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 measure, 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

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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 measure of uncertainty and aggregate flows (Cerutti *et al.*, 2017; Choi and Furceri, 2019). Our paper, in contrast, decomposes different types of funding sources and measures of uncertainty shocks.

We examine 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 innovations allow for differences in uncertainty shocks, funding sectors, countries, and periods. Deconstructing aggregates matter, as the impact of uncertainty on funding varies significantly across these dimensions.[1] That is, our innovations allow us to unmask key heterogeneities, departing from the industry-standard panel-based approach. Responses vary internationally and intertemporally, with volatility-based uncertainty and non-bank funding, particularly during the GFC, displaying the strongest results. Volatility-based uncertainty does not affect international bank funding outside of the GFC, but news-based uncertainty, the only measure of uncertainty

[1] One way of appreciating our decompositions is as follows. On average, cross-border liabilities were flat after the Great Recession. This result masks, however, that flows of liabilities from non-banks grew, while flows of liabilities from banks fell. On an individual country basis, for example, France's positive average growth rate post-crisis was driven by an even higher growth rate in non-bank funding.

that rose since the GFC, dampened funding even after the GFC.[2] Arising from our different uncertainty measures and periods, this nuanced result departs from existing panel studies such as Choi and Furceri (2019).

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 before the GFC. Growth in non-bank funding, particularly during and after the crisis, dominates growth in other sectors of funding. Non-bank funding is also more volatile than bank funding, which is more volatile than overall funding. Sub-components of funding are therefore unlikely to share time-series properties of aggregate funding. Moments of uncertainty mostly peaked during the GFC, except news-based measures, which rose over time. Uncertainty shocks, moreover, 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 paper, we estimate bivariate and multivariate models exploring our multiple sources of heterogeneity (uncertainty measure, borrowing source, country, and time). Both our bivariate and multivariate regressions reflect conservative, parsimonious choices. Funding declines with uncertainty are sizable, but heterogeneous. Funding falls

[2]Stock markets have been calmer after the GFC as reflected by volatility-based uncertainty, but world events have contributed to increasing amounts of uncertainty as mirrored by newspaper-based uncertainty. The pace of the news and communications have increased with the global expansion in internet adaption, reporting on events such as the European sovereign debt crisis, the Arab Spring, ISIS, Brexit, the 2016 US Election and its aftermath, and the Covid-19 global pandemic. Prior to the GFC, 9/11, SARS, the series of wars in Afghanistan and Iraq and other events were communicated mostly through TV and conventional forms of media. As creative destruction from the internet age has threatened cable news and other sources of traditional news media, survival of these forms of media may suggest strategies of reporting more negative or extreme stories to sustain viewership. The rise in news-based uncertainty in contrast to the other measures of uncertainty may therefore reflect either a rise in overall uncertainty or a growing amount of noise as multiple sources of media compete for viewership in our current era of industrial revolution.

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 contributes to the literature on banking and uncertainty. We first provide more detail on the decomposition of international banking, specifically cross-border liabilities, measured by 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.[3] In contrast to the related literature, we innovate 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. The significance of differentiating the counterparty type is that uncertainty shocks may affect cross-border funding differently depending on which sector provides funding.

Our second contribution is to compile a dataset on multiple measures of uncertainty. Rather than argue the merits of relying solely on one measure 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. We discuss our uncertainty measures in greater detail in Section 2.2.

Uncertainty measures may have different impacts in terms of their magnitude and the

[3] 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.

channels through which they affect bank borrowing. Volatility-based uncertainty, tracking the stock market, is narrower than newspaper-based uncertainty, which might suggest newspaper-based measures have a bigger impact on international bank flows. We find, however, that volatility-based uncertainty produces the strongest results. Cross-border banking decisions may be made with greater weight placed on what is happening to financial systems, which volatility-based uncertainty captures. As banks invest in securities, equity risk may require banks re-balance, diversify, or recapitalize by borrowing or lending internationally from a risk-management perspective. Although from theory the direction of borrowing in response to risk is ambiguous, less borrowing may reduce risk by lowering overall exposure. With broader news-based uncertainty, higher uncertainty is more complex to interpret. If higher news-based uncertainty relates to a downturn, banks might be forced to borrow from abroad, similarly to when domestic liquidity dries up in a liquidity crisis. Many channels are plausible. Volatility-based measures might impact bank borrowing from a rebalancing perspective and newspaper-based measures might impact bank borrowing from a liquidity management perspective. We leave investigating channels for future research.

In addition to the heterogeneous measures of uncertainty and sub-components of banking, we expand our country coverage to allow for a third dimension of heterogeneity.[4] The geographically diverse sample includes a mix of advanced and emerging market economies with heterogeneous global banking systems and reliance on cross-border funding as classified by Bénétrix *et al.* (2017).[5] 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

[4]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.

[5]Our diverse sample includes euro area countries, other western European countries, financial centers, large advanced economies with well developed financial markets, and emerging countries.

Turkey with heavy local presence of foreign banks; and we include financial centers 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 measures 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 measures and sub-components of banking data, to uncover a set of nuanced results.

Papers that are similar to ours concentrate on a specific measure 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), as most seek to explain general international capital flows. One takeaway from Cerutti *et al.* (2017) relevant to our paper is 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).[6]

The goal of this paper is to document empirical evidence, not to model mechanisms that

[6]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.

may explain the results such as our finding that uncertainty is associated with lower cross-border borrowing. That said, deleveraging is one plausible channel. Precautionary saving motives lead to increases in savings under higher uncertainty. For banks, the analogous behavior is deleveraging, whereby banks reduce the size of their balance sheets, borrowing less from abroad. An alternative story is that uncertainty could produce concerns over liquidity. Depending on the term horizons of borrowing, banks may want to borrow more or less according to their needs to have cash to shore up their reserves of liquid assets.

2 Data

2.1 International Bank Funding

We measure international bank funding by taking cross-border liabilities (loans plus debt securities) of different banking systems reporting to the BIS Locational Banking Statistics (BIS LBS).[7] In decomposing aggregate flows into different counterparties (banks and non-banks), some data are missing for liabilities vis-à-vis banks. Taking the difference between liabilities vis-à-vis all sectors and the liabilities vis-à-vis non-banks overcomes this limitation.[8] We examine a 24 country sub-sample of the reporter countries list that excludes small states, small islands, or financial centers, almost entirely driven by global shocks. We 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. Covering the start and the end of the contiguous GFC and European Sovereign Debt Crisis, we define our crisis period as 2008Q3-2012Q2. The start date relates to when the TED Spread broke its record and

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

[8] These data are not reported by the BIS, maybe due to an allocation to sector issue or confidentiality, but the impact of this estimation should be minimal for our analysis.

Lehman Brothers collapsed, and the end date relates to when Margio Draghi delivered his "Whatever it takes" speech. Heterogeneity in the time domain arises from our including tranquil and turbulent times and conducting sub-sample analysis analyzing pre-crisis (2003Q1-2008Q2), crisis (2008Q3-2012Q2), and post-crisis (2012Q3-2018Q4) periods.

2.1.1 Dynamic Behavior of International Bank Funding

To understand the dynamic behavior of international bank funding, we plot the data and moments of the data and study the statistical significance of empirical moments. We relegate tables and graphs to the online appendix.

A common feature is the positive trend in bank borrowing for advanced countries and some emerging markets from the early 2000s, a stylized fact documented in the literature led by the seminal work of Lane and Milesi-Ferretti (2007).[9] The crisis and its aftermath witnessed a halt or international deleveraging of most banking systems, in particular European banks (McCauley *et al.*, 2019) and notably in Belgium, Ireland, Italy, and Portugal. Exceptions are Canada, Australia, Japan, Norway, and Singapore. Most emerging markets continued with the pre-crisis trend post-crisis. In general, cross-border liabilities present a variety of dynamics across countries, in the full period, and in the sub-sample periods.

One important result is the heterogeneity in characteristics depending on the counterparty sector.[10] For instance, while for many European countries the post-crisis deleverage process mostly took part vis-à-vis other banks (e.g., Austria, Belgium, Italy, the Nether-

[9] Figures S1–S4 in the online appendix plot time-series liability data. Our 24 country sample is Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, India, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, Turkey, UK, and USA. BIS shows that the full set of 48 reporters (see online appendix Table S1 footnote) accounted for 94% of global coverage of cross-border claims of banks in 2017. To ensure comparability, we plot the logarithms of index numbers taking the value of 100 in 2002Q1, instead of plotting the levels of bank funding in US dollars. To ensure a balanced sample, the data for our regression analysis starts in 2003Q1. We also plot vertical lines to indicate the start and the end of the contiguous GFC and European Debt Crisis in 2008Q3 and 2012Q2.

[10] Figures S5–S8 in the technical appendix present the same set of log indices as S1–S4 but for cross-border liabilities vis-à-vis other banks and non-banks.

lands), 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, however, liabilities vis-à-vis non-banks grew after the crisis, while those vis-à-vis banks continued falling like in the French case.

We next examine the average, standard deviation, and persistence of the quarter-on-quarter growth rate of liabilities.[11] For most countries, total liabilities as well as liabilities vis-à-vis banks and non-banks grew, with liabilities vis-à-vis non-banks growing the fastest. This was a common pattern and not the result of specific countries driving average results.[12] One takeaway of sub-sample analysis 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. Subsequent periods are characterized by a close to 50-50 split between positive and negative growth rates of total liabilities. Growth rates were mostly higher for liabilities vis-à-vis non-banks during and after the crisis. Before 2008, liabilities vis-à-vis non-banks do not differ substantially 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. Post-crisis, 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

[11]Figure S9 in the online appendix charts the cumulative distributions for average growth rates of total liabilities and liabilities vis-à-vis banks and non-banks.

[12]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.

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 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%.

Cross-border liabilities vis-à-vis all sectors are the least volatile.[13] At the extremes, Singapore and Finland have standard deviations of 4.1 and 21. Liabilities vis-à-vis non-banks are the most volatile of all, which is also true in sub-sample analysis.

To study persistence, we report the cumulative distribution of country-specific ρ coefficients obtained from $l^j_{i,t} = \alpha + \rho l^j_{i,t-1} + \epsilon_t$, where l is the growth rate of liabilities, i is the country, and j is the counterparty sector.[14] We find that 64% of countries have positive autocorrelation coefficients in aggregate liabilities for the full period. In contrast, 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 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.[15]

[13] Figure S10 of the technical appendix illustrates the distributions for country-specific standard deviations computed for quarter-on-quarter growth rates.

[14] Figure S11 in the online appendix graphs measures of persistence.

[15] 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

Lastly, we explore statistical significance of moments, examining the means, median, standard deviation, skewness, and kurtosis of banking flows over countries and time.[16] 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.

2.2 Uncertainty Measures

One of our main contributions is constructing a dataset with multiple measures of uncertainty and extending the country and period coverage. 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, 2019). By examining several measures, we ameliorate the limitations of using one measure of uncertainty. For instance, financial volatility 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

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.

[16] 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 S2 in the online appendix presents our results.

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 measures. By collating data on several measures from various sources, we build a dataset to illuminate the relation between uncertainty shocks and bank flows.[17] Next we describe each uncertainty measure.

Our first measurement class of uncertainty is volatility-based uncertainty. Within this class, we explore two variants. First, we employ implied volatility, based on at the money call options. This is constructed from snapshots of implied volatility for call options on national equity indices using Bloomberg's OVM function.[18] As with the VIX and VIX3M global risk proxies, we take one and three months as the maturity 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. Second, we employ realized volatility, 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 national equity indices from Bloomberg. 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.[19] Quarterly annualized realized volatility is the square root of this quantity.[20]

[17]Table S3 in the online appendix reports the correlation matrix of our uncertainty measures.

[18]We take the last value in each quarter in Bloomberg's OVM function using the national stock market indexes reported in online appendix Table S1. This function could not be automated for periods or countries, providing only a default snapshot that requires manual adjustment for each observation.

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

[20]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

Our second set of uncertainty measures derive from news search, where we employ Economic Policy Uncertainty (EPU) and World Uncertainty Index (WUI). EPU and WUI are sourced from `policyuncertainty.com`. 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 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 frequency counts of newspaper mentions of the word 'uncertainty' and its variants in quarterly Economic Intelligence Unit country reports rather than policy-based economic uncertainty (combinations of words that signify policy, the economy, and uncertainty). 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.[21]

Our third group of uncertainty measures, examining forecast errors and forecaster disagreement, pertain to forecast-based uncertainty. Using survey data on forecasts of quarterly GDP growth, we source quarterly real GDP growth forecasts by multiple forecasters from Bloomberg's ECFC function.[22] As forecast-based measures are not comparable across countries, we compute statistics to avoid this limitation.[23] We focus on forecast dispersion defined as the standard deviation of forecasts across the forecasters.[24] We argue that our forecast measures are superior to that published by the IMF on its World Economic Outlook

similar. As we use multilateral data, the counterparty is the rest of the world.

[21]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.

[22]Similar to the OVM function, automating through scripting when creating panel data from the ECFC function is not possible.

[23]GDP growth forecasts mitigate international comparability issues.

[24]In initial investigations, we considered two other measures. First, we used the standard deviation of the forecast error across forecasters, defining the forecast error as the distance between realized GDP and the forecast of GDP. Second, we took the mean of the absolute values of the forecast error across forecasters. A nice property of mean absolute forecast error is that it treats deviations linearly rather than non-linearly (standard deviation) as is true for the forecast dispersion and forecast error dispersion. As results are similar across forecast measures, in the interest of space, we report findings for forecast dispersion.

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.[25]

2.2.1 Dynamic Behavior of Uncertainty Measures

To inform our analysis relating uncertainty with international bank funding, we assess the dynamic properties of our uncertainty measures.[26] For volatility-based measures, group means, medians, standard deviations, skewness, and kurtoses peak during the crisis.[27] Forecast-based uncertainty measures have group means and medians that are the same before and during the crisis, but that weakly decline thereafter; their standard deviations and skewness peak during the crisis and their kurtoses rise over time. Except for EPU, group standard deviations also peak during the crisis. Interestingly, while other measures of uncertainty rose during the crisis and fell afterward, policy-driven news-based uncertainty (EPU and WUI) rose during and since the crisis.[28]

Data on uncertainty are characterized by time-varying differences in distributions. To explore changes in the distributions, we plot quantiles over countries at each point in time.[29,30] This not only allows us to visually assess time-varying cross-country dispersion, but also examine how various quantiles evolve and play a role in driving cross-country

[25] Publicly available historical international forecast data at quarterly frequency is limited. For example, the IMF's WEO provides semi-annual forecasts, but the IMF forbids staff to share quarterly forecasts.

[26] 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 $\ln(100x+1)$.

[27] Table S4 in the online appendix reports moments and significance of group differences using the same procedures as in Section 2.1.1.

[28] Skewness and kurtosis for EPU are lowest during the crisis; for WUI, skewness decreases and kurtosis increases over time.

[29] The online appendix contains quantile plots for uncertainty measures and banking flow data.

[30] To further explore changes in the distributions, we examine the serial correlation of countries' rankings over time. 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 the online appendix. Low correlations imply churning in the rank ordering across countries, while higher correlations suggest the ordering of countries is more persistent. Results are mixed: some measures display turbulence when high, while others display turbulence when low; turbulence changes a lot over time for some variables. Further discussion of these results is relegated to the online appendix due to space considerations.

dispersion. We include comparisons with banking data for illustration. International differences in volatility-based uncertainty are smallest during the crisis. Both the lower and upper quantiles rise to compress during the crisis, falling and expanding afterward. In contrast, international differences in cross-border flows are greatest during the crisis. The lower quantiles decline, while the upper quantiles rise during the crisis and fall afterward. News-based measures become more dispersed internationally over time. International dispersion in forecast-based measures of uncertainty peaks during the crisis. Unlike financial measures of uncertainty and banking flow measures, the changes in dispersion for news-based and forecast-based measures of uncertainty are driven by the upper quantiles.

We examine persistence of our uncertainty measures assuming they each follow the AR(1) process as in Section 2.1.1: $\Delta UNC_t = \alpha + \rho UNC_{t-1} + \epsilon_t$, where UNC_t denotes the uncertainty variable.[31] Clear patterns emerge with S-curve relations, irrespective of whether we examine AR(1) coefficients or half-lives.[32] 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.[33] 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.

[31]Figure S17 in the online appendix plots the cumulative distribution functions of the AR(1) coefficients.

[32]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 S18 in the online appendix plots cumulative distribution functions of the half-lives.

[33]Half-lives are about one quarter with most below one quarter and only a few around two quarters.

3 The Impact of Uncertainty Shocks

3.1 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

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

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.[34] 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.[35]

[34] 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.

[35] 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

3.1.1 Bivariate Panel Analysis

Our baseline results are found in panels A and B of Table 1. All models produce negative coefficients, as expected, for most liability and uncertainty measures.[36] 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.

Ranking the sectoral borrowing source contraction from uncertainty shocks, the greatest contraction 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 counteract each other, making the aggregate funding response proportionally less.

Our dataset is balanced across the funding components, but it is unbalanced across the uncertainty measures.[37] 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 measures of uncertainty shocks on a given funding type. Following the previous strategy, panels C and D of Table 1 compare the effects of the uncertainty measures on cross-border borrowing overall, from banks, and from non-banks.

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.

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

[37] 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).

To ensure a balanced panel, panels C and D restrict the sample to 13 countries.[38] Similar negative relations emerge. Again, results are sizable and heterogeneous with coefficients on implied volatility and realized volatility lying between 1.7% and 3.9%. For overall flows, realized volatility is the strongest. Bank flows fall the most with three-month maturity implied volatility in the panel model and with realized volatility in the MG model. The largest declines in non-bank flows are associated with three-month maturity implied volatility. 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 before, WUI is now 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 panels A and B, we find our strongest magnitudes for non-bank flows, followed by bank flows, with our smallest magnitudes for overall flows.

The finding that funding declines with uncertainty is *economically* significant. Consider the range of coefficients for implied volatility and realized volatility from Table 1, as these uncertainty measures are based on the same sample. Implied volatilities have standard deviations of 42.2% and 46.3%, and one percent 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-

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

month maturity implied volatility is a conservative choice for 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.[39] Our results are thus both statistically and *economically* significant.

3.1.2 Country-by-Country Analysis

We estimate (1) country-by-country and plot cumulative distributions for the estimates of the βs with those from models in Table 1 in Figures 1–6. The size of these coefficients is on the x-axis, while the vertical axis captures the proportion. The proportion indicates how uncertainty affects bank funding in the majority of countries and 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. Estimates related to liabilities vis-à-vis all sectors are in **black**, while those vis-à-vis banks and non-banks are in **blue** and **green**. We also organize this information by country in Table 2 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 of funding accounts for much of the variation in 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. Ignor-

[39] 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.

ing 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. The only non-negative elasticities are all statistically insignificant. The majority of countries show a negative response of cross-border funding to an increase in three-month implied volatility, with a few showing statistically significant elasticities. 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.

Realized volatility presents a larger range of variation for the elasticities, lying between −18.7 and 14. 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.

Most countries exhibit a negative response of cross-border funding to news-based uncertainty shocks. Due to data limitations for EPU, we limit our analysis to a 16 country sample. As is true with other uncertainty measures, the majority of the estimates are statistically insignificant. Elasticities for EPU range from −11.2 to 20.9, with a tighter range for WUI 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.

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 1 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.

One consistent story across the uncertainty measures is that we observe riskier countries (emerging markets such as Brazil and Turkey and peripheral euro area members such as Italy, Portugal, and Spain) showing significance for bank flows and a safer group of countries (safe havens such as Germany and the USA) showing significance for non-bank flows. Banks are less willing to lend to risky countries with higher uncertainty, even less so when combining the underlying riskier status with the uncertainty shock. The economic story for safe havens is less obvious. It is unlikely that the supply channel dominates because safe havens will remain to be viewed as safe by the rest of the world. Safe haven countries likely significantly reduce their demand for and dependence on non-bank funding following an uncertainty shock. As overall funding does not fall significantly, it is likely that there is a shift between bank and non-bank funding, with non-bank funding falling significantly.[40]

Beyond cumulative distribution functions, Table 2 reports elasticities by country and funding sector. One takeaway is the considerable variation in the direction and magnitude banking systems' funding responds to uncertainty shocks. Countries like Singapore show negative elasticities for most measures and funding sources, all being statistically insignif-

[40]The prior level of non-bank funding is lower than bank funding, so smaller changes in non-bank funding can be significant when looking at percentage changes.

icant. This is also true for Norway, where many elasticities are statistically insignificant with some showing positive signs, or Switzerland with cross-border funding unaffected by uncertainty, possibly related to the scale of international operations by Credit Suisse and UBS 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.

Uncertainty could affect flows through a demand-side story and a supply-side story; that is, higher uncertainty may reduce demand for funds by a country's banks or reduce supply of funds from abroad. More advanced countries may witness a weaker supply effect because the rest of the world may continue to trust advanced countries. Evidence is consistent with a weaker supply channel for advanced countries. Country-specific uncertainty has a significant negative relation with overall cross-border flows more frequently for our less developed sample. Ireland, Italy, Portugal, and Spain were amongst the peripheral euro area members during the Great Recession and European Sovereign Debt Crisis. Three of four emerging markets display significant negative relations, or seven of eight, if we include the peripheral euro area. Five of sixteen advanced economies have significant negative coefficients, or nine of twenty, if we include the peripheral euro area.

This section presented evidence of a negative link between uncertainty shocks and cross-border funding, consistent with the related literature taking one uncertainty measure, a panel approach, and an aggregate measure of capital inflows. Our contribution is reporting the heterogeneities associated with the uncertainty indicator, counterparty sector, and borrowing country. In Section 3.3, we study heterogeneities along the time dimension by examining the global financial crisis. 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.

3.2 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

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

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 suggested by 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, monetary policy rates, credit growth, exchange rate growth, inflation rates, 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, higher policy rates, and credit growth (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. Their results suggest a positive relation between private bank credit growth and cross-border flows. The policy rate captures the bank lending channel of monetary policy globally (Bruno and Shin, 2015b; Rey, 2015; Correa *et al.*, 2018). Higher local rates makes it more attractive for banks to look for funding across the border.

Theory is ambiguous on the drivers of funding such as exchange rate growth, inflation, and external debt, leaving the signs of the relations open to empirical investigation. Changes in the exchange rate matter for cross-border funding if loans are denominated in foreign currency. A stronger domestic currency makes it more affordable to borrow in other currencies; 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. 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. 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 3 and 4 report regression outputs for panel and MG models following equation (2), exhibiting coefficients consistent with expectations. Uncertainty covaries negatively with cross-border funding, the multivariate approach producing elasticities of similar sizes and signs to those from the bivariate model.

To be specific, panel regression models in Table 3 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 uncertainty indicators, albeit some 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, conditioning factors reduce the precision of these estimates, with more coefficients being statistically insignificant. Abstracting from these larger standard errors, multivariate MG models yield less negative responses to most uncertainty shocks than bivariate MG models. 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%.

Conducting a country-by-country analysis, 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 inclusion of conditioning factors does not homogeneously change the bivariate point estimates of the elasticities. Similar to Section 3.1.2, Table 5 reports country-specific point estimates for regressions models including the conditioning factors. Reductions in cross-border funding for countries like Portugal, Ireland, and France are robust to the inclusion of the additional regressors. As expected, many coefficients lose statistical significance in the country-level regressions. 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.

3.3 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 final dimension we consider is time. Our candidate is the potential structural break of the GFC as global banks were at the center 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). From an international investment position perspective, Lane and Milesi-Ferretti (2018) show that the halt in 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 our approach of stressing the role of heterogeneity, the Great Retrenchment in international capital flows was 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, 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 crisis dummy and interaction effects with uncertainty. We estimate the following model

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

where GFC_t is one during 2008Q3–2012Q12 and zero otherwise, $UNC_{i,t} * GFC_t$ is the interaction term between the crisis dummy and the uncertainty measure, and $X_{i,t-1}$ is the set of conditioning factors. As we focus on subperiods rather than cross-country heterogeneity in this section, we omit MG estimates. Tables 6 and 7 present the bivariate and multivariate models. In addition, Tables 8 and 9 present the 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 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 significantly negative 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 mattered during the crisis.

The alternative approach of analyzing periods before and after the GFC shows that most uncertainty measures are insignificant, except EPU and WUI, which have negative coefficients. Recalling Section 2.2.1, news-based policy-driven uncertainty measures are the only measures whose first two moments rose 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 the euro area, with some effects for advanced and G7 nations, but no effect for non-European and emerging markets.

To conclude, uncertainty mattered during the crisis. Outside the crisis, and especially for European countries, news-based uncertainty had a negative effect likely because news-based uncertainty rose since the crisis, unlike other uncertainty measures.

4 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. With conservative assumptions, funding declines in response to uncertainty are statistically and economically significant. The non-banking sector and volatility-based uncertainty measures display the largest effects. 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 nations 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 measures of uncertainty, between a diverse set of countries with differing banking systems, and over different 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.

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Table 1: 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
Panel C: Panel Regressions – Fixed Sample				
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 D Mean-Group Regressions – Fixed Sample				
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: Panels A and C: bivariate panel regressions with fixed effects for equation (1). Panels B and D: bivariate mean-group regressions for equation (1). Panels C and D use 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 in parenthesis. ***: 1% significance; **: 5% significance; *: 10% significance.

Table 2: 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 3: 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 4: 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 5: 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 6: 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)
GFC	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)
GFCxUNC	-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 7: 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)
GFC	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)
GFCxUNC	-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 8: 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.

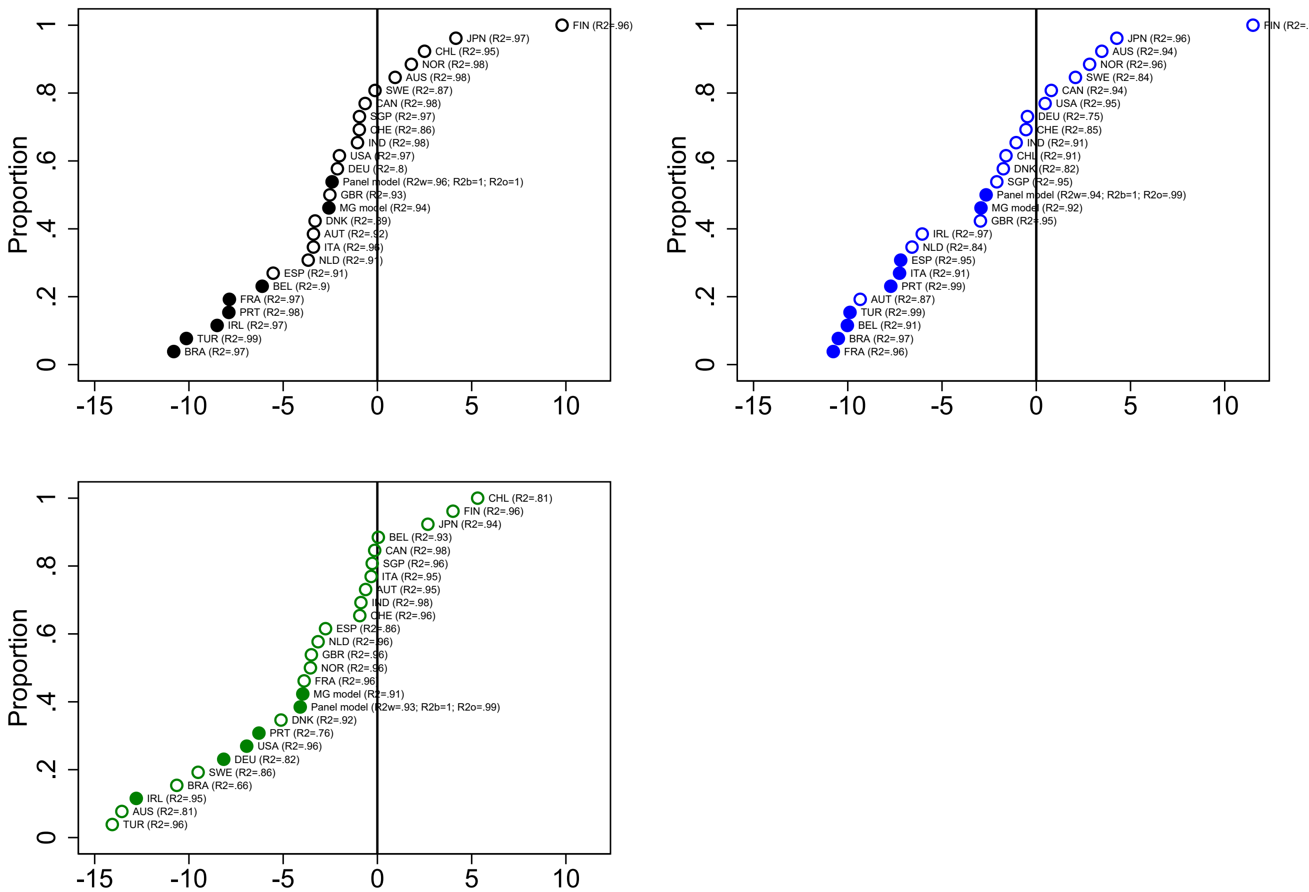
Table 9: Multivariate Panel Regression Model – Non-Crisis

		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

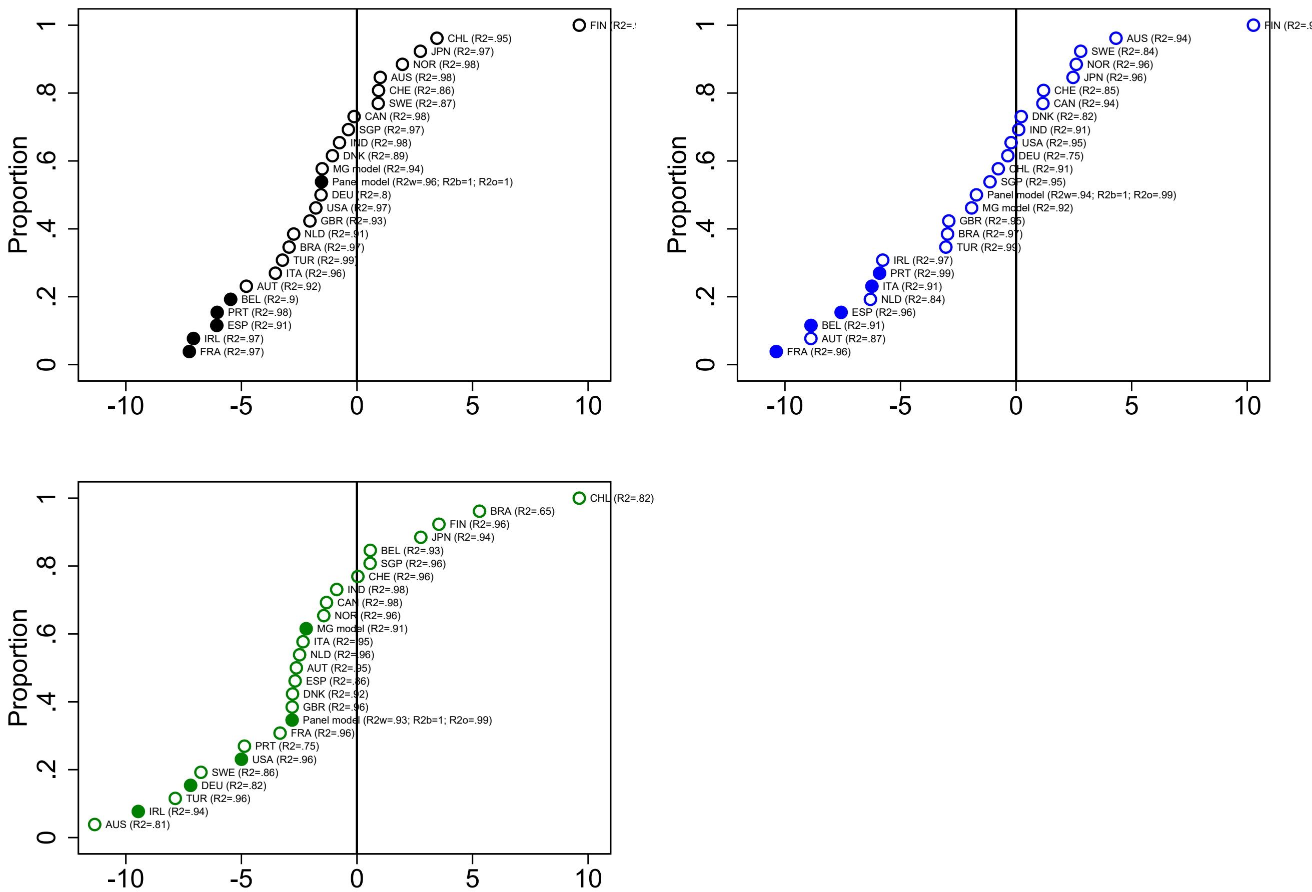
Notes: Constant and AR(1) terms included in regression but not reported. Robust standard errors are in parenthesis. *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

Figure 1: Bivariate Regression Coefficients: Three-Month Implied Volatility



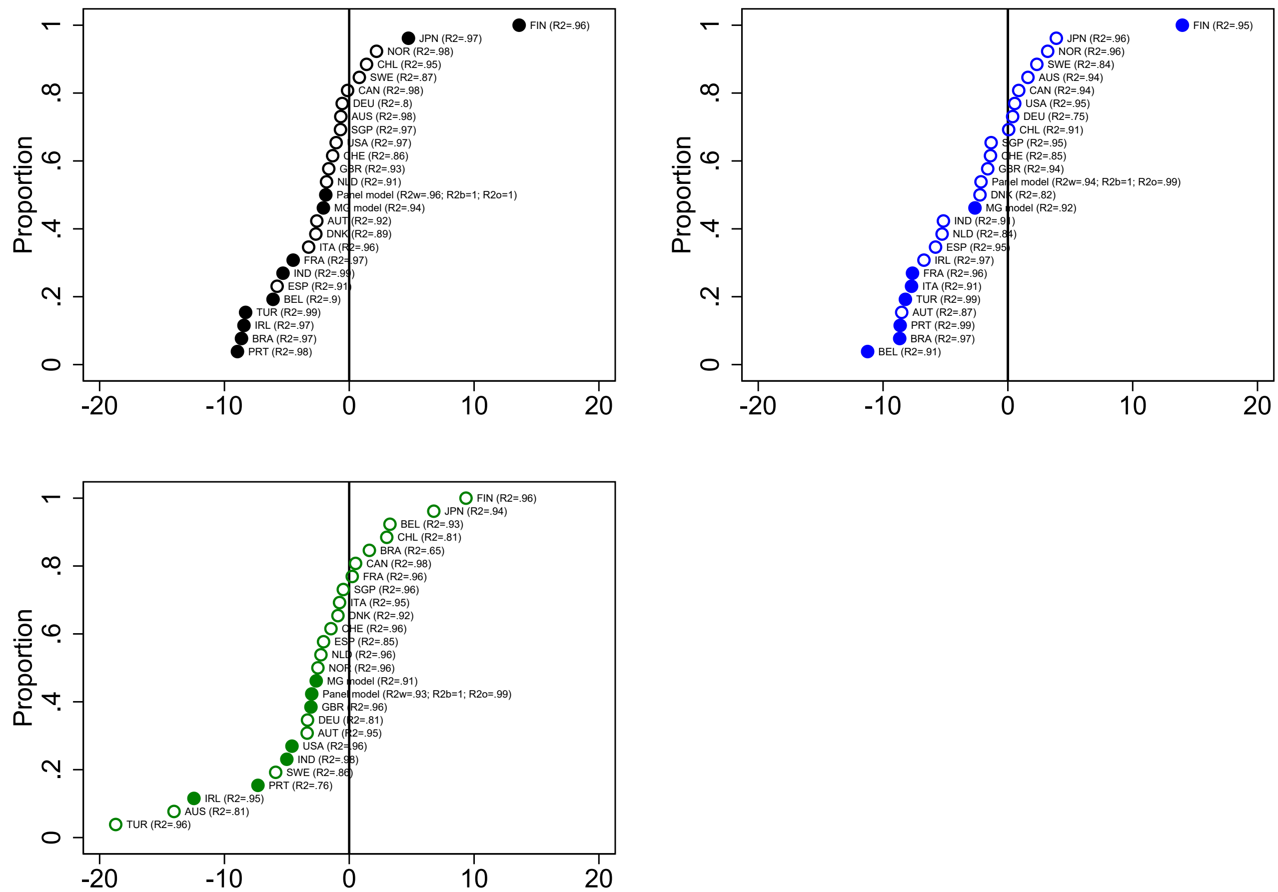
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis all **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by implied volatility based on three-month 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 2: Bivariate Regression Coefficients: One-Month Implied Volatility



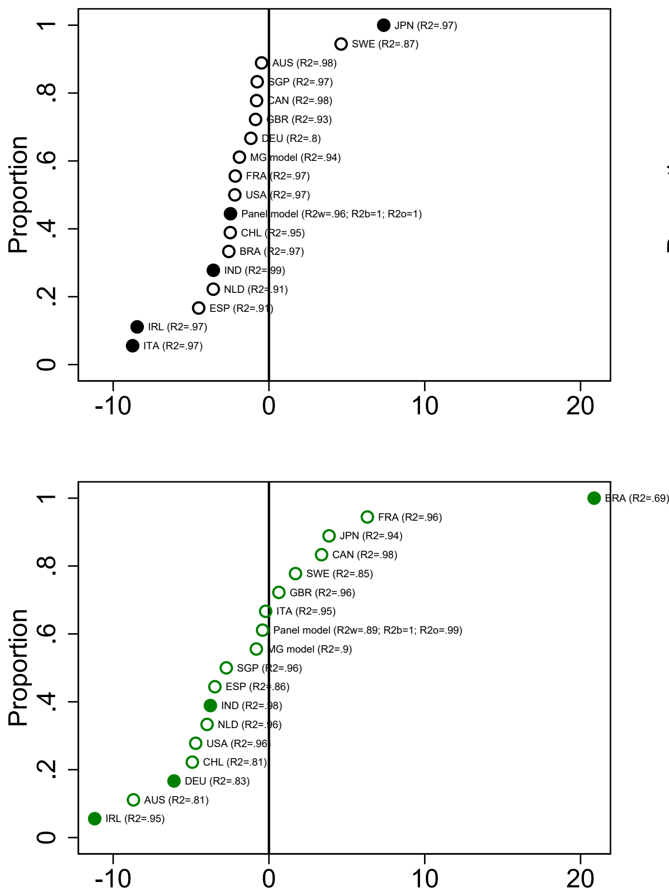
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by implied volatility based on one-month option 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 3: Bivariate Regression Coefficients: Realized Volatility



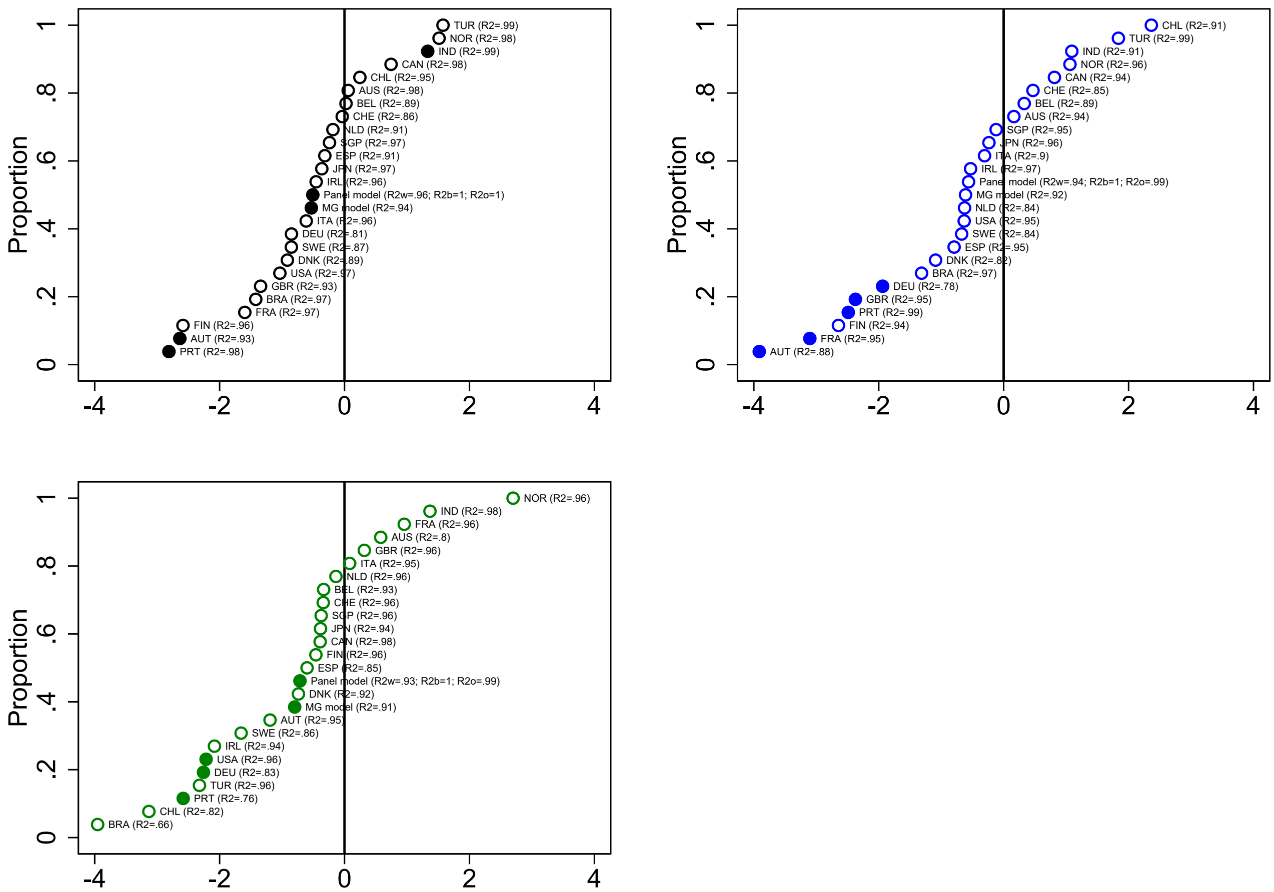
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by realized volatility. All models include a 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 4: Bivariate Regression Coefficients: Economic Policy Uncertainty



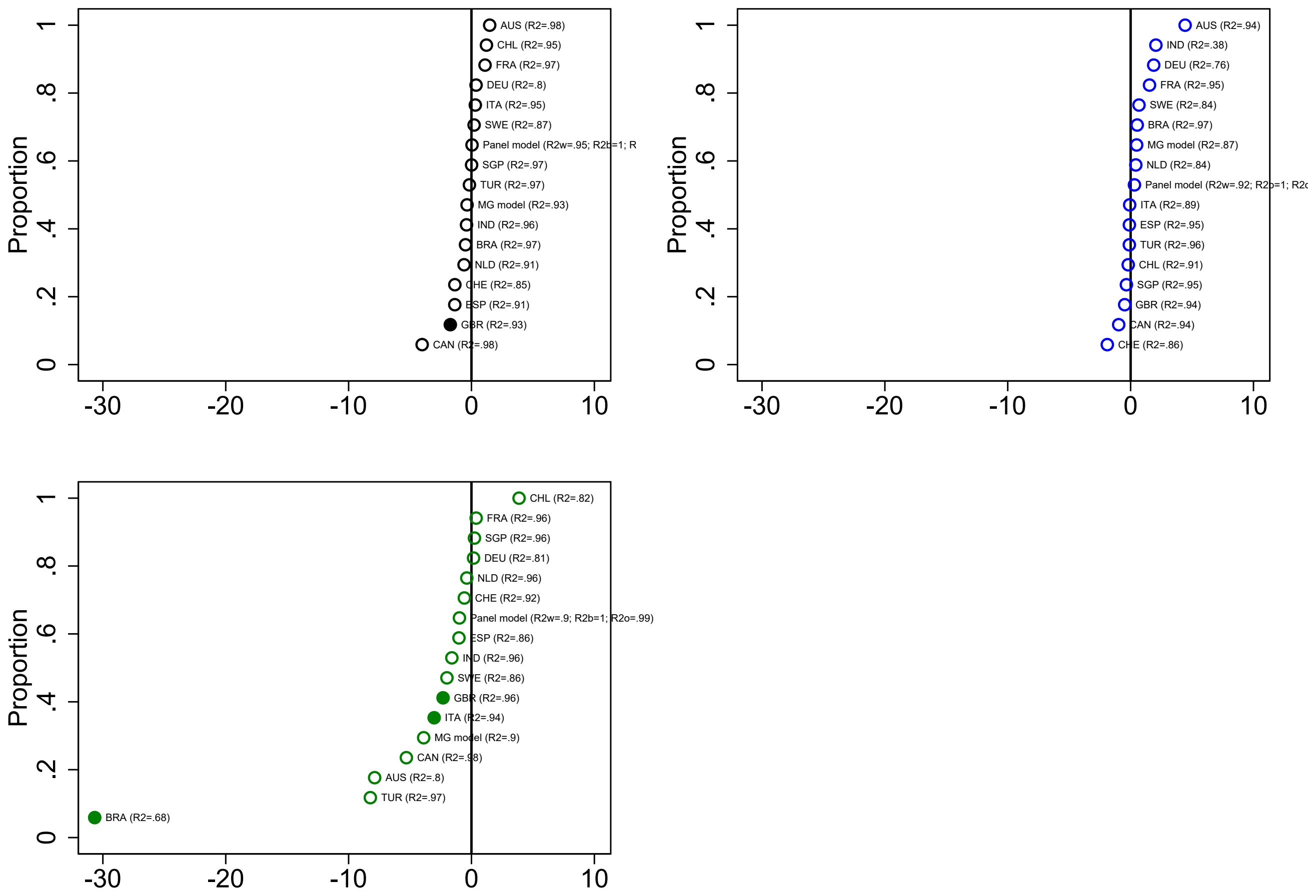
Notes: Point estimates from bivariate regression models from equation (1) for the log-level of cross-border bank liabilities vis-à-vis **all** counterparties, **banks**, and **non-banks**. The explanatory variable is the logarithm of uncertainty, captured by the EPU index. All models include a constant 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 5: 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 6: 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.