canada	SPTSX	Italy	ITLMS	Switzerland	SPI
Chile	IGPA	Japan	NKY	Turkey	XU100
Denmark	KAX	Netherlands	AEX	UK	UKX
Finland	HEX	Norway	OSEBX	USA	SPX

Notes: We source data from Bloomberg. We use Bloomberg's OVM function to compute implied volatility at the money for one- and three-month maturities and take the last value in each quarter. We use quarterly frequency US Dollar nominal price index data to build measures of realized volatility.

Table 2: Moments for Cross-Border Flows of Liabilities

	Mean		Median		Standard Deviation		Skewness		Kurtosis	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Overall										
All	6.17	2.11	3.92	0.90	51.06	25.96	0.64	0.43	7.32	5.00
Pre-2008Q3	26.71	9.95	23.45	5.61	44.79	24.10	0.78	0.44	5.01	3.24
2008Q3-2012Q2	−9.55	−5.52	−8.43	−3.95	52.81	26.73	−0.14	−0.36	3.87	3.59
Non-Crisis	11.44	4.50	7.26	1.62	46.44	27.56	0.85	0.37	6.38	4.10
Post-2008Q3	−4.59	−3.11	−4.51	−2.97	49.39	30.22	0.27	0.12	5.68	4.28
Post-2012Q2	−0.07	−0.54	−3.33	−2.64	43.56	26.84	0.53	0.24	4.28	3.09
Post-2012Q2/Crisis	0.01*	0.10	0.39	0.67	0.83	1.00	−3.70***	−0.68*	1.11	0.86
Banks										
All	0.29	0.19	0.51	0.35	39.08	31.37	0.25	0.37	7.53	5.60
Pre-2008Q3	23.80	10.02	22.93	6.59	37.40	21.22	0.44	0.19	4.09	2.85
2008Q3-2012Q2	−10.20	−4.16	−8.42	−2.56	43.28	26.88	−0.18	−0.19	4.54	3.38
Non-Crisis	4.40	2.18	2.39	0.59	34.53	23.42	0.58	0.52	6.40	4.70
Post-2008Q3	−6.54	−2.99	−6.08	−3.16	36.44	25.13	−0.09	0.08	6.96	5.24
Post-2012Q2	−3.20	−1.01	−3.88	−1.92	26.01	20.56	0.13	0.12	4.22	3.12
Post-2012Q2/Crisis	0.31	0.24	0.46	0.75	0.60*	0.76	−0.76	−0.64	0.93	0.92
Non-Banks										
All	2.56	0.62	1.57	0.20	18.89	8.46	0.11	0.02	8.57	6.41
Pre-2008Q3	7.39	1.31	5.97	1.31	13.29	4.91	0.82	0.76	4.78	4.02
2008Q3-2012Q2	−0.82	−0.19	−0.36	0.04	19.45	9.38	−0.13	−0.11	5.29	3.74
Non-Crisis	4.02	0.96	2.60	0.47	17.62	8.82	0.37	0.06	7.65	6.36
Post-2008Q3	0.04	0.06	0.05	−0.22	19.82	10.14	−0.17	−0.34	7.38	6.07
Post-2012Q2	0.82	−0.10	0.63	−0.22	19.29	9.09	0.14	0.12	5.08	3.34
Post-2012Q2/Crisis	−0.99	0.51	−1.76	−5.88	0.99	0.97	−1.06	−1.13	0.96	0.89

Notes: Each *Mean-Median* column pair present the mean and median of the moment in question across the core 24 countries and over the period corresponding to that row. See Table 2 in the main paper for the list of the 24 core countries. Periods are indicated in each row, where All denotes full sample (2003Q1–2018Q4), Non-Crisis denotes the subset of the full sample that excludes 2008Q3–2012Q2, and Crisis denotes the period 2008Q3–2012Q2. In the Post-2012Q2/Crisis rows, we test the statistical difference between the post-crisis period (2012Q3–2018Q4) and the crisis period (2008Q3–2012Q2). * significant at 10%; ** significant at 5%; *** significant at 1%. Significance corresponds to the Welch test for group differences between means and the Mood's test for group differences between medians. Cross-border flows are in growth rates, where, for example, −4 means −4%.

Table 3: Moments for Uncertainty Measures

	Mean		Median		Standard Deviation		Skewness		Kurtosis	
	Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
IV3										
All	2.91	2.93	2.87	2.89	0.37	0.36	0.72	0.70	3.98	3.31
Pre-2008Q3	2.81	2.79	2.79	2.74	0.33	0.34	0.42	0.46	2.46	2.31
2008Q3-2012Q2	3.12	3.19	3.02	3.03	0.38	0.37	0.83	0.67	3.23	2.85
Non-Crisis	2.81	2.82	2.78	2.77	0.31	0.30	0.42	0.36	3.18	2.55
Post-2008Q3	2.96	2.97	2.91	2.93	0.37	0.34	0.93	0.84	4.06	3.46
Post-2012Q2	2.81	2.79	2.76	2.74	0.27	0.26	0.43	0.31	2.78	2.09
Post-2012Q2/Crisis	0.90***	0.87***	0.91***	0.90***	0.69	0.70***	0.52***	0.46***	0.86	0.73***
IV1										
All	2.86	2.88	2.82	2.86	0.42	0.40	0.61	0.48	3.56	2.94
Pre-2008Q3	2.75	2.73	2.70	2.66	0.38	0.39	0.52	0.45	2.68	2.53
2008Q3-2012Q2	3.07	3.15	2.99	3.00	0.42	0.39	0.63	0.53	2.81	2.38
Non-Crisis	2.76	2.75	2.72	2.67	0.37	0.36	0.53	0.47	3.43	2.79
Post-2008Q3	2.91	2.92	2.86	2.86	0.41	0.38	0.74	0.62	3.51	3.04
Post-2012Q2	2.76	2.72	2.72	2.67	0.33	0.32	0.61	0.47	3.30	2.61
Post-2012Q2/Crisis	0.90***	0.86***	0.91***	0.89***	0.80**	0.83**	0.98	0.89	1.17	1.10
Realized Volatility										
All	3.01	3.01	2.96	2.92	0.39	0.41	0.78	0.74	3.88	3.68
Pre-2008Q3	2.93	2.87	2.88	2.84	0.29	0.30	0.79	0.77	3.16	2.90
2008Q3-2012Q2	3.30	3.32	3.21	3.21	0.40	0.40	0.82	0.86	3.41	3.31
Non-Crisis	2.89	2.85	2.86	2.82	0.30	0.30	0.43	0.34	3.06	2.96
Post-2008Q3	3.06	3.06	3.02	3.00	0.42	0.43	0.67	0.69	3.69	3.55
Post-2012Q2	2.83	2.79	2.80	2.74	0.29	0.29	0.28	0.30	2.91	2.71
Post-2012Q2/Crisis	0.86***	0.84***	0.87***	0.85***	0.74***	0.74***	0.34**	0.35***	0.86**	0.82**
EPU										
All sample	4.74	4.70	4.76	4.69	0.45	0.47	−0.03	0.02	2.63	2.55
Pre-2008Q3	4.37	4.37	4.35	4.36	0.37	0.35	0.59	0.64	3.59	3.59
2008Q3-2012Q2	4.94	4.93	4.94	4.92	0.31	0.34	−0.03	−0.07	2.40	2.25
Non-Crisis	4.68	4.65	4.70	4.64	0.47	0.50	0.11	0.10	2.61	2.67
Post-2008Q3	4.94	4.83	4.93	4.85	0.35	0.35	0.10	0.14	2.74	2.71
Post-2012Q2	4.94	4.81	4.95	4.84	0.33	0.33	0.20	0.14	2.89	2.72
Post-2012Q2/Crisis	1.00	0.98	1.00	0.98	1.09	0.98	−5.89*	−2.12	1.21**	1.21***
WUI										
All sample	2.43	2.48	2.72	2.77	1.20	1.24	−0.89	−1.08	3.34	3.09
Pre-2008Q3	2.07	2.19	2.25	2.35	1.14	1.20	−0.58	−0.64	2.64	2.36
2008Q3-2012Q2	2.31	2.35	2.54	2.74	1.24	1.28	−0.80	−0.70	3.45	2.06
Non-Crisis	2.53	2.55	2.79	2.83	1.15	1.14	−0.91	−1.02	3.33	2.96
Post-2008Q3	2.62	2.65	2.85	2.98	1.18	1.19	−1.19	−1.33	4.24	3.93
Post-2012Q2	2.90	2.96	3.11	3.21	0.93	0.93	−1.10	−1.26	4.48	3.74
Post-2012Q2/Crisis	1.26***	1.26***	1.23**	1.17**	0.75***	0.72**	1.37	1.79	1.30	1.82**
Forecast Dispersion										
All sample	2.48	3.01	2.37	2.89	0.70	0.64	0.18	0.26	2.65	2.36
Pre-2008Q3	2.75	2.91	2.78	2.81	0.62	0.57	−0.12	−0.19	2.31	2.26
2008Q3-2012Q2	2.46	3.09	2.24	3.03	0.68	0.67	0.35	0.30	2.76	2.27
Non-Crisis	2.45	2.82	2.50	2.81	0.68	0.61	−0.01	−0.03	2.40	2.20
Post-2008Q3	2.36	3.00	2.19	2.99	0.67	0.67	0.42	0.37	3.03	2.78
Post-2012Q2	2.27	2.73	2.14	2.84	0.61	0.55	0.20	0.20	2.52	2.42
Post-2012Q2/Crisis	0.92	0.88	0.95	0.94	0.90	0.83	0.58	0.67	0.91	1.06

Notes: See notes to Table 2. To ensure consistency across uncertainty measures throughout the analysis, we use $\ln(\text{EPU}+1)$ for EPU. Similarly, denoting WUI and the forecast-based measures by x, we transform x to $\ln(100x+1)$.

Table 4: Bivariate Regression Models

Uncertainty	(1) All	(2) Banks	(3) Non-Banks	Observations / Countries
Panel A: Panel Regressions				
Implied Volatility (3M)	−2.40***	−2.66**	−4.10***	1512
	(0.80)	(1.05)	(1.12)	24
Implied Volatility (1M)	−1.53**	−1.72*	−2.81***	1512
	(0.74)	(0.96)	(0.92)	24
Realized Volatility	−1.88**	−2.15*	−3.01**	1512
	(0.89)	(1.12)	(1.91)	24
EPU	−2.47***	−2.87***	−0.41	1008
	(0.72)	(0.87)	(1.91)	16
WUI	−0.51**	−0.56*	−0.71*	1512
	(0.23)	(0.29)	(0.35)	24
Forecast Dispersion	0.04	0.31	−0.98	899
	(0.30)	(0.29)	(0.65)	15
Panel B: Mean-Group Regressions				
Implied Volatility (3M)	−2.57***	−2.93**	−3.96***	1512
	(0.96)	(1.16)	(1.10)	24
Implied Volatility (1M)	−1.51*	−1.92*	−2.20**	1512
	(0.79)	(1.00)	(0.96)	24
Realized Volatility	−2.07**	−2.64**	−2.65**	1512
	(1.01)	(1.16)	(1.86)	24
EPU	−1.90*	−1.65	−0.81	1008
	(1.00)	(1.25)	(1.86)	16
WUI	−0.53**	−0.61*	−0.80**	1512
	(0.24)	(0.32)	(0.31)	24
Forecast Dispersion	−0.36	0.49	−3.89*	899
	(0.36)	(0.39)	(2.08)	15

Notes: Panel A reports results of bivariate panel regressions with fixed effects for the model in equation (1). Panel B report results of bivariate mean-group regressions for the model in equation (1). Dependent variable: logarithm of cross-border funding. Explanatory variables are in logarithms. Lagged dependent variable included but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 5: Bivariate Regression Models – Fixed Sample

Uncertainty	(1) All	(2) Banks	(3) Non-Banks	Observations / Countries
Panel A: Panel Regressions				
Implied Volatility (3M)	−2.35***	−2.72**	−3.83**	787
	(0.72)	(1.09)	(1.39)	13
Implied Volatility (1M)	−1.71**	−1.86*	−2.60*	787
	(0.61)	(1.00)	(1.22)	13
Realized Volatility	−2.38***	−2.47**	−3.49**	787
	(0.66)	(0.99)	(2.05)	13
EPU	−2.16***	−2.49***	0.71	787
	(0.51)	(0.80)	(2.05)	13
WUI	−0.24	−0.22	−0.79	787
	(0.23)	(0.35)	(0.59)	13
Forecast Dispersion	0.09	0.38	−0.95	787
	(0.31)	(0.29)	(0.72)	13
Panel B: Mean-Group Regressions				
Implied Volatility (3M)	−2.71***	−3.45***	−3.87***	787
	(1.02)	(1.29)	(1.46)	13
Implied Volatility (1M)	−1.69**	−2.36**	−1.94	787
	(0.81)	(1.19)	(1.47)	13
Realized Volatility	−2.73***	−3.46***	−2.76**	787
	(0.98)	(1.29)	(2.15)	13
EPU	−2.32**	−2.11*	−0.40	787
	(0.90)	(1.28)	(2.15)	13
WUI	−0.34	−0.38	−0.64	787
	(0.28)	(0.48)	(0.47)	13
Forecast Dispersion	−0.30	0.72*	−3.81	787
	(0.41)	(0.40)	(2.37)	13

Notes: Panel A reports results of bivariate panel regressions with fixed effects for the model in equation (1) with a fixed sample. Panel B report results of bivariate mean-group regressions robust to outliers for the model in equation (1) with a fixed sample. Dependent variable: logarithm of cross-border funding. Explanatory variables are in logarithms. Lagged dependent variable included but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level. The 13 countries are the following: Australia, Brazil, Canada, Chile, France, Germany, India, Italy, Netherlands, Singapore, Spain, Sweden, and the United Kingdom.

Table 6: Bivariate Regression Models – Country-Specific Coefficients

Country	**UNC**	**All**	**Banks**	**NBanks**	**country**	**UNC**	**All**	**Banks**	**NBanks**
Australia	IV3	0.94	3.48	-13.56*	Italy	IV3	-3.4	-7.25***	-0.33
	IV1	1.01	4.32	-11.35		IV1	-3.53*	-6.24**	-2.33
	RV	-0.68	1.61	-14.04*		RV	-3.25	-7.72***	-0.78
	EPU	-0.48	4.15	-8.7		EPU	-8.75***	-8.61***	-0.21
	WUI	0.06	0.16	0.58		WUI	-0.61	-0.31	0.08
	FD	1.48	4.44	-7.88		FD	0.31	-0.08	-3.04**
Austria	IV3	-3.39	-9.34	-0.63	Japan	IV3	4.16	4.27	2.68
	IV1	-4.79	-8.88*	-2.62		IV1	2.74	2.47	2.76
	RV	-2.6	-8.51*	-3.38		RV	4.74**	3.88	6.77
	EPU	n/a	n/a	n/a		EPU	7.37***	7.15***	3.86
	WUI	-2.64***	-3.91***	-1.19		WUI	-0.36	-0.24	-0.38
	FD	n/a	n/a	n/a		FD	n/a	n/a	n/a
Belgium	IV3	-6.11**	-10.02***	0.05	Netherlands	IV3	-3.67	-6.59*	-3.15
	IV1	-5.47**	-8.87***	0.57		IV1	-2.74	-6.30*	-2.48
	RV	-6.11**	-11.24***	3.26		RV	-1.82	-5.27	-2.27
	EPU	n/a	n/a	n/a		EPU	-3.58	-8.20**	-3.97
	WUI	0.02	0.33	-0.33		WUI	-0.19	-0.63	-0.14
	FD	n/a	n/a	n/a		FD	-0.6	0.42	-0.38
Brazil	IV3	-10.81**	-10.50**	-10.65	Norway	IV3	1.8	2.83	-3.55
	IV1	-2.94	-2.96	5.3		IV1	1.97	2.6	-1.44
	RV	-8.63**	-8.67**	1.61		RV	2.18	3.19	-2.51
	EPU	-2.58	-3.03	20.87**		EPU	n/a	n/a	n/a
	WUI	-1.42	-1.31	-3.95		WUI	1.51	1.06	2.70*
	FD	-0.49	0.54	-30.66**		FD	n/a	n/a	n/a
Canada	IV3	-0.65	0.8	-0.15	Portugal	IV3	-7.88***	-7.72***	-6.29**
	IV1	-0.12	1.16	-1.32		IV1	-6.05***	-5.91***	-4.87*
	RV	-0.14	0.87	0.51		RV	-8.96***	-8.63***	-7.32**
	EPU	-0.79	-1.37	3.38		EPU	n/a	n/a	n/a
	WUI	0.74	0.81	-0.39		WUI	-2.81***	-2.49***	-2.58**
	FD	-4.01*	-0.97	-5.3		FD	n/a	n/a	n/a
Chile	IV3	2.5	-1.61	5.32	Singapore	IV3	-0.95	-2.09	-0.28
	IV1	3.46	-0.77	9.62		IV1	-0.37	-1.13	0.57
	RV	1.39	0.07	3		RV	-0.7	-1.34	-0.48
	EPU	-2.48	3.79	-4.92		EPU	-0.76	0.65	-2.74
	WUI	0.25	2.36	-3.13		WUI	-0.24	-0.12	-0.37
	FD	1.22	-0.19	3.87		FD	0.01	-0.34	0.24
Denmark	IV3	-3.31	-1.75	-5.12	Spain	IV3	-5.53*	-7.19**	-2.75
	IV1	-1.06	0.22	-2.79		IV1	-6.07**	-7.57***	-2.68
	RV	-2.68	-2.23	-0.91		RV	-5.78*	-5.80*	-2.06
	EPU	n/a	n/a	n/a		EPU	-4.51*	-5.97***	-3.47
	WUI	-0.92	-1.09	-0.74		WUI	-0.32	-0.79	-0.6
	FD	n/a	n/a	n/a		FD	-1.36	-0.1	-1.02
Finland	IV3	9.8	11.5	4.01	Sweden	IV3	-0.13	2.08	-9.51
	IV1	9.62	10.27*	3.55		IV1	0.92	2.79	-6.75
	RV	13.61**	13.98**	9.35		RV	0.81	2.32	-5.89
	EPU	n/a	n/a	n/a		EPU	4.63	5.66	1.7
	WUI	-2.59	-2.64	-0.46		WUI	-0.85	-0.67	-1.66
	FD	n/a	n/a	n/a		FD	0.21	0.68	-2
France	IV3	-7.85***	-10.77***	-3.89	Switzerland	IV3	-0.96	-0.55	-0.93
	IV1	-7.25***	-10.38***	-3.33		IV1	0.93	1.19	0.04
	RV	-4.50**	-7.64***	0.24		RV	-1.33	-1.39	-1.47
	EPU	-2.16	-6.19***	6.32		EPU	n/a	n/a	n/a
	WUI	-1.6	-3.10***	0.96		WUI	-0.04	0.47	-0.34
	FD	1.1	1.54*	0.38		FD	-1.36	-1.9	-0.58
Germany	IV3	-2.12	-0.47	-8.15**	Turkey	IV3	-10.14***	-9.88***	-14.07
	IV1	-1.55	-0.36	-7.20**		IV1	-3.22	-3.04	-7.86
	RV	-0.57	0.38	-3.35		RV	-8.30***	-8.21***	-18.71
	EPU	-1.16	-2.68	-6.10**		EPU	n/a	n/a	n/a
	WUI	-0.85	-1.94**	-2.26**		WUI	1.58	1.84	-2.32
	FD	0.37	1.88*	0.17		FD	-0.17	-0.1	-8.23
India	IV3	-1.06	-1.07	-0.87	United Kingdom	IV3	-2.52	-2.96	-3.50*
	IV1	-0.76	0.11	-0.88		IV1	-2.04	-2.91	-2.8
	RV	-5.31***	-5.16	-5.00**		RV	-1.64	-1.61	-3.07**
	EPU	-3.57***	-0.08	-3.76**		EPU	-0.86	-2.95***	0.64
	WUI	1.33**	1.09	1.37*		WUI	-1.34*	-2.37***	0.32
	FD	-0.4	2.06	-1.6		FD	-1.72**	-0.48	-2.32**
Ireland	IV3	-8.50**	-6.05	-12.79***	United States	IV3	-2.01	0.47	-6.93***
	IV1	-7.07**	-5.77*	-9.46**		IV1	-1.78	-0.22	-5.00**
	RV	-8.44**	-6.72	-12.44***		RV	-1.05	0.55	-4.59**
	EPU	-8.46***	-7.79***	-11.19***		EPU	-2.19	-0.97	-4.7
	WUI	-0.46	-0.53	-2.08		WUI	-1.04*	-0.63	-2.22**
	FD	n/a	n/a	n/a		FD	n/a	n/a	n/a

Notes: *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 7: Multivariate Regression Models – Panel Regressions

		IV3			IV1			RV	
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-1.73**	-2.21**	-2.14	-1.08*	-1.41*	-1.28	-1.36*	-1.87*	-1.19
	(0.65)	(0.86)	(1.25)	(0.62)	(0.78)	(1.02)	(0.77)	(0.93)	(1.24)
GDP	0.24*	0.09	0.68*	0.25*	0.11	0.70*	0.24*	0.10	0.70*
	(0.13)	(0.15)	(0.36)	(0.13)	(0.16)	(0.36)	(0.13)	(0.15)	(0.36)
STMKT	0.02	-0.00	0.01	0.03	0.01	0.02	0.02	0.00	0.02
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)
INFL	0.52*	0.34	0.41	0.53*	0.36	0.43	0.56**	0.40	0.47
	(0.26)	(0.34)	(0.56)	(0.26)	(0.35)	(0.56)	(0.26)	(0.34)	(0.54)
MP	0.11	0.16	-0.66*	0.09	0.13	-0.68*	0.11	0.16	-0.68*
	(0.15)	(0.21)	(0.33)	(0.15)	(0.21)	(0.33)	(0.15)	(0.21)	(0.33)
EER	-0.07	-0.02	-0.24	-0.08	-0.02	-0.25	-0.07	-0.01	-0.24
	(0.06)	(0.07)	(0.23)	(0.07)	(0.07)	(0.23)	(0.07)	(0.07)	(0.23)
CREDIT	0.13*	0.18**	0.18	0.14*	0.19**	0.18*	0.13*	0.18**	0.18
	(0.07)	(0.08)	(0.11)	(0.07)	(0.09)	(0.11)	(0.07)	(0.08)	(0.11)
DEBT	-3.14***	-3.24***	-1.28	-3.20***	-3.31***	-1.39	-3.21***	-3.34***	-1.42
	(0.78)	(1.15)	(1.80)	(0.79)	(1.16)	(1.78)	(0.80)	(1.16)	(1.75)
Obs.	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485
R^2	0.96	0.94	0.93	0.96	0.94	0.93	0.96	0.94	0.93
Countries	24	24	24	24	24	24	24	24	24

		EPU			WUI			FD	
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-1.84***	-1.86***	0.47	-0.33	-0.28	-0.67*	-0.15	0.05	-1.03*
	(0.50)	(0.53)	(2.35)	(0.27)	(0.33)	(0.38)	(0.39)	(0.39)	(0.54)
GDP	0.33**	0.15	0.76**	0.30**	0.16	0.76**	0.84***	0.86***	1.34***
	(0.12)	(0.15)	(0.32)	(0.14)	(0.17)	(0.37)	(0.25)	(0.29)	(0.40)
STMKT	0.03	-0.01	0.06	0.03*	0.01	0.03	0.03	-0.02	0.05
	(0.02)	(0.03)	(0.06)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)	(0.05)
INFL	0.70***	0.51	0.30	0.56**	0.40	0.45	0.65***	0.42	0.18
	(0.19)	(0.39)	(0.64)	(0.25)	(0.33)	(0.55)	(0.18)	(0.44)	(0.66)
MP	0.00	0.10	-0.22	0.03	0.05	-0.78**	-0.18	-0.11	-0.33*
	(0.16)	(0.31)	(0.20)	(0.12)	(0.19)	(0.31)	(0.16)	(0.29)	(0.18)
EER	-0.03	0.02	-0.26	-0.07	-0.02	-0.23	-0.02	-0.02	-0.27
	(0.06)	(0.07)	(0.26)	(0.07)	(0.07)	(0.24)	(0.07)	(0.09)	(0.30)
CREDIT	0.10*	0.19*	0.28*	0.13*	0.18*	0.17	0.10*	0.22*	0.19*
	(0.05)	(0.10)	(0.14)	(0.07)	(0.09)	(0.10)	(0.05)	(0.11)	(0.10)
DEBT	-2.80***	-2.47	-0.56	-3.16***	-3.31***	-1.26	-2.55***	-2.10	0.19
	(0.90)	(1.72)	(2.15)	(0.81)	(1.13)	(1.76)	(0.67)	(1.75)	(2.52)
Obs.	989	989	989	1,485	1,485	1,485	888	888	888
R^2	0.96	0.93	0.89	0.96	0.94	0.93	0.95	0.92	0.90
Countries	16	16	16	24	24	24	15	15	15

Notes: Constant and AR(1) terms included in regression but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 8: Multivariate Regression Models – Mean Group

	IV3			IV1			RV		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-2.20*	-1.62	-4.31**	-1.15	-0.94	-2.00	-1.94	-2.05	-3.22*
	(1.23)	(1.54)	(1.79)	(1.03)	(1.24)	(1.43)	(1.33)	(1.48)	(1.69)
GDP	0.54*	0.78*	0.98**	0.61**	0.88*	1.04**	0.57*	0.74*	0.96*
	(0.29)	(0.44)	(0.48)	(0.30)	(0.47)	(0.49)	(0.29)	(0.41)	(0.50)
STMKT	0.02	-0.01	-0.02	0.03	-0.01	0.00	0.04	-0.00	-0.01
	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
INFL	1.43	1.08	1.58	1.46	1.09	1.60	1.45	1.10	1.48
	(0.95)	(1.01)	(1.18)	(0.97)	(1.02)	(1.20)	(0.95)	(0.99)	(1.16)
MP	1.68*	1.87*	0.43	1.49*	1.77	0.17	1.81*	2.16*	0.32
	(0.92)	(1.12)	(0.99)	(0.90)	(1.09)	(1.01)	(0.94)	(1.17)	(0.97)
EER	-0.30	-0.37*	-0.15	-0.31	-0.39*	-0.16	-0.31*	-0.44**	-0.14
	(0.21)	(0.22)	(0.33)	(0.20)	(0.21)	(0.32)	(0.19)	(0.21)	(0.31)
CREDIT	0.01	0.06	0.09	0.02	0.07	0.09	-0.00	0.06	0.08
	(0.07)	(0.10)	(0.09)	(0.07)	(0.10)	(0.09)	(0.07)	(0.10)	(0.10)
DEBT	6.39***	3.02	9.98***	6.06***	3.15	9.33***	6.86***	4.06	9.83***
	(2.42)	(2.73)	(3.73)	(2.26)	(2.62)	(3.54)	(2.46)	(2.55)	(3.44)
Obs.	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485
Countries	24	24	24	24	24	24	24	24	24

	EPU			WUI			FD		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-1.05	-0.08	-0.86	-0.41	-0.36	-0.50	-0.18	0.43	-4.09*
	(0.94)	(1.31)	(2.53)	(0.28)	(0.37)	(0.48)	(0.38)	(0.56)	(2.31)
GDP	0.68**	0.78*	1.92***	0.59*	0.73*	1.23*	0.93***	1.43***	1.86**
	(0.33)	(0.41)	(0.70)	(0.34)	(0.43)	(0.67)	(0.34)	(0.47)	(0.91)
STMKT	0.02	-0.01	-0.04	0.04	-0.01	0.02	0.02	-0.06	0.00
	(0.03)	(0.06)	(0.05)	(0.02)	(0.05)	(0.03)	(0.03)	(0.06)	(0.05)
INFL	0.65	0.37	1.20	1.43	0.88	1.38	0.73*	0.27	0.98
	(0.41)	(0.73)	(0.90)	(0.92)	(0.97)	(1.12)	(0.40)	(0.77)	(0.95)
MP	0.63	0.70	-0.39	1.51**	1.88**	-0.34	0.84	1.04*	-0.17
	(0.54)	(0.79)	(0.78)	(0.68)	(0.88)	(0.86)	(0.53)	(0.58)	(0.63)
EER	-0.09	-0.14	-0.32	-0.35	-0.39*	-0.12	-0.09	-0.18	-0.30
	(0.11)	(0.20)	(0.35)	(0.22)	(0.24)	(0.32)	(0.11)	(0.22)	(0.38)
CREDIT	0.02	0.09	0.20**	0.02	0.09	0.08	0.06	0.20	0.11
	(0.05)	(0.13)	(0.09)	(0.06)	(0.10)	(0.09)	(0.07)	(0.13)	(0.08)
DEBT	5.46*	4.98*	6.13	5.50**	2.71	8.01**	5.52*	2.24	7.73*
	(2.87)	(2.92)	(4.53)	(2.45)	(2.51)	(3.95)	(3.08)	(3.72)	(4.32)
Obs.	989	989	989	1,485	1,485	1,485	888	888	888
Countries	16	16	16	24	24	24	15	15	15

Notes: Constant and AR(1) terms included in regression but not reported. Standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 9: Multivariate Regression Models – Country-Specific Coefficients

Country	UNC	All	Banks	NBanks	Country	UNC	All	Banks	NBanks
Australia	IV3	4.31	19.40***	-20.12*	Italy	IV3	-1.92	-7.90**	-4.77
	IV1	3.24	15.15**	-13.03		IV1	-2.76	-6.40**	-6.31
	RV	0.42	8.73	-17.80*		RV	-1.83	-8.01**	-6.06
	EPU	0.89	-11.26	-11.26		EPU	-5.96**	-4.25	-4.25
	WUI	0.12	1.07	1.52		WUI	-0.24	-0.36	0.79
	FD	2.33	5.47	-2.2		FD	-1.02	-1.4	-3.07*
Austria	IV3	-6.14	-8.89	-2.7	Japan	IV3	4.14	4.9	1.2
	IV1	-6.36	-9.32	-5.02		IV1	2.9	3.07	1.74
	RV	-10.17**	-14.46**	-9.27*		RV	4.01	3.48	4.63
	EPU	n/a	n/a	n/a		EPU	8.29***	7.77	7.77
	WUI	-1.59	-3.64**	-0.77		WUI	-1.03	-0.75	-0.78
	FD	n/a	n/a	n/a		FD	n/a	n/a	n/a
Belgium	IV3	0.19	-5.39	7.74	Netherlands	IV3	-4.4	-6.08	-5.76
	IV1	-1.4	-5.04	4.64		IV1	-2.56	-5.53	-3.65
	RV	-0.36	-8.09*	10.46**		RV	-0.91	-4.39	-3.7
	EPU	n/a	n/a	n/a		EPU	-3.42	-6.57	-6.57
	WUI	0.43	0.39	0.2		WUI	-0.79	-0.23	-0.5
	FD	n/a	n/a	n/a		FD	-1.15	-2.74*	-0.43
Brazil	IV3	-11.13**	-11.72**	-3.0	Norway	IV3	-4.63	-4.54	-9.95*
	IV1	-2.13	-2.69	8.79		IV1	-3.04	-2.86	-4.95
	RV	-8.99**	-9.70**	9.43		RV	-4.43	-4.35	-8.07
	EPU	-0.35	25.98***	25.98***		EPU	n/a	n/a	n/a
	WUI	-1.94	-1.71	-9.07*		WUI	2.17	1.66	3.60**
	FD	-0.66	0.08	-32.91*		FD	n/a	n/a	n/a
Canada	IV3	0.39	0.3	0.65	Portugal	IV3	-8.38**	-8.59***	-2.77
	IV1	0.8	0.73	-0.5		IV1	-5.08*	-5.00**	-2.86
	RV	0.39	-0.49	1.51		RV	-8.51***	-8.83***	-5.1
	EPU	0.47	2.34	2.34		EPU	n/a	n/a	n/a
	WUI	1.14	1.3	-0.1		WUI	-2.84***	-2.55***	-1.9
	FD	-2.12	1.17	-5.55		FD	n/a	n/a	n/a
Chile	IV3	5.51	4.03	3.33	Singapore	IV3	-0.07	-0.87	1.22
	IV1	5.22	1.35	11.15		IV1	-0.08	-0.48	1.28
	RV	3.31	4.04	-2.62		RV	-0.01	-0.3	0.68
	EPU	1.12	9.11	9.11		EPU	-0.83	-3.78*	-3.78*
	WUI	0.41	3.9	-1.05		WUI	-0.09	0.15	-0.64
	FD	0.63	-0.01	0.35		FD	0.38	0.23	0.16
Denmark	IV3	-6.69	-6.05	-7.16	Spain	IV3	-6.9	-5.95	-5.34
	IV1	-3.37	-2.9	-4.49		IV1	-6.96*	-6.61**	-6.04
	RV	-6.99	-7.62	-3.93		RV	-5.99	-3.21	-3.71
	EPU	n/a	n/a	n/a		EPU	-3.27	-4.62	-4.62
	WUI	-0.79	-1.09	-0.47		WUI	-0.19	-0.49	-0.54
	FD	n/a	n/a	n/a		FD	-2.35**	-1.4	-1.03
Finland	IV3	17.23*	17.95*	17.32	Sweden	IV3	-5.24	-1.63	-25.91***
	IV1	16.96**	16.23**	14.84		IV1	-1.95	0.15	-13.09*
	RV	22.44**	21.78**	17.76		RV	-0.9	1.25	-14.76**
	EPU	n/a	n/a	n/a		EPU	-8.2	-19.27	-19.27
	WUI	-3.37	-3.37	2.75		WUI	-2.29*	-2.31*	-3
	FD	n/a	n/a	n/a		FD	2.18	2.96	-1.16
France	IV3	-10.19***	-9.32**	-8.08	Switzerland	IV3	-0.33	0.12	-1.69
	IV1	-8.78***	-7.23**	-7.23		IV1	1.32	2.55	-0.51
	RV	-5.49**	-5.29*	-0.29		RV	-0.18	-0.02	-2.25
	EPU	-1.85	3.62	3.62		EPU	n/a	n/a	n/a
	WUI	-1.45	-2.29*	0.66		WUI	0.32	0.67	-0.06
	FD	0.69	0.41	1.98		FD	-1.1	-2.48	-0.26
Germany	IV3	-2.44	-0.33	-14.46***	Turkey	IV3	-5.69*	-5.79*	-6.4
	IV1	-1.67	-0.16	-10.67***		IV1	-3.52	-3.79	-0.4
	RV	-0.94	0.53	-5.62*		RV	-5.18*	-5.20*	-12.85
	EPU	-0.21	-5.47**	-5.47**		EPU	n/a	n/a	n/a
	WUI	-0.56	-1.90**	-1.54		WUI	0.47	0.87	-1.58
	FD	0.94	2.51**	0.71		FD	-0.54	-0.14	-15.13
India	IV3	-0.96	-0.17	-1.15	United Kingdom	IV3	-3.31	-0.22	-5.07
	IV1	-0.77	1.02	-1.22		IV1	-2.13	-1.07	-3.25
	RV	-7.45***	-7.38	-7.83**		RV	-1.81	0.24	-3.59*
	EPU	-3.52**	-4.11**	-4.11**		EPU	1.86	1.6	1.6
	WUI	1.64**	1.18	1.84**		WUI	-0.35	-0.51	0.63
	FD	0.89	2.18	-0.28		FD	-1.73*	-0.32	-2.53**
Ireland	IV3	-5.63	-1.32	-12.35**	United States	IV3	-0.45	-0.81	1.77
	IV1	-5.02*	-2.57	-9.38**		IV1	-0.53	-1.24	2.1
	RV	-6.80*	-1.84	-14.64**		RV	-0.19	-0.17	0.28
	EPU	-3.37	-7.39*	-7.39*		EPU	1.52	2.63	2.63
	WUI	1.45	1.86	-0.96		WUI	-0.58	-0.39	-0.95
	FD	n/a	n/a	n/a		FD	n/a	n/a	n/a

Notes: *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 10: Global Financial Crisis – Bivariate models

	IV3			IV1			RV		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-0.46	-0.54	-1.86	0.36	0.36	-0.43	1.09	1.13	0.55
	(0.70)	(0.85)	(1.46)	(0.66)	(0.79)	(1.18)	(0.90)	(1.05)	(1.94)
GFC	16.30***	17.99***	24.15**	15.72***	17.60***	23.88***	22.89***	25.96***	33.53***
	(3.79)	(4.37)	(10.41)	(2.82)	(3.76)	(7.23)	(4.28)	(5.20)	(10.44)
GFCxUNC	-5.52***	-6.10***	-7.82**	-5.53***	-6.19***	-8.05***	-7.35***	-8.32***	-10.42***
	(1.20)	(1.37)	(3.30)	(0.92)	(1.22)	(2.28)	(1.29)	(1.58)	(3.25)
Obs.	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512
R^2	0.96	0.94	0.93	0.96	0.94	0.93	0.96	0.94	0.93
Countries	24	24	24	24	24	24	24	24	24

	EPU			WUI			FD		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-1.81**	-2.33**	0.59	-0.82***	-0.95***	-0.98*	0.19	0.46	-0.44
	(0.73)	(0.84)	(2.40)	(0.28)	(0.34)	(0.56)	(0.36)	(0.28)	(0.67)
CRISIS	13.73**	13.15*	13.56	-3.28*	-4.01**	-3.04	-1.07	-1.15	0.07
	(5.48)	(6.51)	(22.48)	(1.59)	(1.83)	(2.33)	(1.16)	(1.24)	(2.24)
CRISxUNC	-3.06**	-2.89**	-3.25	0.66	0.92*	0.50	-0.22	-0.20	-1.30
	(1.11)	(1.31)	(4.55)	(0.44)	(0.51)	(0.83)	(0.40)	(0.49)	(0.82)
Obs.	1,008	1,008	1,008	1,512	1,512	1,512	899	899	899
R^2	0.96	0.94	0.89	0.96	0.94	0.93	0.95	0.92	0.90
Countries	16	16	16	24	24	24	15	15	15

Notes: Constant and AR(1) terms included in regression but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 11: Global Financial Crisis – Multivariate models

	IV3			IV1			RV		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-0.06	-0.39	-0.23	0.62	0.49	0.72	1.29*	0.99	2.23
	(0.48)	(0.58)	(1.54)	(0.53)	(0.60)	(1.17)	(0.70)	(0.73)	(1.88)
GFC	14.62***	17.36***	19.59**	15.05***	17.89***	19.56**	21.31***	25.38***	28.96***
	(3.95)	(4.68)	(9.12)	(3.18)	(4.12)	(7.00)	(4.85)	(6.02)	(8.89)
GFCxUNC	-5.01***	-5.88***	-6.54**	-5.31***	-6.26***	-6.75***	-6.89***	-8.10***	-9.28***
	(1.25)	(1.47)	(2.91)	(1.03)	(1.33)	(2.20)	(1.47)	(1.81)	(2.79)
GDP	0.16	0.00	0.57	0.17	0.02	0.59	0.14	-0.02	0.55
	(0.12)	(0.13)	(0.38)	(0.12)	(0.13)	(0.37)	(0.11)	(0.13)	(0.36)
STMKT	0.01	-0.02	-0.00	0.01	-0.01	0.00	0.01	-0.02	0.00
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
INFL	0.53**	0.34	0.42	0.61**	0.44	0.53	0.54**	0.36	0.45
	(0.25)	(0.34)	(0.55)	(0.26)	(0.35)	(0.56)	(0.26)	(0.34)	(0.54)
MP	0.14	0.20	-0.62	0.13	0.18	-0.65*	0.13	0.19	-0.67*
	(0.17)	(0.23)	(0.36)	(0.17)	(0.24)	(0.37)	(0.18)	(0.25)	(0.36)
EER	-0.06	0.01	-0.22	-0.06	0.01	-0.22	-0.06	0.01	-0.22
	(0.06)	(0.07)	(0.24)	(0.06)	(0.07)	(0.24)	(0.06)	(0.07)	(0.24)
CREDIT	0.11*	0.15*	0.15	0.12*	0.16*	0.16	0.10	0.15*	0.14
	(0.06)	(0.08)	(0.10)	(0.06)	(0.08)	(0.10)	(0.06)	(0.08)	(0.11)
DEBT	-3.40***	-3.57**	-1.45	-3.50***	-3.68***	-1.57	-3.58***	-3.75**	-1.72
	(0.90)	(1.30)	(1.66)	(0.91)	(1.31)	(1.66)	(0.97)	(1.35)	(1.61)
Obs.	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485
R^2	0.96	0.94	0.93	0.96	0.94	0.93	0.96	0.94	0.93
Countries	24	24	24	24	24	24	24	24	24

	EPU			WUI			FD		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-1.07*	-1.11**	1.38	-0.60*	-0.60	-0.85	0.05	0.28	-0.40
	(0.51)	(0.51)	(2.87)	(0.29)	(0.36)	(0.61)	(0.44)	(0.38)	(0.53)
CRISIS	15.73***	17.45**	12.84	-2.70**	-3.13**	-2.19	-0.41	-0.32	1.16
	(5.19)	(6.70)	(21.68)	(1.25)	(1.46)	(2.38)	(1.00)	(1.15)	(2.63)
CRISxUNC	-3.47***	-3.78**	-3.05	0.52	0.67	0.25	-0.47	-0.52	-1.57
	(1.09)	(1.37)	(4.38)	(0.38)	(0.46)	(0.80)	(0.32)	(0.40)	(0.90)
GDP	0.32**	0.16	0.73**	0.26*	0.12	0.72*	0.73***	0.75**	1.14***
	(0.12)	(0.15)	(0.34)	(0.13)	(0.15)	(0.37)	(0.23)	(0.26)	(0.37)
STMKT	0.02	-0.01	0.05	0.03	0.01	0.03	0.03	-0.02	0.04
	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)	(0.05)
INFL	0.77***	0.56	0.40	0.62**	0.47	0.52	0.72***	0.49	0.29
	(0.19)	(0.38)	(0.60)	(0.25)	(0.33)	(0.52)	(0.16)	(0.44)	(0.60)
MP	0.06	0.17	-0.18	0.01	0.03	-0.80**	-0.24	-0.17	-0.49***
	(0.18)	(0.32)	(0.20)	(0.12)	(0.18)	(0.31)	(0.17)	(0.30)	(0.16)
EER	-0.04	0.01	-0.26	-0.05	0.01	-0.20	-0.01	-0.01	-0.26
	(0.07)	(0.08)	(0.24)	(0.06)	(0.07)	(0.25)	(0.07)	(0.09)	(0.30)
CREDIT	0.11*	0.20*	0.28*	0.11	0.16*	0.15	0.10*	0.23*	0.21*
	(0.05)	(0.10)	(0.14)	(0.07)	(0.09)	(0.10)	(0.05)	(0.11)	(0.11)
DEBT	-2.86***	-2.63	-0.50	-3.15***	-3.27***	-1.14	-2.85***	-2.44	-0.40
	(0.92)	(1.76)	(2.35)	(0.75)	(1.04)	(1.83)	(0.56)	(1.68)	(2.77)
Obs.	989	989	989	1,485	1,485	1,485	888	888	888
R^2	0.96	0.93	0.89	0.96	0.94	0.93	0.95	0.92	0.90
Countries	16	16	16	24	24	24	15	15	15

Notes: Constant and AR(1) terms included in regression but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Table 12: Bivariate Panel Regression Model – Non-Crisis

Uncertainty	(1) All	(2) Banks	(3) Non-Banks	Observations / Countries
Implied Volatility (3M)	0.17	0.11	−1.08	1,128
	(0.77)	(0.91)	(1.10)	24
Implied Volatility (1M)	0.81	0.83	0.16	1,128
	(0.71)	(0.83)	(0.85)	24
Realized Volatility	2.09**	2.21**	1.58	1,128
	(0.93)	(1.03)	(1.74)	24
EPU	−2.26***	−2.67***	0.92	752
	(0.76)	(0.80)	(2.58)	16
WUI	−0.98***	−1.07***	−1.12*	1,128
	(0.29)	(0.33)	(0.64)	24
Forecast Dispersion	0.51	0.93**	−0.68	659
	(0.48)	(0.40)	(0.74)	15

Notes: Constant and AR(1) terms included in regression but not reported. Bivariate panel regressions with fixed effects for the model in equation (1) using the non-crisis period. Dependent variable: logarithm of cross-border funding. Explanatory variables are in logarithms. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

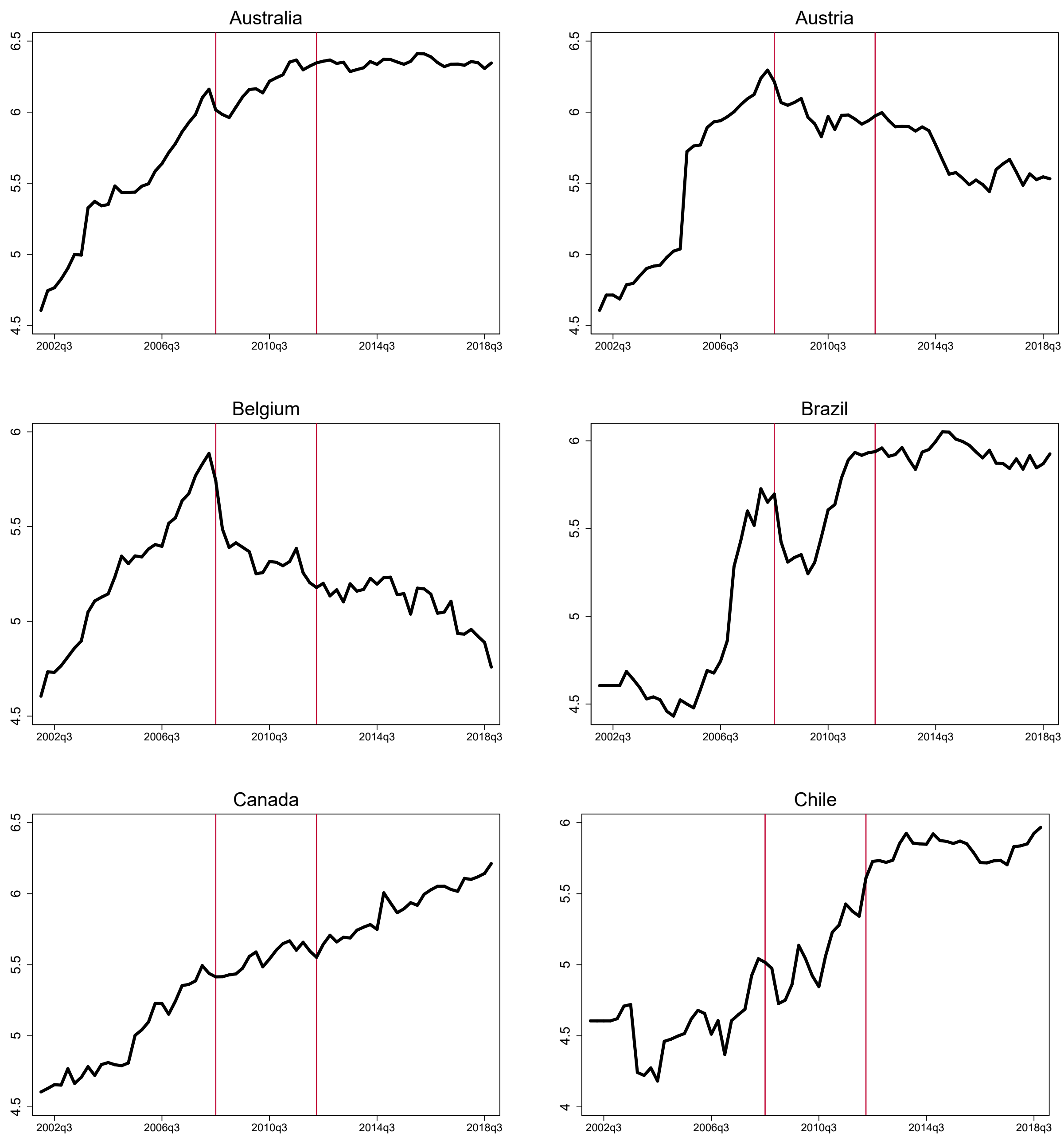
Table 13: Multivariate Panel Regression Model – Non-Crisis

	IV3			IV1			RV		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	0.40	0.30	0.23	0.88	0.92	0.97	1.83**	1.73**	2.71
	(0.49)	(0.53)	(1.31)	(0.52)	(0.57)	(0.89)	(0.65)	(0.75)	(1.81)
GDP	0.10	-0.01	0.63	0.10	-0.01	0.64	0.10	-0.01	0.63
	(0.16)	(0.13)	(0.49)	(0.16)	(0.13)	(0.49)	(0.16)	(0.13)	(0.48)
STMKT	0.01	0.00	0.01	0.01	0.00	0.01	0.02	0.01	0.01
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)
INFL	0.54	0.37	0.90	0.58	0.41	0.95	0.54	0.38	0.92
	(0.42)	(0.50)	(0.83)	(0.41)	(0.51)	(0.85)	(0.41)	(0.50)	(0.83)
MP	0.38	0.39	-0.60	0.37	0.38	-0.62	0.34	0.35	-0.66
	(0.23)	(0.28)	(0.44)	(0.23)	(0.28)	(0.44)	(0.22)	(0.27)	(0.42)
EER	-0.13	-0.09	-0.22	-0.12	-0.09	-0.21	-0.13	-0.09	-0.22
	(0.11)	(0.13)	(0.24)	(0.11)	(0.13)	(0.24)	(0.11)	(0.13)	(0.24)
CREDIT	0.17**	0.17**	0.29*	0.16**	0.16**	0.29*	0.16**	0.16**	0.29*
	(0.06)	(0.07)	(0.14)	(0.06)	(0.07)	(0.14)	(0.06)	(0.07)	(0.14)
DEBT	−3.67***	−4.20***	-1.00	−3.76***	−4.32***	-1.13	−3.77***	−4.29***	-1.22
	(1.02)	(1.17)	(1.64)	(1.01)	(1.17)	(1.65)	(1.01)	(1.17)	(1.62)
Obs.	1,101	1,101	1,101	1,101	1,101	1,101	1,101	1,101	1,101
R^2	0.97	0.95	0.94	0.97	0.95	0.94	0.97	0.95	0.94
Countries	24	24	24	24	24	24	24	24	24

	EPU			WUI			FD		
	All	Banks	Nbanks	All	Banks	Nbanks	All	Banks	Nbanks
UNC	-0.89	-0.73	2.36	-0.64*	-0.59	-0.92	0.08	0.35	-0.72
	(0.58)	(0.50)	(2.73)	(0.32)	(0.36)	(0.70)	(0.57)	(0.53)	(0.71)
GDP	0.32*	0.13	0.58	0.10	-0.02	0.63	0.88***	0.66**	0.86
	(0.16)	(0.07)	(0.38)	(0.17)	(0.13)	(0.49)	(0.25)	(0.26)	(0.60)
STMKT	0.02	-0.01	0.02	0.01	-0.00	-0.00	0.02	-0.02	0.04
	(0.03)	(0.03)	(0.06)	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.07)
INFL	0.97**	0.67	0.96	0.54	0.38	0.91	0.85**	0.53	0.83
	(0.39)	(0.61)	(1.14)	(0.42)	(0.50)	(0.83)	(0.37)	(0.63)	(1.11)
MP	0.45	0.56	0.12	0.35	0.35	-0.66	0.14	0.17	-0.35
	(0.28)	(0.43)	(0.21)	(0.21)	(0.27)	(0.43)	(0.25)	(0.37)	(0.25)
EER	-0.18**	-0.12	-0.34	-0.09	-0.06	-0.17	-0.09	-0.11	-0.33
	(0.08)	(0.11)	(0.29)	(0.12)	(0.13)	(0.24)	(0.09)	(0.14)	(0.37)
CREDIT	0.13**	0.14**	0.45**	0.14*	0.14*	0.25	0.08*	0.11	0.36**
	(0.06)	(0.06)	(0.18)	(0.07)	(0.07)	(0.15)	(0.04)	(0.07)	(0.14)
DEBT	-2.91**	-3.59*	0.46	-3.34***	-3.84***	-0.55	-3.35***	-3.72**	1.60
	(1.20)	(1.71)	(1.71)	(0.93)	(1.08)	(1.65)	(0.99)	(1.62)	(1.57)
Obs.	733	733	733	1,101	1,101	1,101	648	648	648
R^2	0.97	0.95	0.90	0.97	0.95	0.94	0.96	0.93	0.89
Countries	16	16	16	24	24	24	15	15	15

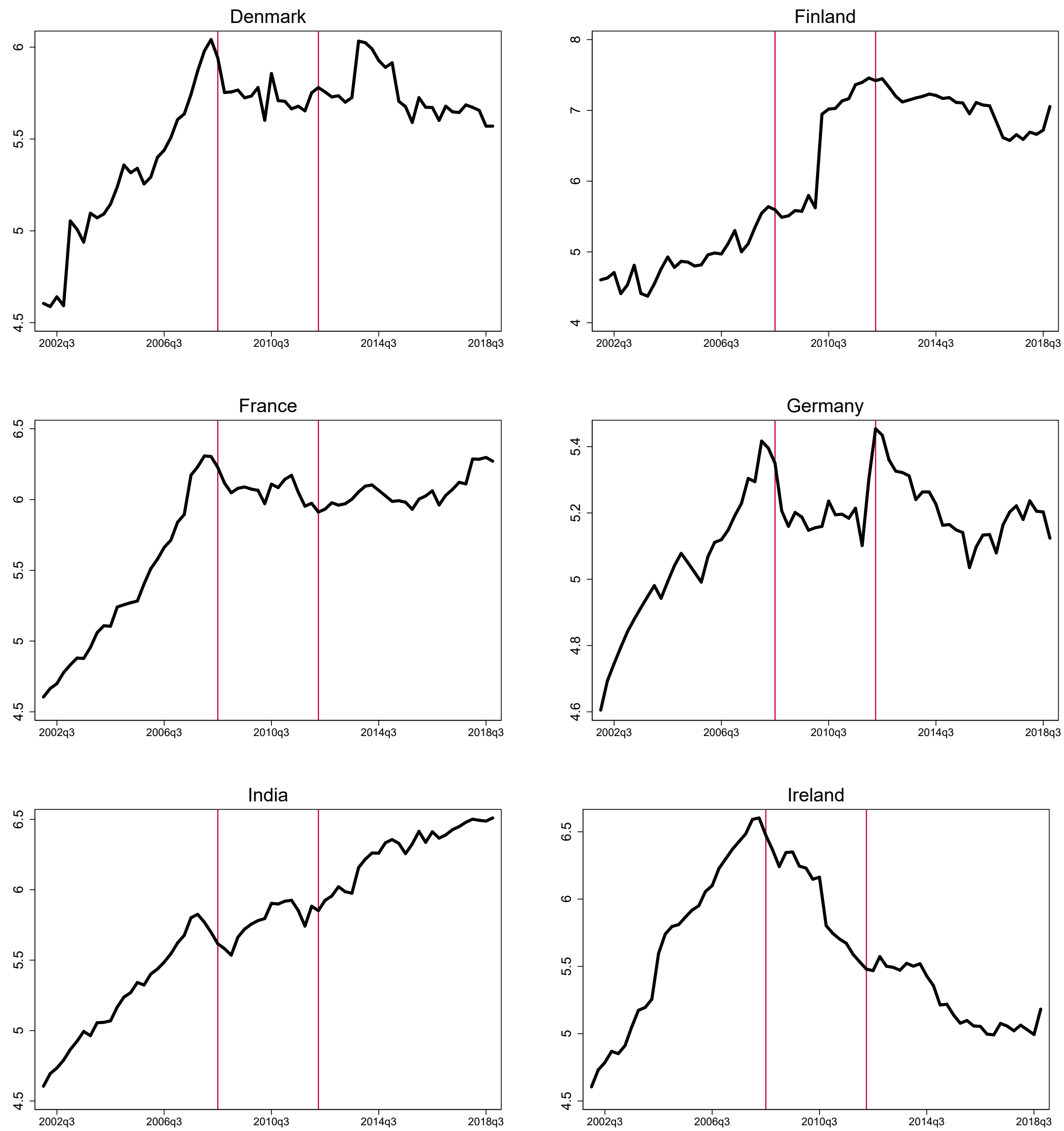
Notes: Constant and AR(1) terms included in regression but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Figure 1: Cross-border liabilities



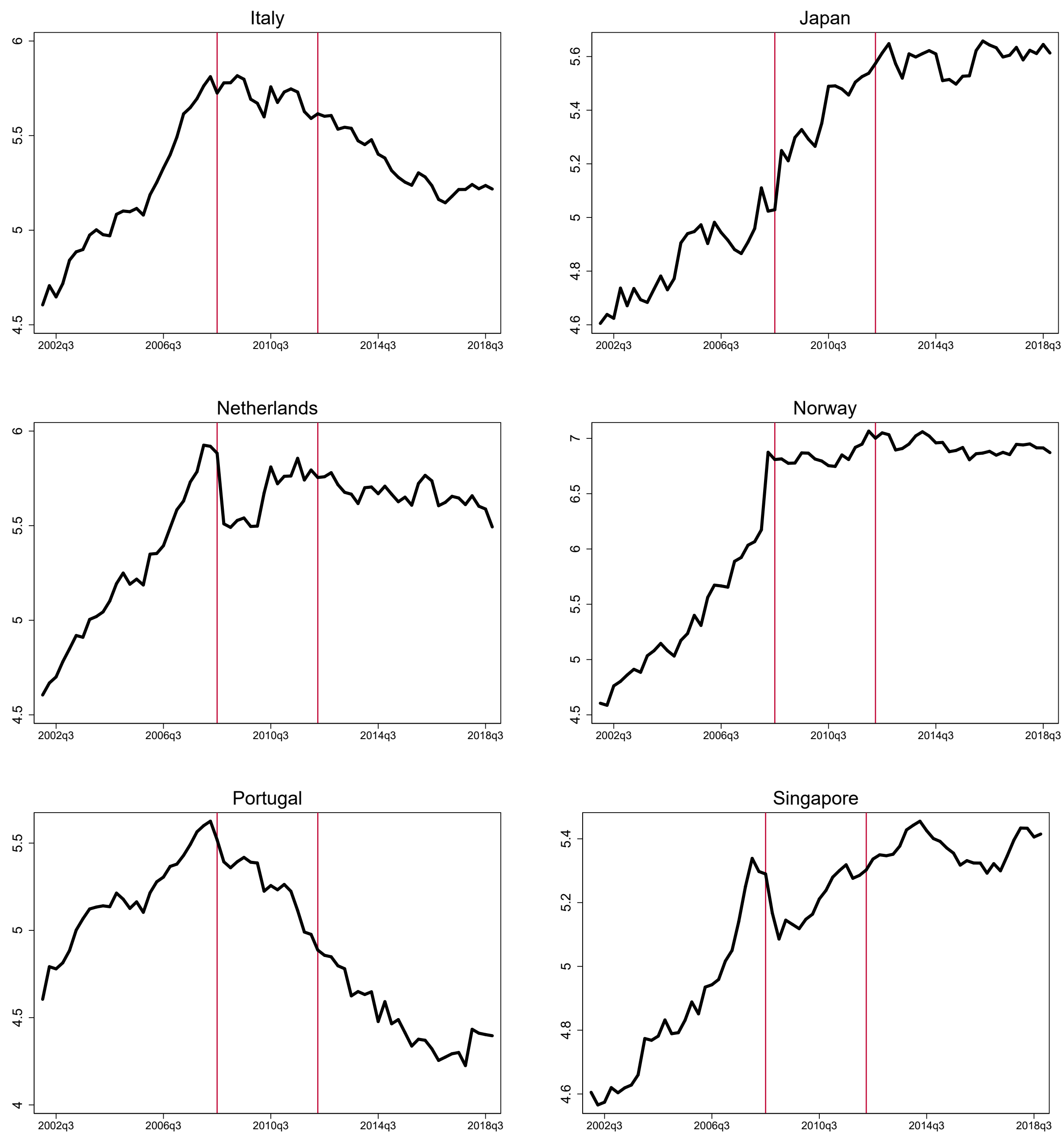
Notes: Total cross-border liabilities reported to BIS by country. Log-level of index=100 for 2002Q1.

Figure 2: Cross-border liabilities



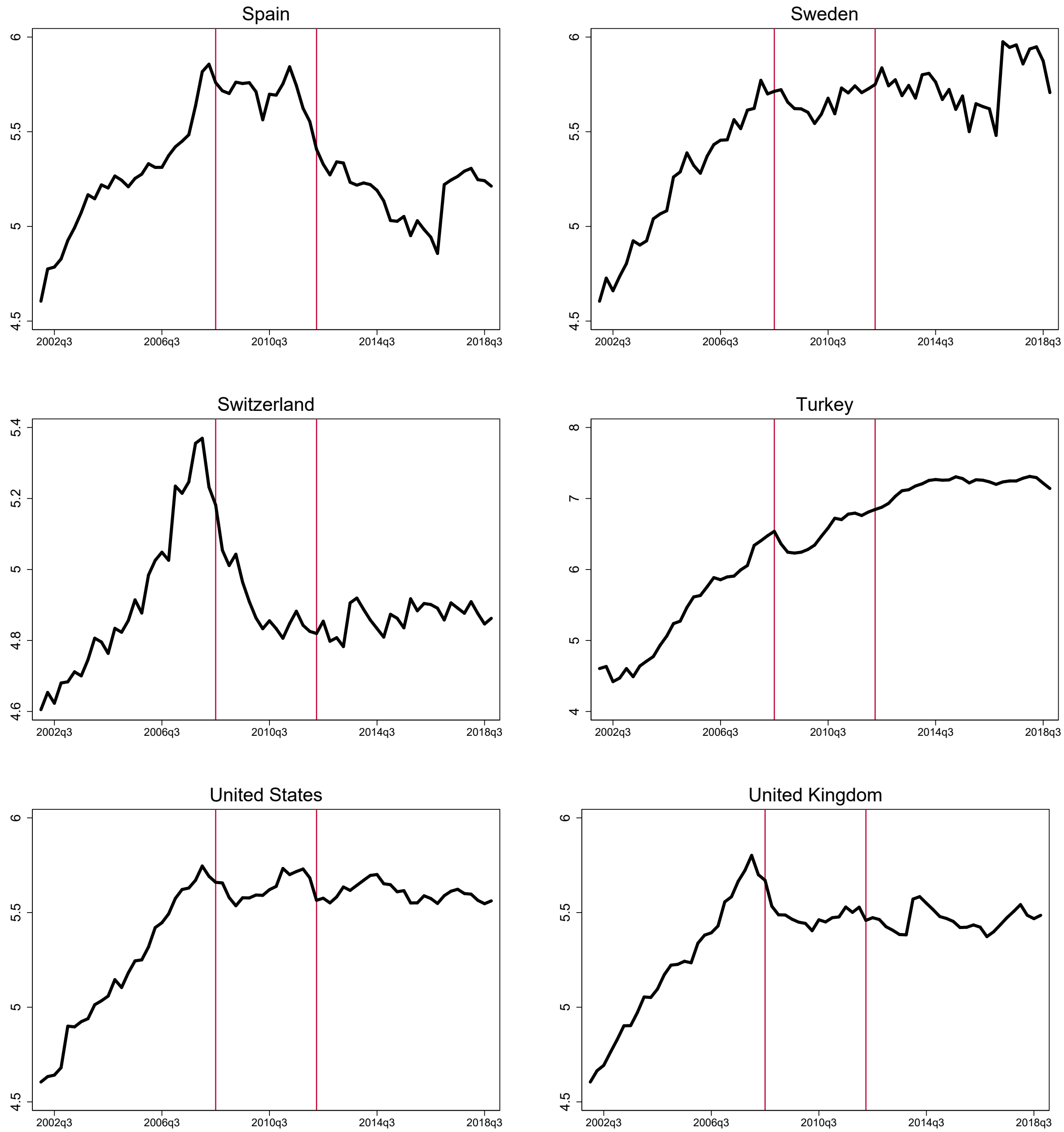
Notes: Total cross-border liabilities reported to BIS by country. Log-level of index=100 for 2002Q1.

Figure 3: Cross-border liabilities



Notes: Total cross-border liabilities reported to BIS by country. Log-level of index=100 for 2002Q1.

Figure 4: Cross-border liabilities



Notes: Total cross-border liabilities reported to BIS by country. Log-level of index=100 for 2002Q1.

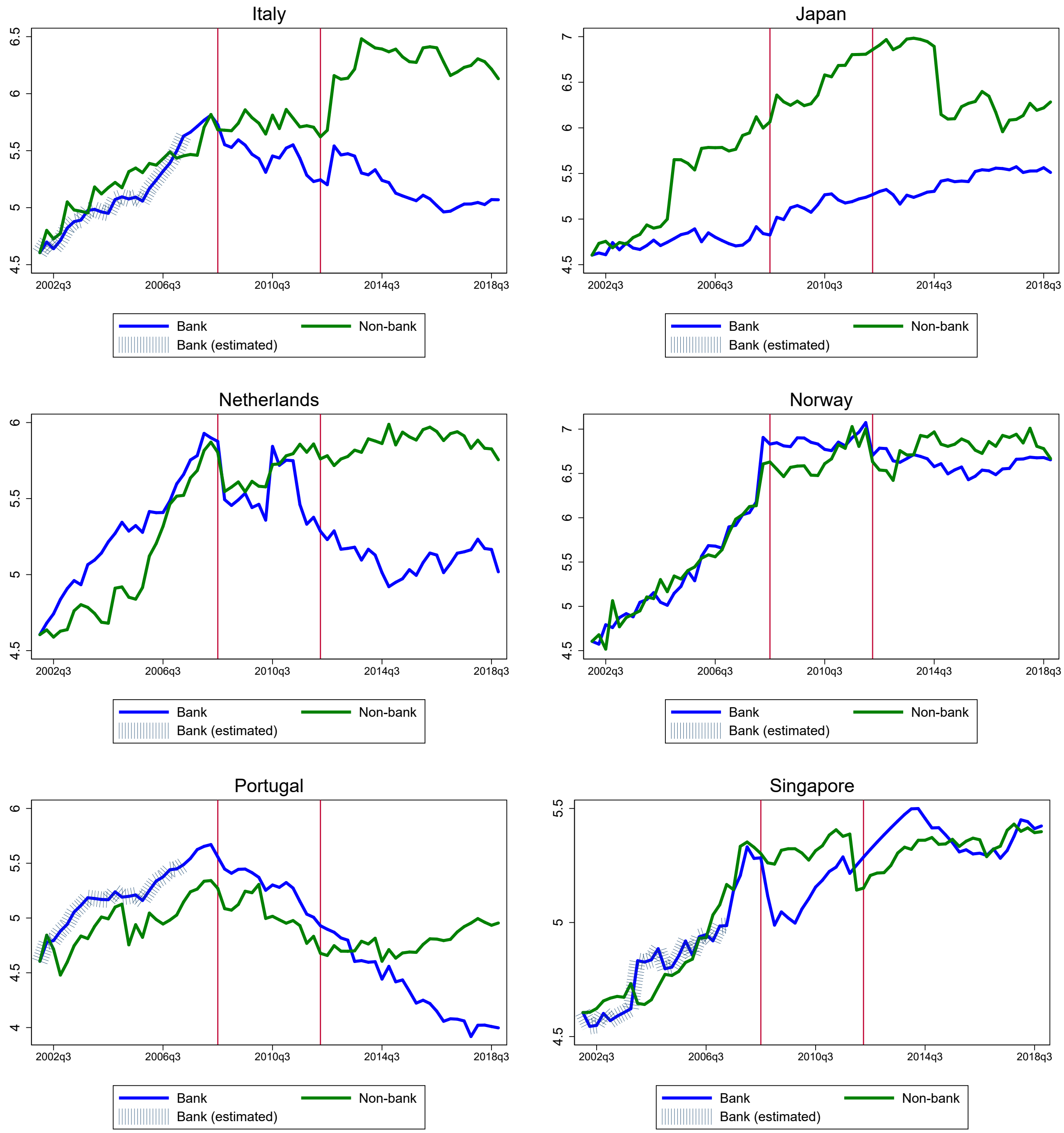
Figure 5: Cross-border liabilities vis-à-vis banks and non-banks

Notes: Total cross-border liabilities reported to BIS by country broken down between banks and non-banks. For cases where vis-à-vis bank data were not available, we compute it as the residual between total liabilities and liabilities vis-à-vis non-banks. These cases are indicated with green vertical lines for cases where this approach was followed to fill in missing data. Log-level of index=100 for 2002Q1.

Figure 6: Cross-border liabilities vis-à-vis banks and non-banks

Notes: Total cross-border liabilities reported to BIS by country broken down between banks and non-banks. For cases where vis-à-vis bank data were not available, we compute it as the residual between total liabilities and liabilities vis-à-vis non-banks. These cases are indicated with green vertical lines for cases where this approach was followed to fill in missing data. Log-level of index=100 for 2002Q1.

Figure 7: Cross-border liabilities vis-à-vis banks and non-banks

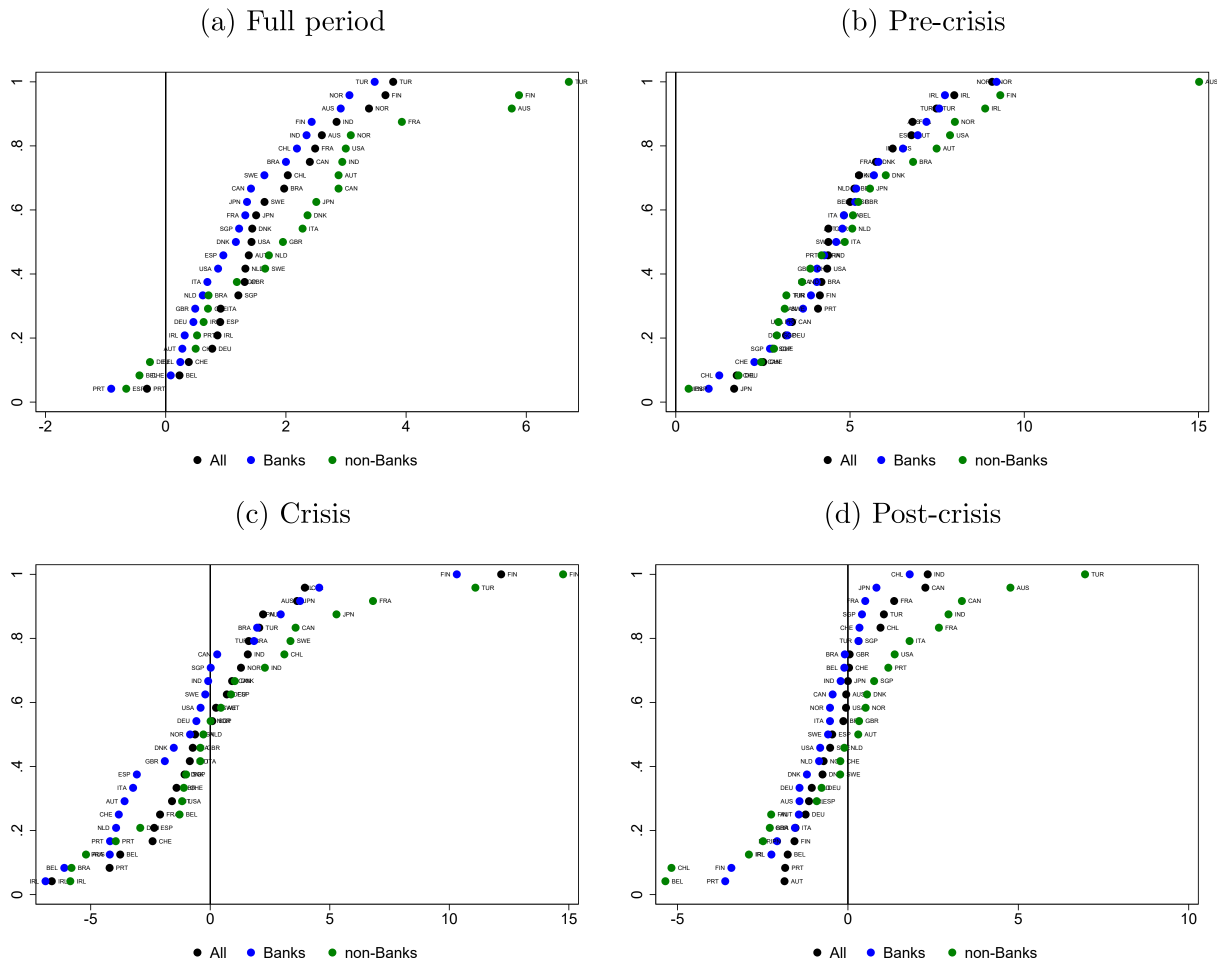


Notes: Total cross-border liabilities reported to BIS by country broken down between banks and non-banks. For cases where vis-à-vis bank data were not available, we compute it as the residual between total liabilities and liabilities vis-à-vis non-banks. These cases are indicated with green vertical lines for cases where this approach was followed to fill in missing data. Log-level of index=100 for 2002Q1.

Figure 8: Cross-border liabilities vis-à-vis banks and non-banks

Notes: Total cross-border liabilities reported to BIS by country broken down between banks and non-banks. For cases where vis-à-vis bank data were not available, we compute it as the residual between total liabilities and liabilities vis-à-vis non-banks. These cases are indicated with green vertical lines for cases where this approach was followed to fill in missing data. Log-level of index=100 for 2002Q1.

Figure 9: Cross-border liabilities: average growth rates



(a) Full period

(b) Pre-crisis

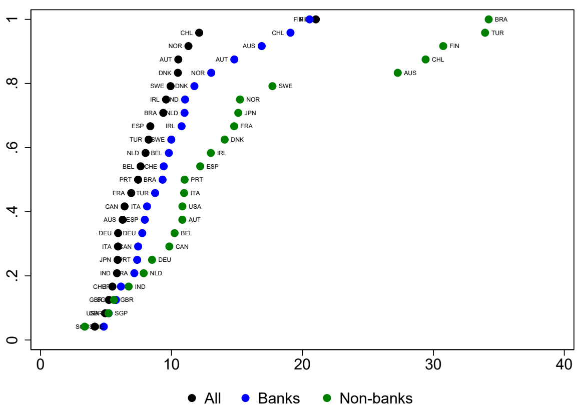
(c) Crisis

(d) Post-crisis

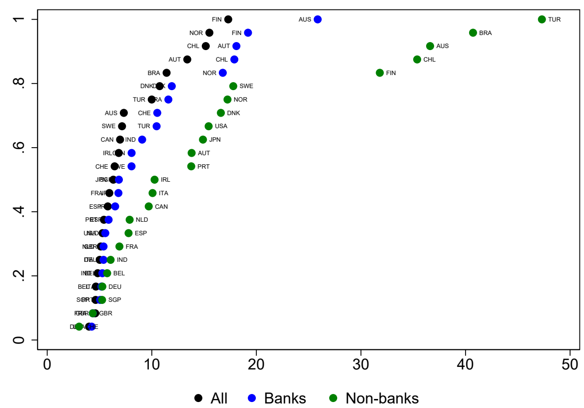
Notes: Cumulative distribution of country-specific quarter-on-quarter average growth rates. Full period 2002Q1-2018Q4 and sub periods before, during, and after the Global Financial Crisis reported in panels (a), (b), (c), and (d). Horizontal axis report average growth rates. Vertical axis shows the cumulative distribution. Black filled markers represent cross-border liabilities vis-à-vis all sectors. Blue filled markers show cross-border liabilities vis-à-vis banks, while blue markers are liabilities vis-à-vis non-banks.

Figure 10: Cross-border liabilities: standard deviation

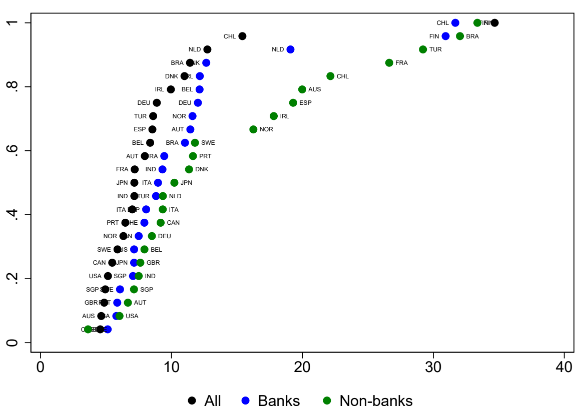
(a) Full period



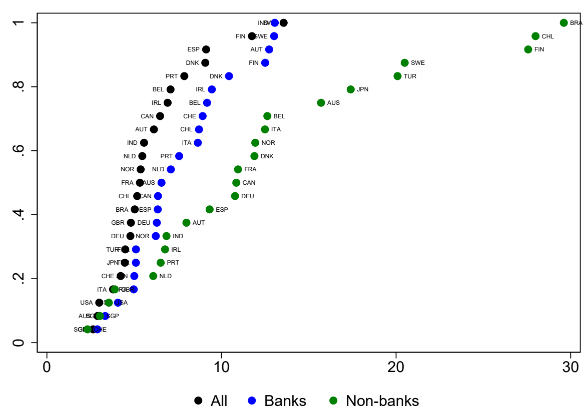
(b) Pre-crisis



(c) Crisis



(d) Post-crisis

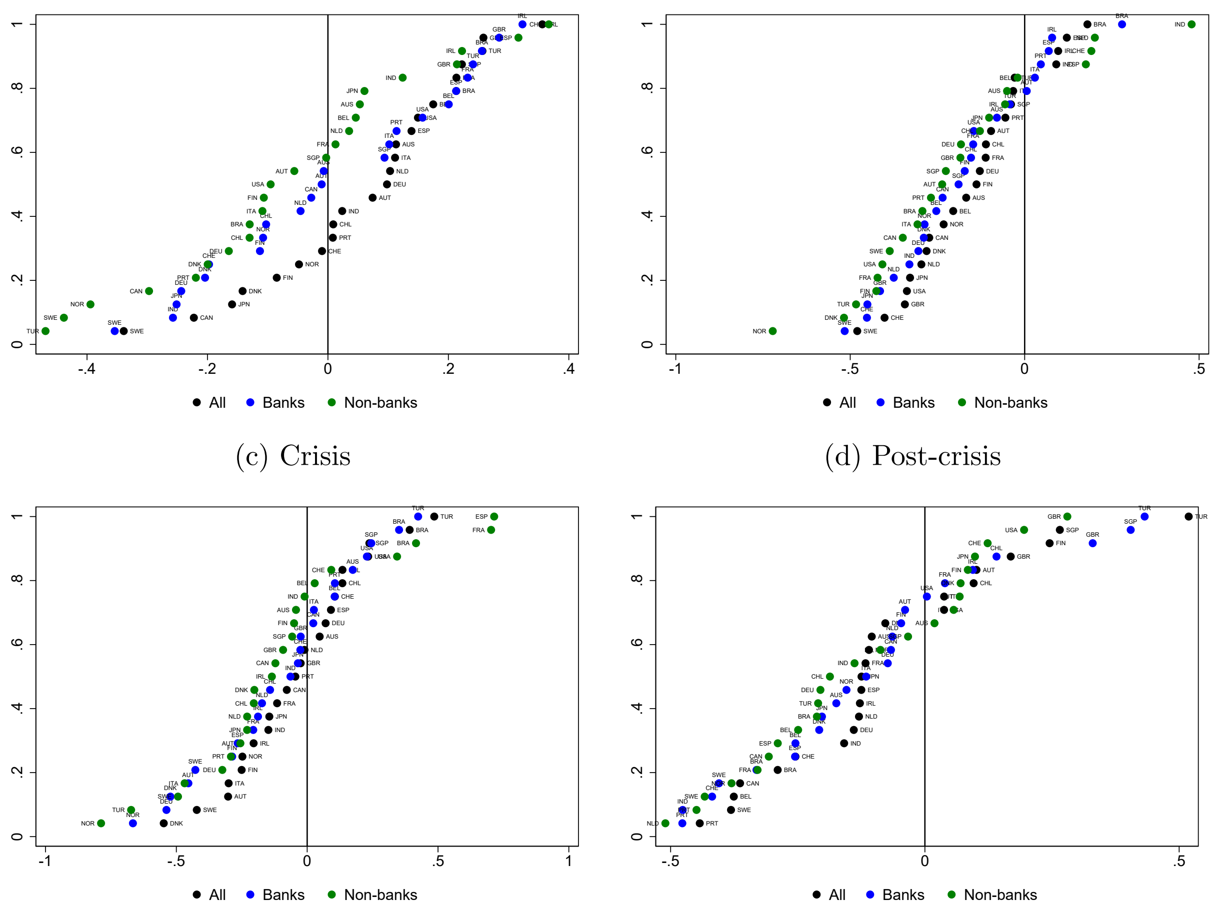


Notes: Cumulative distribution of country-specific standard deviations computed using quarter-on-quarter growth rates. Full period 2002Q1-2018Q4 and sub periods before, during, and after the Global Financial Crisis reported in panels (a), (b), (c), and (d). Horizontal axis report standard deviations. Vertical axis shows the cumulative distribution. Black filled markers represent cross-border liabilities vis-à-vis all sectors. Blue filled markers show cross-border liabilities vis-à-vis banks, while blue markers are liabilities vis-à-vis non-banks.

Figure 11: Cross-border liabilities: persistence of growth rates

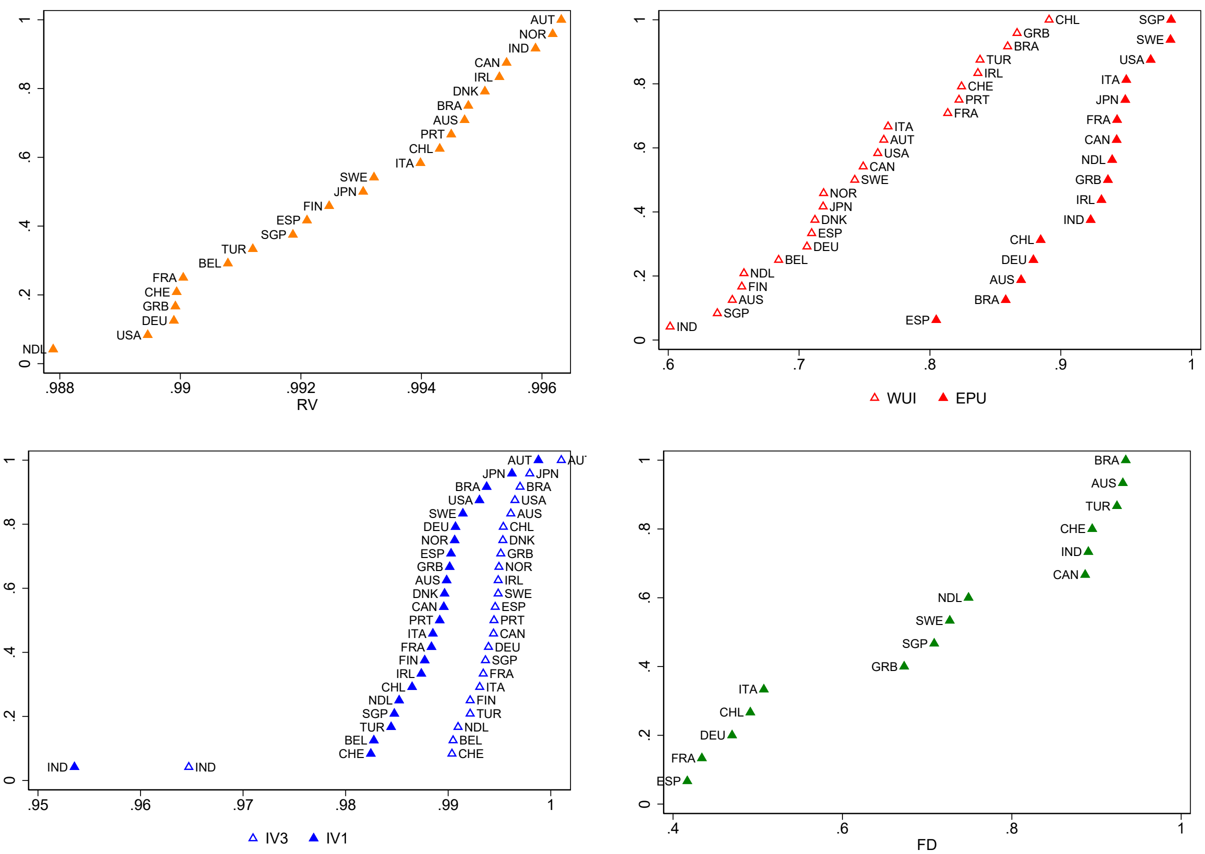
(a) Full period (b) Pre-crisis

(c) Crisis (d) Post-crisis



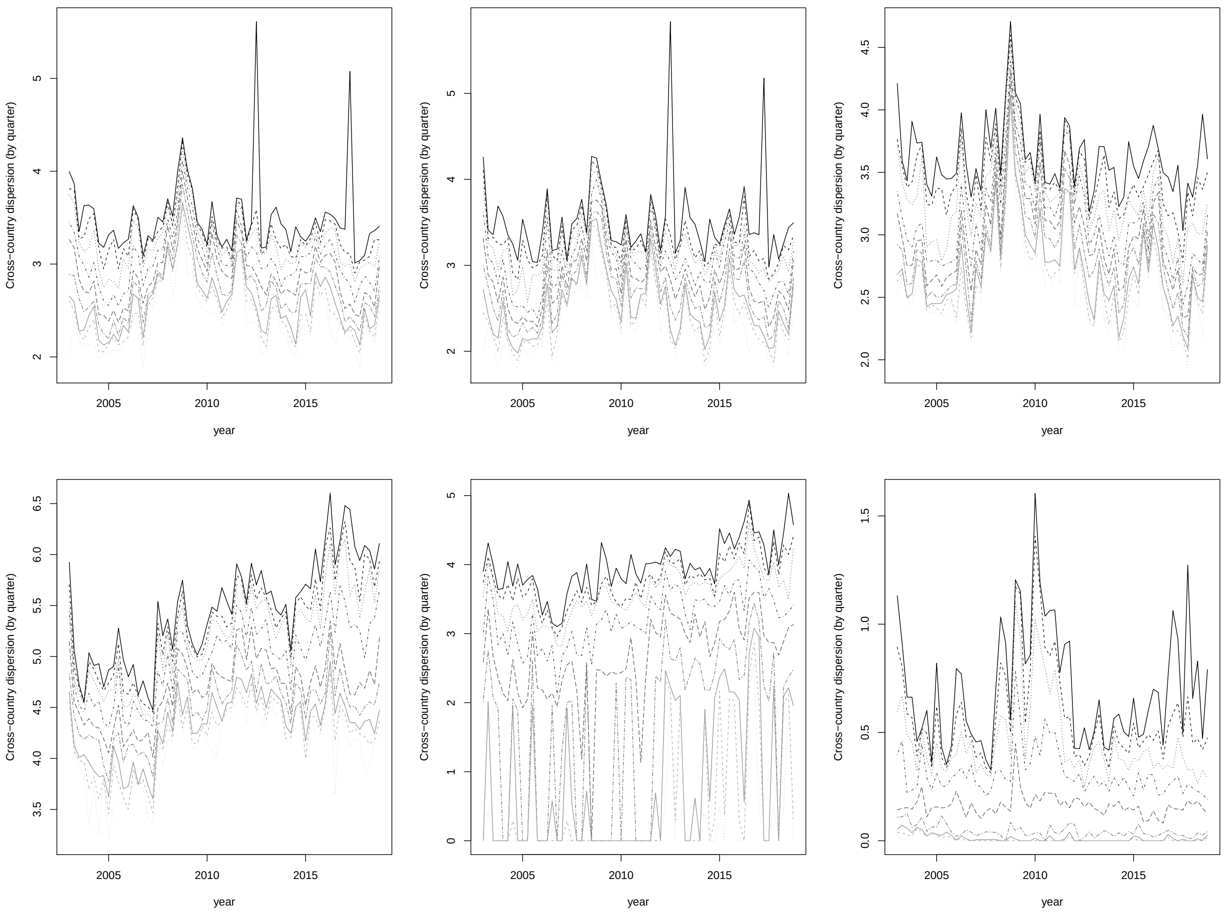
Notes: Cumulative distribution of country-specific autoregressive coefficients computed by running a linear regression model of bank liabilities quarter-on-quarter growth rates in its first lag and a constant. Full period 2002Q1-2018Q4 and sub periods before, during, and after the Global Financial Crisis, reported in panels (a), (b), (c), and (d). Horizontal axis report the autoregressive coefficients. Vertical axis shows the cumulative distribution. Black filled markers represent cross-border liabilities vis-à-vis all sectors. Blue filled markers show cross-border liabilities vis-à-vis banks, while blue markers are liabilities vis-à-vis non-banks.

Figure 12: AR(1) Persistence of Uncertainty



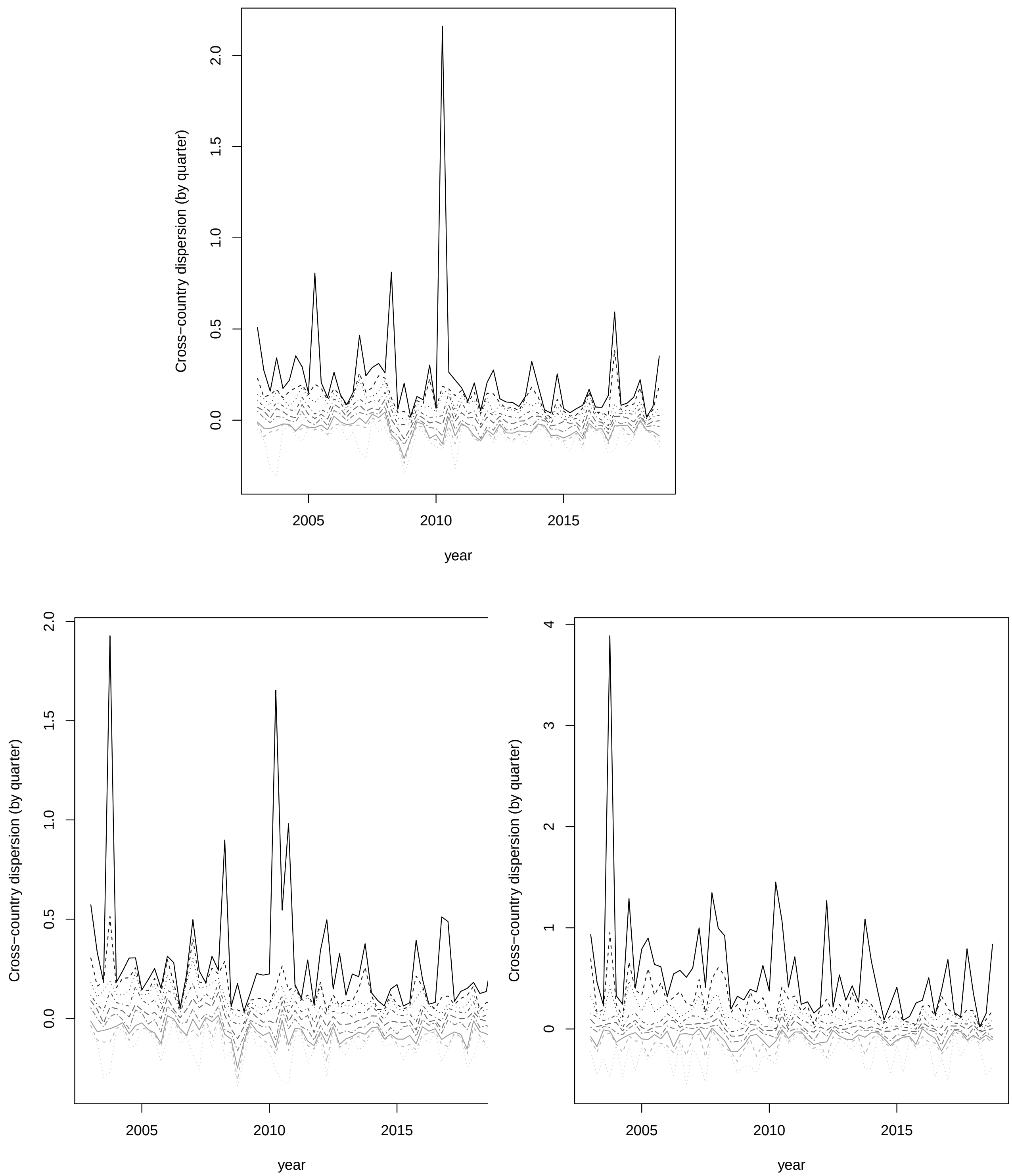
Notes: Cumulative distributions of AR(1) coefficients (ρ) from $\Delta UNC_t = \rho UNC_{t-1} + \epsilon_t$. Results are robust to the inclusion of the constant term. Top left: realized volatility (RV). Top right: world uncertainty index (WUI) and economic policy uncertainty (EPU) index. Bottom left: implied volatility at 3 and 1 month maturities (IV3 and IV1). Bottom right: forecast dispersion (FD). See Section 2 for detailed description of uncertainty measures.

Figure 13: Dispersion of Uncertainty Measures



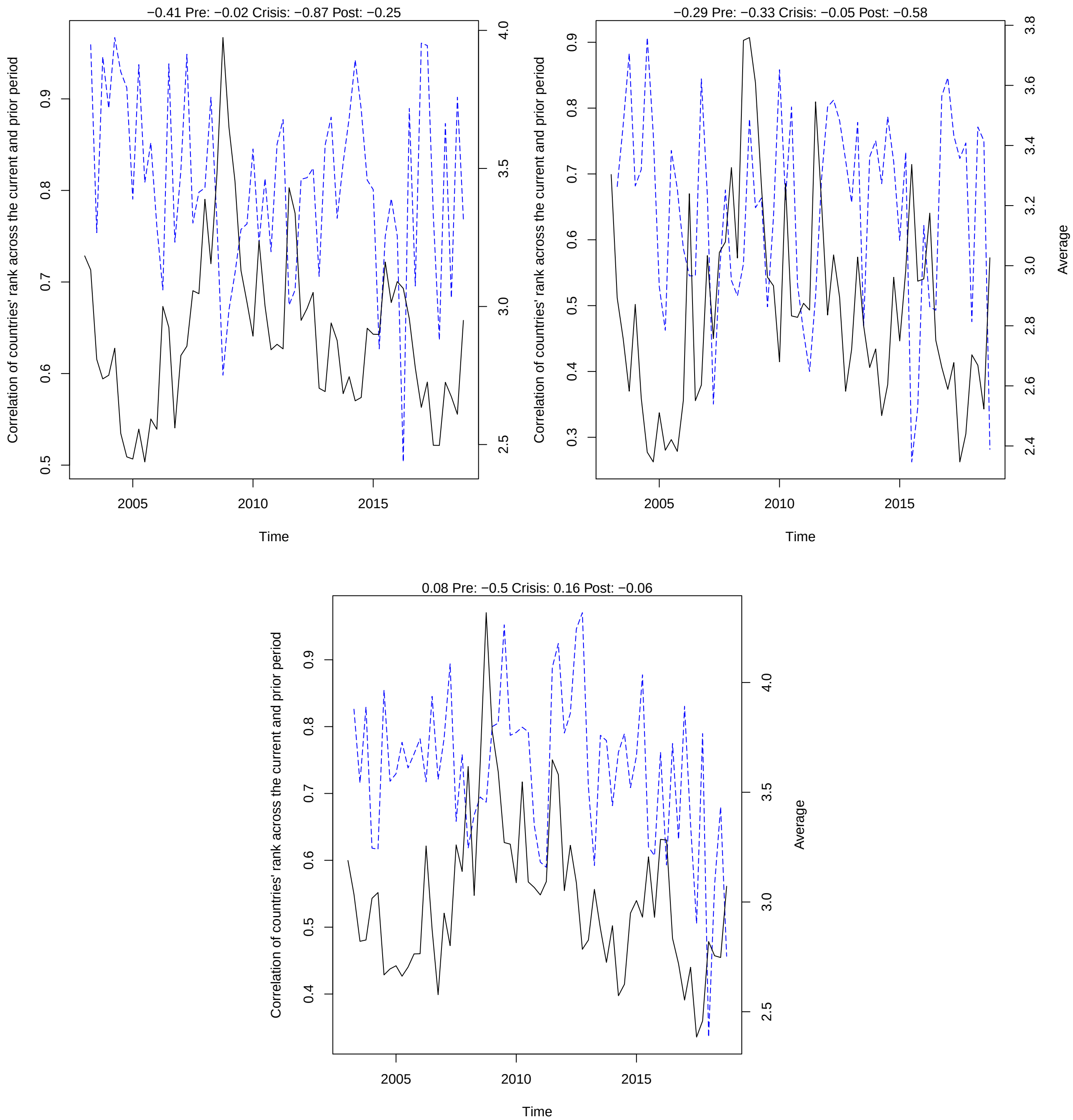
Notes: Top row from left to right: implied-volatility at 3 month maturity (IV3), implied-volatility at 1 month maturity (IV1), realized volatility (RV). Bottom row from left to right: economic policy uncertainty (EPU) index, world uncertainty index (WUI), forecast dispersion. See Section 2 for detailed description of uncertainty measures.

Figure 14: Dispersion of Cross-Border Flows of Liabilities



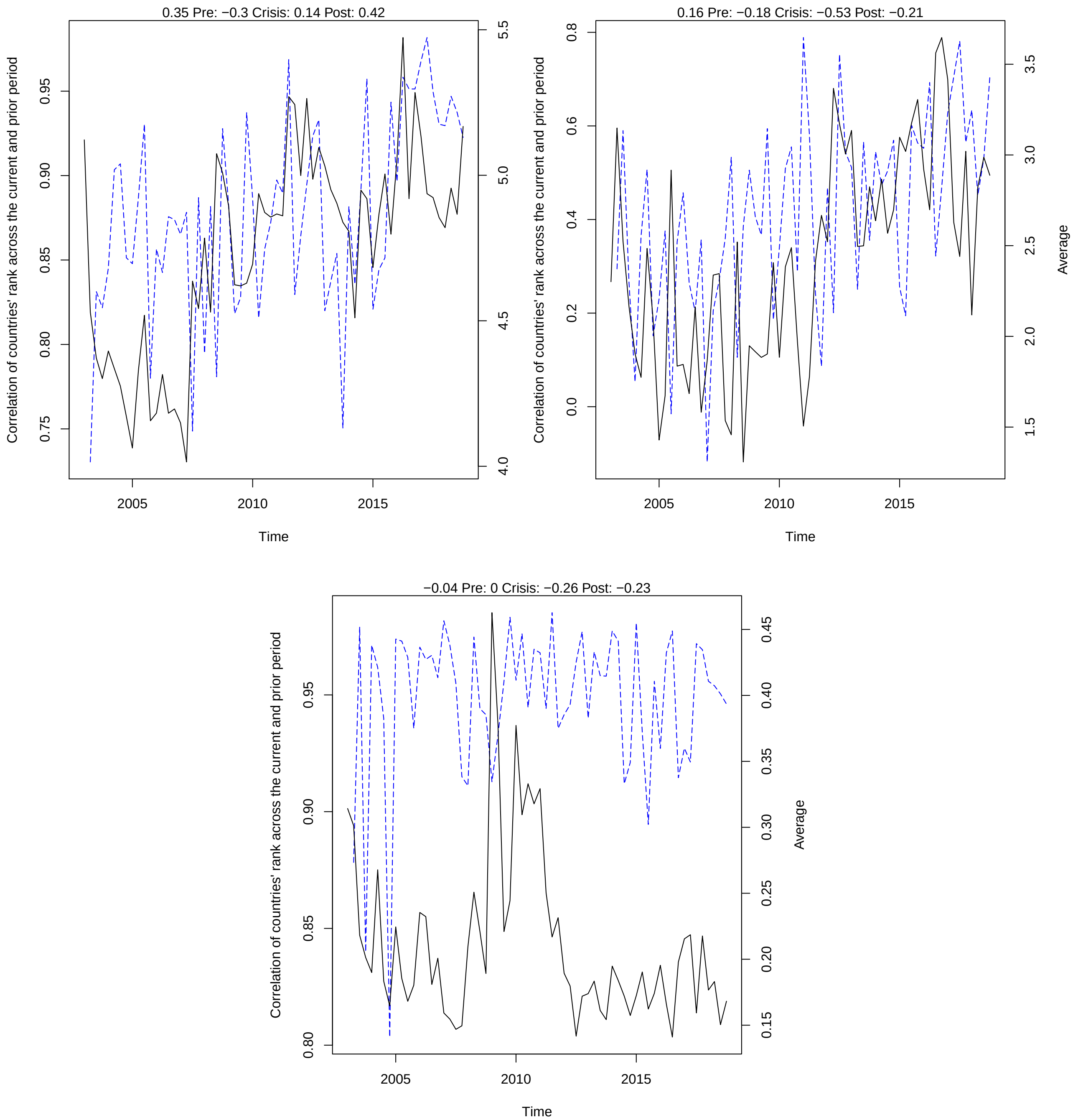
Notes: Top: overall cross-border flows. Bottom left: bank cross-border flows. Bottom right: non-bank cross-border flows. Cross-border flows are in growth rates, where, for example, −0.05 means −5%.

Figure 15: Turbulence of Uncertainty Measures – 1 of 2



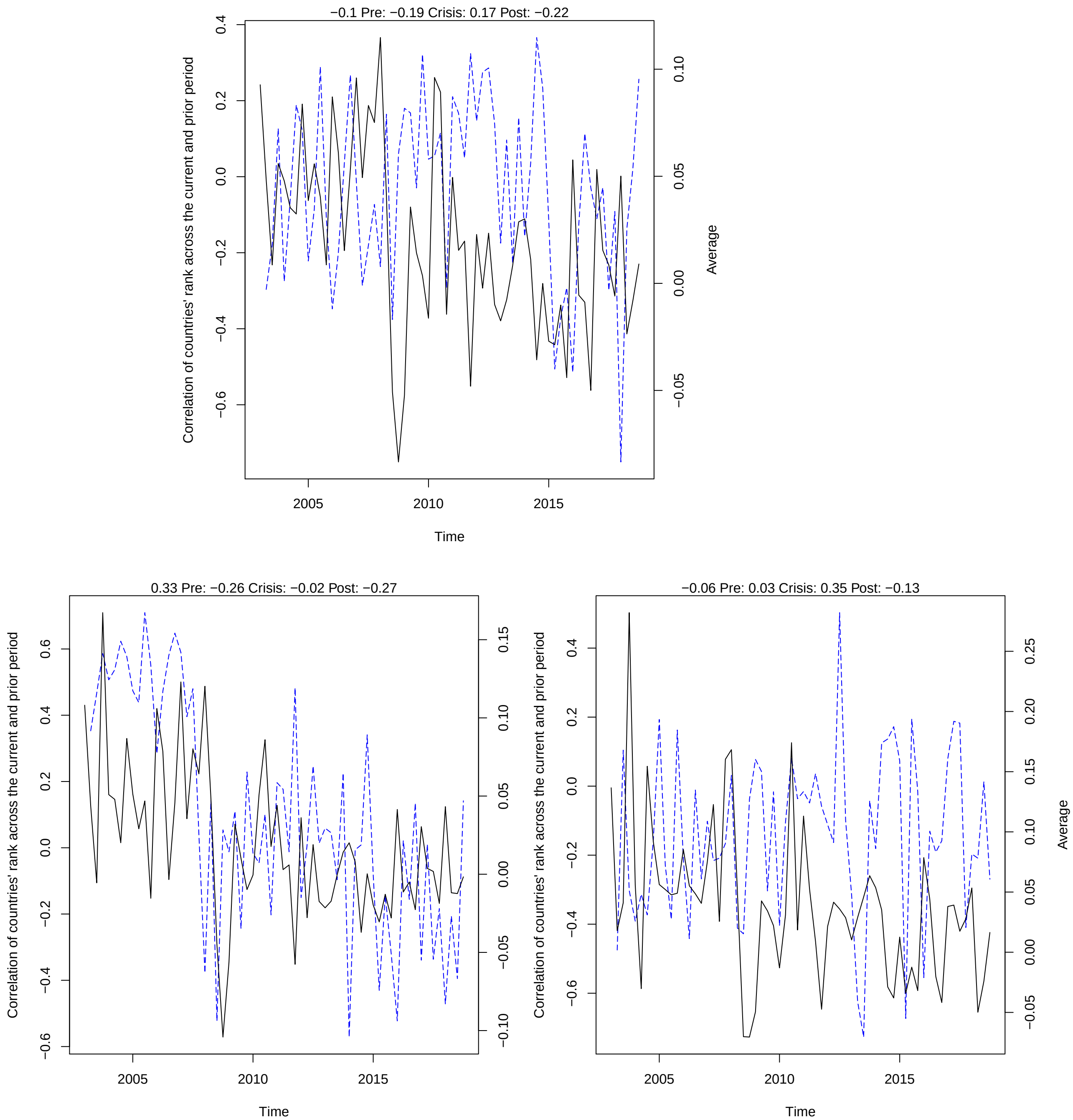
Notes: Black line: cross-country average, blue dotted line: correlation of countries' rank across the current and prior year. Top left: implied volatility at 3 month maturity (IV3). Top right: implied volatility at 1 month maturity (IV1). Bottom: realized volatility (RV). See Section 2 for detailed description of uncertainty measures.

Figure 16: Turbulence of Uncertainty Measures – 2 of 2



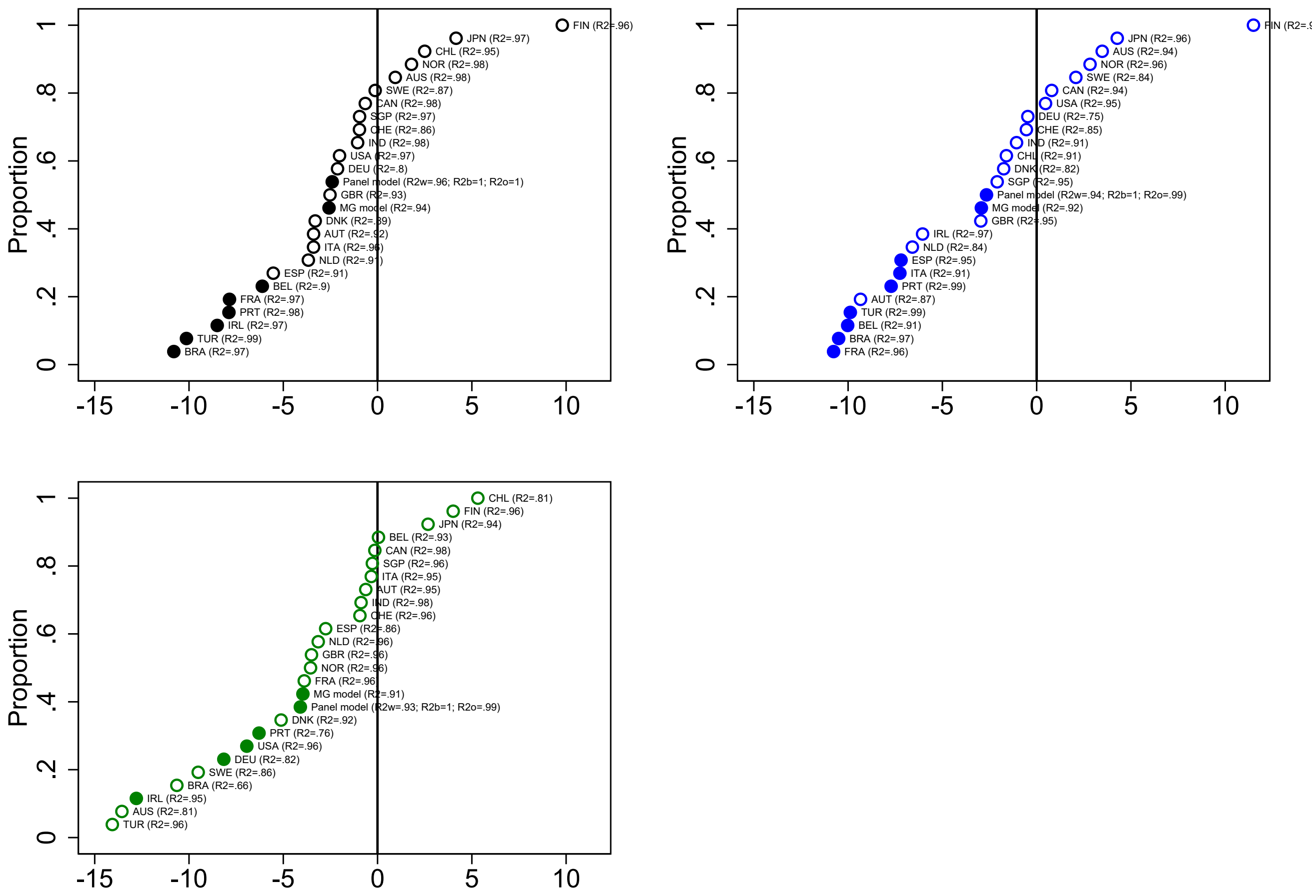
Notes: Black line: cross-country average, blue dotted line: correlation of countries' rank across the current and prior year. Top left: economic policy uncertainty (EPU) index. Top right: world uncertainty index (WUI). Bottom: forecast dispersion. See Section 2 for detailed description of uncertainty measures.

Figure 17: Turbulence of Cross-Border Flows of Liabilities



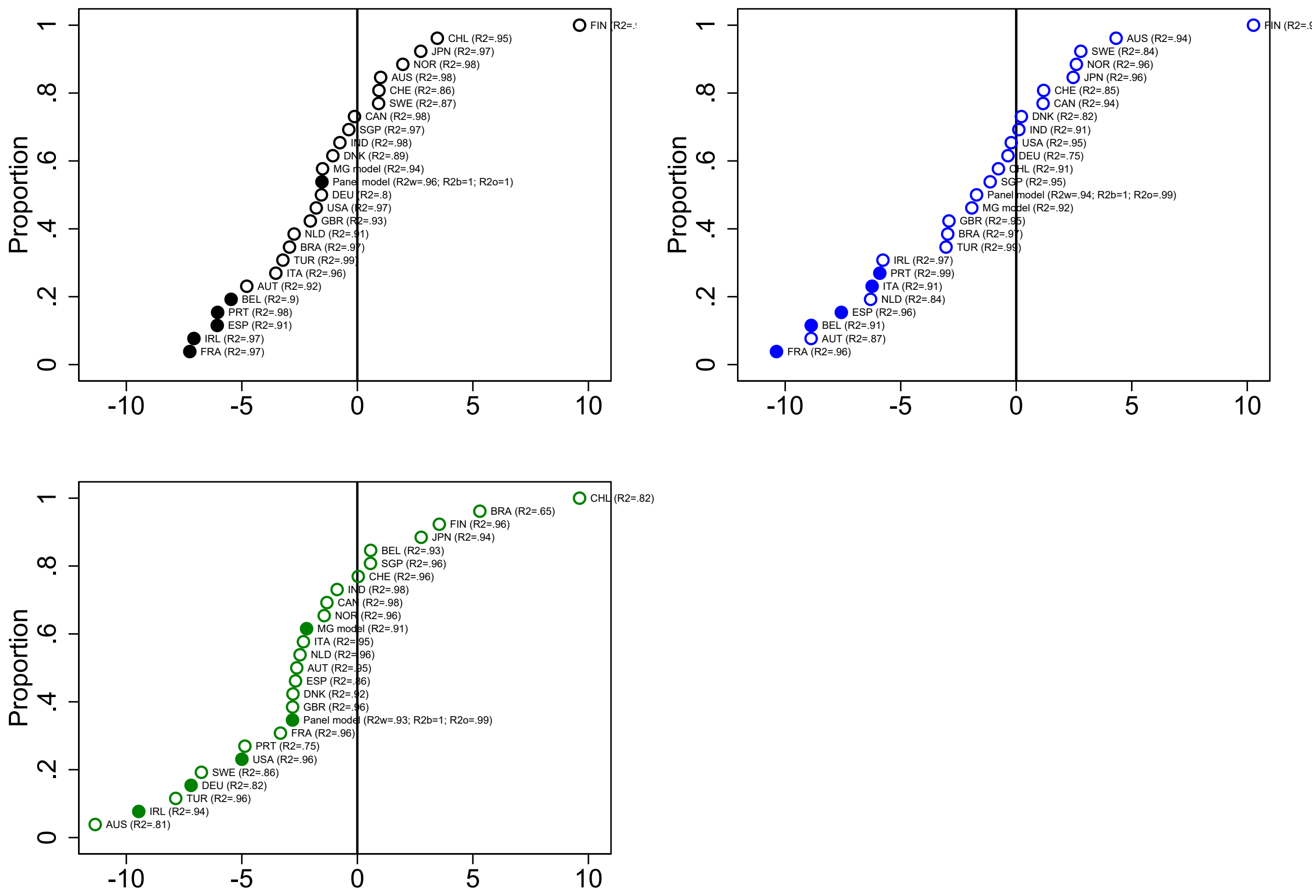
Notes: Black line: cross-country average, blue dotted line: correlation of countries' rank across the current and prior year. Top: overall cross-border flows. Bottom left: bank cross-border flows. Bottom right: non-bank cross-border flows. Cross-border flows are in growth rates, where, for example, −0.05 means −5%.

Figure 18: Bivariate Regression Coefficients: Three-Month Implied Volatility



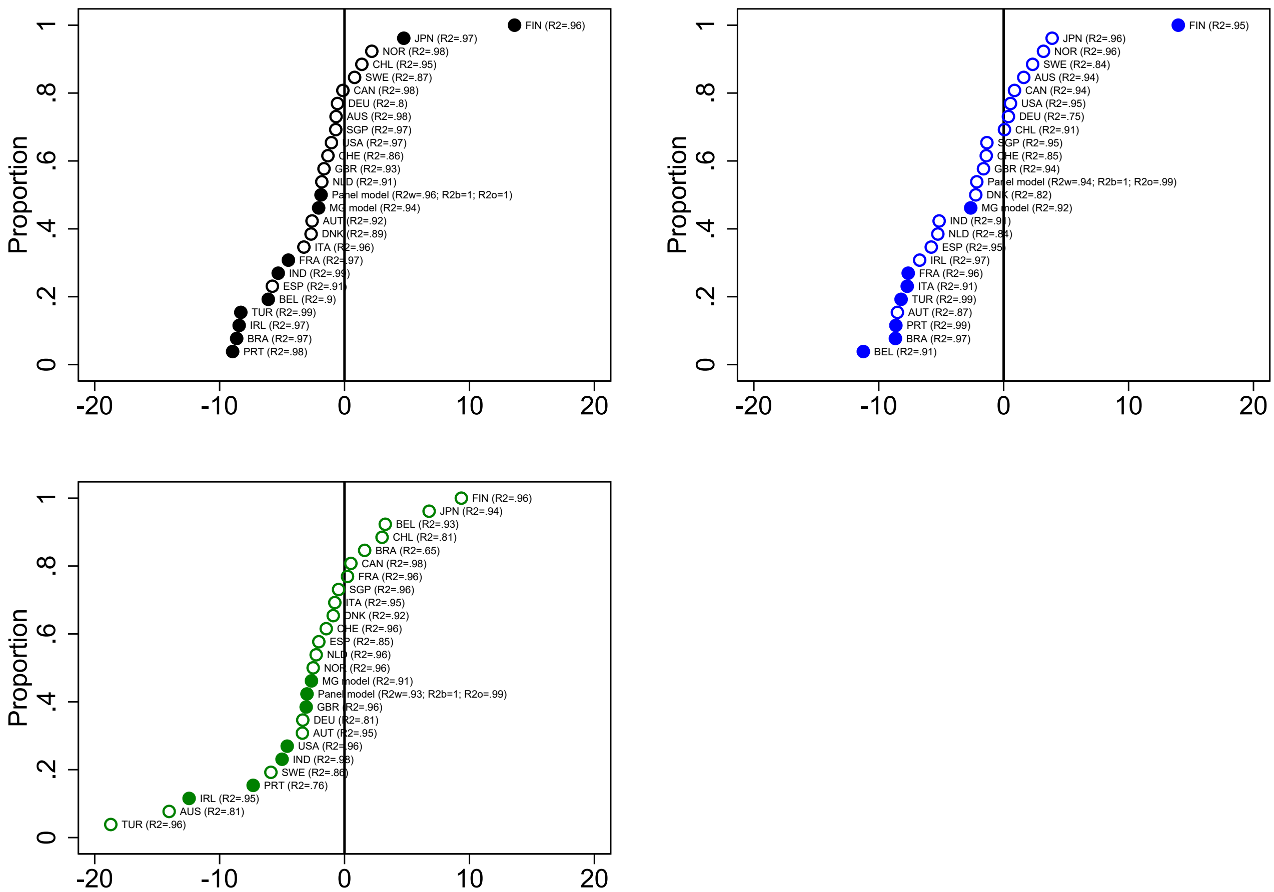
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis all **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by implied volatility based on three-month option prices. All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Figure 19: Bivariate Regression Coefficients: One-Month Implied Volatility



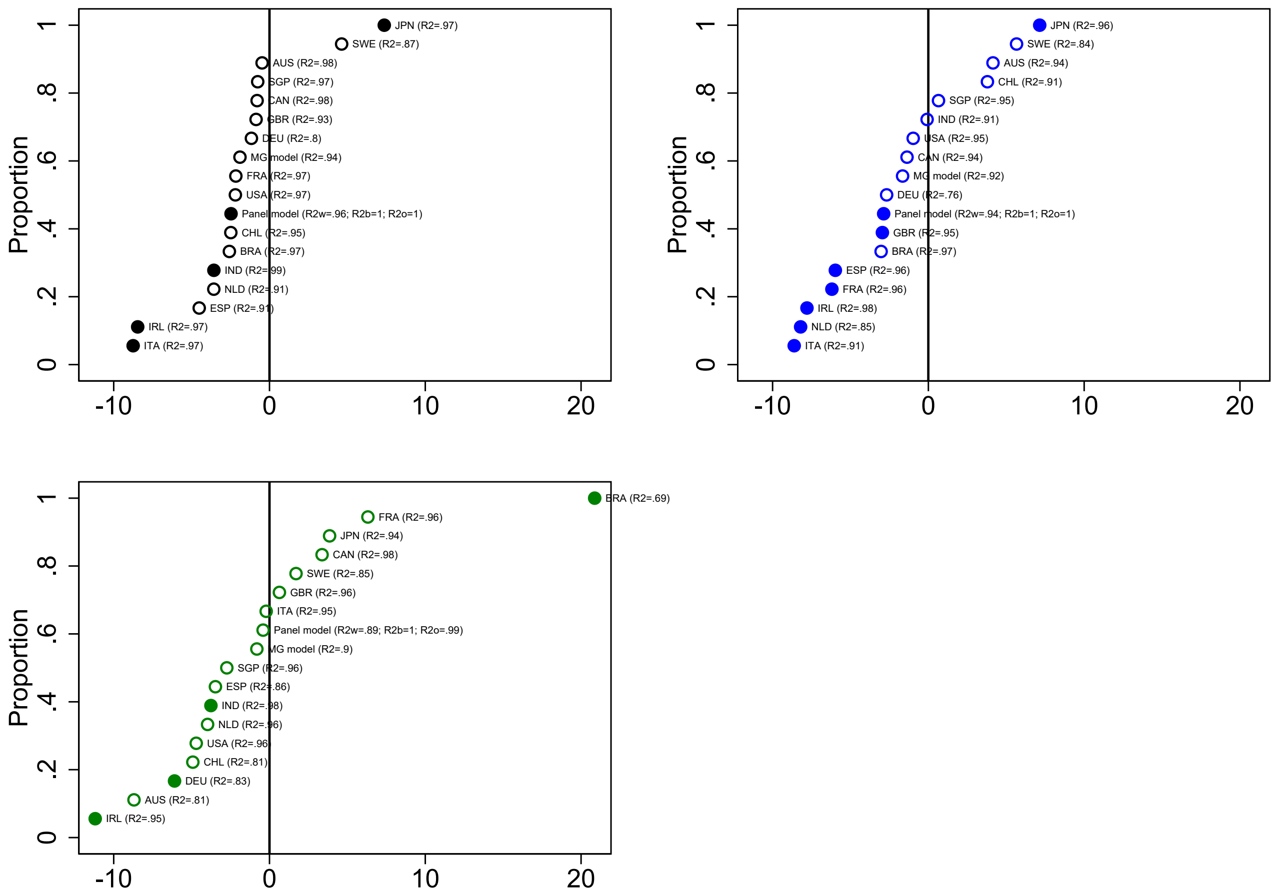
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by implied volatility based on one-month option prices. All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Figure 20: Bivariate Regression Coefficients: Realized Volatility



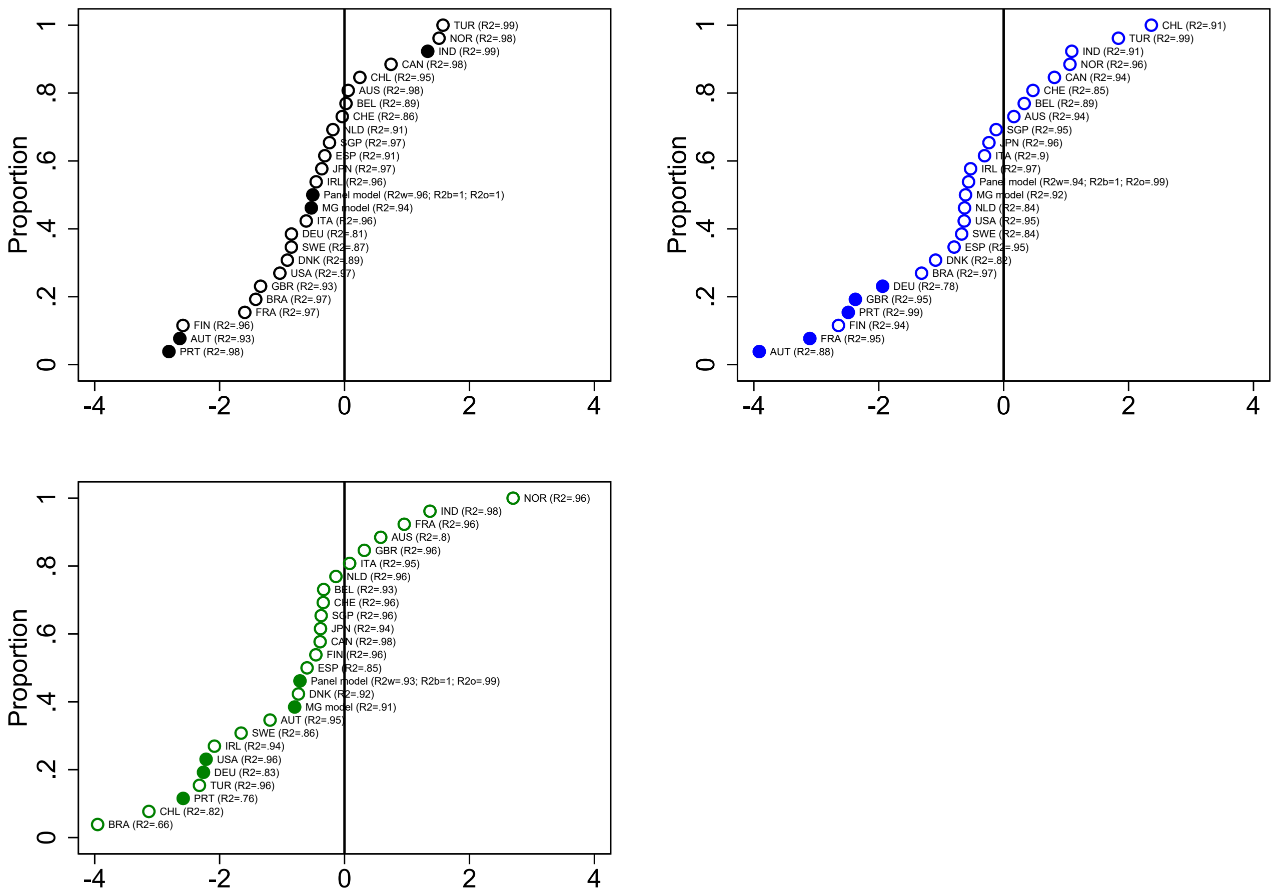
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by realized volatility. All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Figure 21: Bivariate Regression Coefficients: Economic Policy Uncertainty



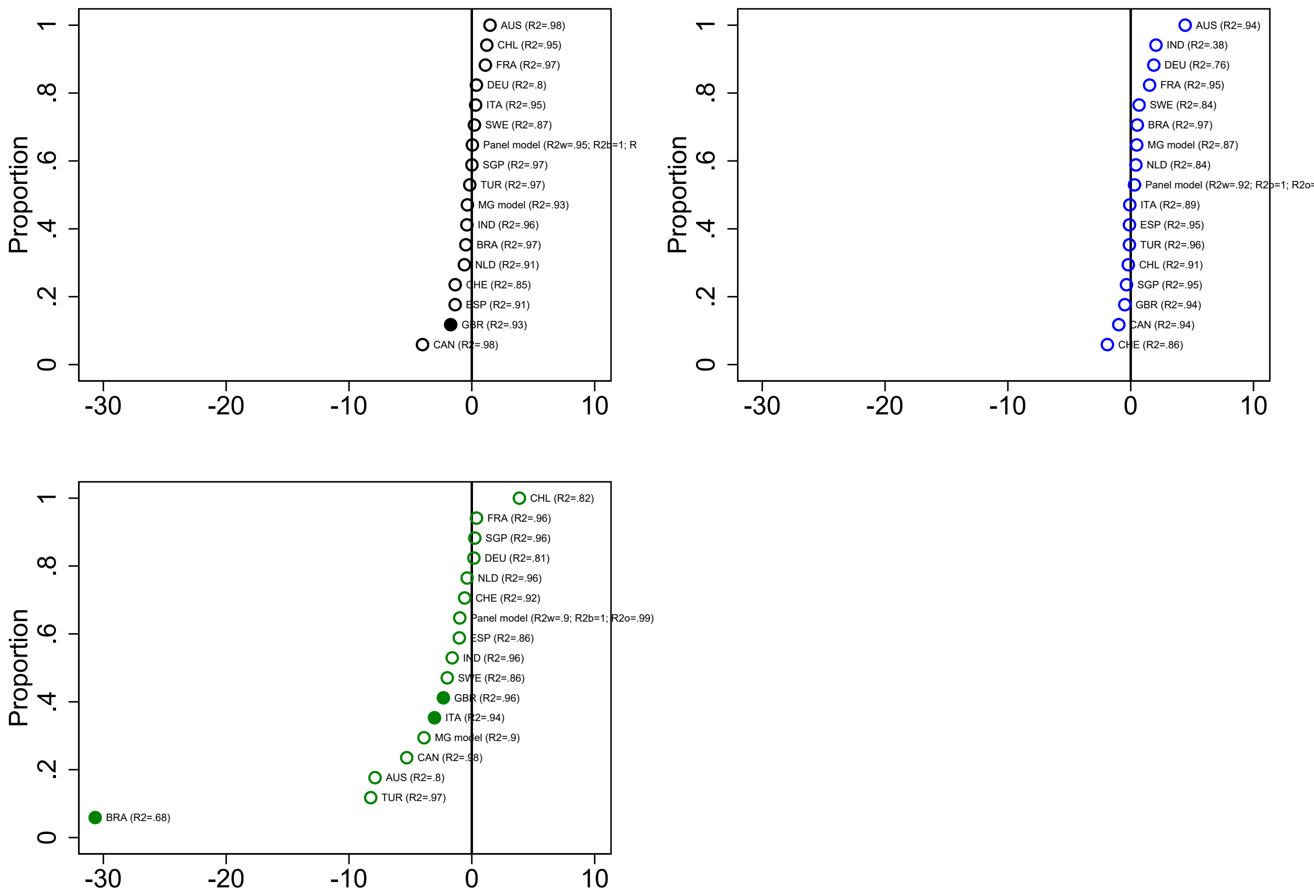
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by the EPU index. All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Figure 22: Bivariate Regression Coefficients: World Uncertainty Index



Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by the World Uncertainty Index (WUI). All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Figure 23: Bivariate Regression Coefficients: Forecast Dispersion



Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by the professional forecast survey dispersion (FD). All models include a constant and the lagged dependent variable. In addition to country-specific regression models, these figures include the point estimates of bivariate models obtained from Pesaran and Smith (1995)'s mean group estimator and a panel model with country fixed effects. The size of these coefficients is measured on the x-axis. The vertical axis captures the proportion of countries in the cumulative distribution of coefficients. All models are estimated using the full time period: 2003Q1–2018Q4. Filled circles represent statistically significant coefficient estimates based on 2 standard deviation error bands. Country-specific estimates are identified with ISO3 codes. R^2s for each regression reported in parenthesis. For the mean group estimator, we report the average R^2s across all countries. For the panel data model, we report within, between, and overall R^2s.

Appendices

A Data Sources and Construction

A.1 Data Sources

To construct real GDP growth, we obtain data on GDP, exchange rates, GDP deflators, and CPI mostly from the IMF's IFS.[30] We regress GDP deflators on CPI to extend GDP deflator series in some instances and use GDP deflators, along with bilateral exchange rates with respect to the US dollar, to convert nominal GDP to real GDP in billions of US dollars. For most countries we use seasonally unadjusted data and subsequently seasonally adjust with X12-ARIMA. Data on stock market capitalization is sourced from Bloomberg.[31] Inflation rates are based on CPI from Bloomberg. We use quarter-on-quarter growth in our analysis for real GDP growth, stock market growth, and the inflation rate. Monetary policy rates are sourced from Bloomberg, from BIS central bank policy rates, and by our calculations from national central bank websites. Data on exchange rates come from the IMF IFS, where we use nominal effective exchange rate growth in our analysis. Data on exchange rates come from the IMF IFS.[32] We investigate effective exchange rates in robustness checks. Credit growth is bank credit growth to the private non-financial sector and is sourced from BIS. We take external debt-to-GDP as outstanding debt securities from the BIS as a percentage of GDP. We restrict our sample to the core group of 24 countries over the period 2003Q1-2018Q4 to achieve a balanced sample. Table 1 lists these core countries.

[30]In a few cases we source data from Bloomberg, OECD, St. Louis FRED, Eurostat, and national central bank websites.

[31]We extend the sample by interpolating annual data from the World Bank's World Development Indicators.

[32]An increase in the exchange rate against the US dollar corresponds to a a weakening or depreciation of the local currency.

A.2 Construction

Real GDP

Nominal GDP in domestic currency (GDP^{DC}) is converted to real GDP in billions of US dollars ($RGDP^{USD}$), where $b = 2010Q3$ is the base period, using nominal exchange rate (E) and price level (P) through the equation

$$RGDP_t^{USD} = \frac{GDP_t^{DC} \times E_t}{\frac{P_t}{P_b}\frac{E_t}{E_b}}$$

Monetary Policy Target Rates

Australia: RBA cash rate target [RBATCTR].

Brazil: Selic target rate [BZSTSETA].

Canada: Bank of Canada overnight lending rate [CABROVER].

Chile: monetary policy rate (TPM): [CHOVCHOV].

Denmark: repurchase rate repo [DERE].

Euro area: ECB main refinancing operation announcement rate [EURR002W].

India: Reserve Bank of India repurchase effective cut off rate [INRPYLD].

Japan: Bank of Japan unsecured overnight call rate [MUTKCALM].

Norway: deposit rate Norges bank announcement rate [NOBRDEPA].

Singapore: overnight rate: annualized rate of interest bank charges for lending or pay for borrowing a currency [SDDR1T].

Sweden: repo rate (decision rate) [SWRRATEI].

Switzerland: national bank Libor target [SZLTTR].

Turkey: 1 week repo announcement [TUBR1WRA].

United Kingdom: Bank of England official bank rate [UKBRBASE].

United States: US Fed target rate midpoint and US Fed Funds effective rate (source: BIS).