Cross-Border Bank Flows and Systemic Risk[1]

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Abstract

Using data on cross-border bank flows from Bank for International Settlement (BIS) reporting source countries to 114 recipient countries, we find that heightened bank flows are associated with lower systemic risk in the bank systems in the recipient country. The link between increased flows and reductions in marginal expected shortfall (*MES*) are concentrated among banks that are larger, profitable, and more efficient. The decline in *MES* is concentrated among banks in developed markets and those in countries with banking sectors that are larger and have lower capital bases. Additional evidence helps to identify the channels through which cross-border bank flows help to reduce *MES*, which is by improving recipient-country bank asset quality, efficiency, and profitability. Overall, our findings are consistent with dynamic models of multinational banking that predict lower risk-taking by stimulating local competition and suggest a positive impact of international bank flows on global financial stability.

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1. Introduction.

A period of rapid global expansion of bank activities preceded the global financial crisis in 2007-2008. In its aftermath, policymakers have been asking whether opening up to global influences strengthens or destabilizes a banking system. Globalization leads to increased cross-border lending activity, which has been shown to facilitate risk sharing and diversification and to reduce banks' exposure to domestic shocks (Allen, et al., 2011; Schoenmaker and Wagner, 2011; Faia, et al., 2017; Kalemli-Ozcan, et al., 2013). On the other hand, internationalization of banks has also been linked to increased risk (among others, Goetz, et al., 2016; Berger, et al., 2016). There is considerable evidence that the proliferation of cross-border lending activities by global banks help transmit foreign shocks to recipient markets (Iyer and Peydró, 2011; Schnabl, 2012; Bruno and Shin, 2015; and, Morais, et al., 2017). In addition, given the vast differences in banking regulation and supervision across countries, there are concerns about banks from countries with stricter regulations engaging in cross-border activities in other countries with fewer regulations. Thus, regulatory arbitrage may be a problem, as these banks may invest in countries with looser regulations and increase their risk-taking, destabilizing the financial system (Acharya, Wachtel, and Walter, 2009). Indeed, regulatory arbitrage has been shown to be an important determinant of both cross-border bank flows and bank acquisition activity (Houston, Lin, and Ma, 2012; Karolyi and Taboada, 2015). Whatever the drivers of banking globalization, there is not yet a clear answer on whether the risk sharing, diversification, and competitive benefits dominate or whether negative externalities associated with excessive foreign bank risk-taking and other contagion effects subsume those benefits, particularly for the stability of a financial system. This is the goal of our study.

We pursue this question armed with two relatively new data. We obtain the Consolidated and Locational Banking Statistics data from the Bank for International Settlements (BIS) on bilateral bank claims to build a matrix of bilateral flows from 1995 to 2014. In addition, we operationalize new measures of systemic risk (namely, marginal expected shortfall (*MES*), Acharya, et al., 2017; SRISK, Brownlees and Engle, 2017) for over one thousand banks in 64 countries. There are different channels through which global expansion can spill over to strengthen or weaken local banking sectors in which foreign banks are active. It is our focus on the *individual* banks in recipient markets impacted by these flows, on how their estimated contributions to systemic risk adjust, and on how they react operationally that allows us to identify the potential channels at work. We lean on existing theories of bank risk-taking and competition, including those in a multinational context, to guide us with different predictions depending on how market entry makes competition endogenous and generates a feedback loop with endogenous risk-taking (Boyd and De Nicoló, 2005; Faia and Ottaviano, 2017).

We leverage for our analysis the large increase in cross-border bank lending activity that has arisen since the mid-1980s. Banks' foreign claims increased from $750 billion as of 1983 to a peak of $34 trillion as of 2007, tapering off since the financial crisis to $30.5 trillion in 2014 (Bank for International Settlements Quarterly Review, 2015). Foreign claims on developed countries have seen a decline since the financial crisis driven primarily by retrenchment of European banks (IMF, 2015, Faia, et al., 2017). In contrast, as Figure 1 shows, foreign claims on emerging countries have continued to increase since 2008 reaching a peak of $5.9 trillion as of 2014. This is important because many of the policy concerns about the increase in risk contagion arising from banking globalization focuses on emerging markets.[1]

1.1 The competing hypotheses.

Cross-border bank lending continues to be an important channel for the transfer of capital across countries even after the global financial crisis. Yet, theory is ambiguous on the potential positive or negative consequences for the target country. Traditional portfolio theory suggests that geographic expansion can lower a bank's risk if it involves adding assets with returns imperfectly correlated with existing assets. Diamond (1984) and Boyd and Prescott (1986) emphasize how diversified banks enjoy cost efficiencies that can enhance their stability. In line with this view, several studies document that geographic expansion leads to lower bank risk (see e.g. Goetz, et al., 2016; Akhigbe and Whyte, 2003; Deng and Elyasiani, 2008). We could observe positive economic consequences for the recipient country as multinational banks engaging in such activities maximize value for shareholders, improve capital

[1] See the IMF/World Bank speech by Vice Chairman Stanley Fischer of the Federal Reserve (2014) and a speech by then Reserve Bank of India Governor Raghu Rajan (2014).

allocation, and stimulate healthy competition among local banks in the target country. Claessens, et al. (2001), Mian (2006), and Micco, et al. (2007) furnish evidence in favor of this "competition" channel. The dynamic multinational banking model of Faia and Ottaviano (2017) specifically links tougher local competition from global bank entry to better project selection, higher future discounted profits, less risk taking and potentially lower systemic risk for the target bank system.

On the other hand, agency-based models suggest banks might expand geographically to extract private benefits of managing a larger "empire" even if this lowers loan quality and increases bank fragility. Berger, et al. (2005) stress that distance can hinder the ability of a bank's headquarters to monitor its subsidiaries with potential adverse effects on asset quality. Winton (1999) shows how diversification can increase complexity and hinder the ability of banks to monitor loans and to manage risk. In the case of foreign banks operating in emerging markets, the distance between headquarters and local subsidiaries is likely to be especially large. Many, if not most, potential borrowers lack usable collateral and reliable accounting information and are informationally difficult. Detragiache, et al. (2008) develop a model that shows when domestic banks are better than foreign banks at monitoring soft information that foreign bank "cream-skim" to build a less-risky portfolio, their entry may hurt customers, credit is constrained, and welfare worsens. Regulatory arbitrage motives may also prompt foreign banks inhibited by tough regulations at home to pursue value-destroying activities in the form of excessive risk-taking. This form of regulatory arbitrage could have adverse consequences on bank performance and shareholder value and could destabilize the recipient country's financial system. Iyer and Peydró (2011) demonstrate how a sudden shock can propagate from foreign banks to local banks via interbank linkages leading to large deposit withdrawals and heightened host market instability.

1.2 Our identification strategy.

Identifying the impact of cross-border bank flows on the aggregate systemic risk of recipient countries is elusive because of the challenge of identifying exogenous sources of variation in cross-border bank flows. To address this identification challenge, we employ a three-pronged strategy. First, we project bank flows to a given recipient bank system onto a variable based on a *source country's* propensity to operate abroad. The identifying assumption is that global expansion from that source country is not directly linked to the recipient country, but rather it stems *indirectly* from the same fundamental forces that govern bilateral ties, in general - namely, through a "gravity model" of cross-border bank flows. Second, we estimate *predicted* bank flows from our gravity model across source-recipient country-pair-years. The gravity model incorporates time-varying macroeconomic and market fundamentals, but also includes time-invariant predetermined measures of geographic, cultural, and institutional distance. Third, we exploit heterogeneity of the potential impact of bank flows *across* the different banks in a given recipient country for their respective contributions to systemic risk and for their operational changes in the years following the flows.

Regarding the first prong of the approach, we construct an instrumental variable for a given recipient country that captures international activity through ownership of banks in foreign countries by *source* countries with which that recipient country is linked. The instrument measures bank ownership across countries for each source country *s* using data on foreign bank ownership from Claessens and Van Horen (2014). We compute the assets of all banks owned (50 percent or more) by residents from source country *s* across all other countries. Since our focus is on systemic risk in a recipient country *r*, we obtain a measure of foreign bank ownership at the source-recipient and country-year level by aggregating the assets of all banks owned by residents of source country *s* across all other countries excluding those that are in the same region as recipient county *r*. We re-scale this measure of foreign bank assets owned by source country *s* by the source country's total banking sector assets. This measure at the recipient country-year level uses the total distance between source *s* and recipient country *r* as a weight (in kilometers between capital cities). The critical assumption is that bank ownership by source country *s* in foreign countries is relevant for cross-border bank outflows, but should not have a direct effect on recipient country *i*'s systemic risk other than through its impact on bank flows. Since the measure excludes ownership of banks by the source country in the recipient country's region, we believe our instrument reasonably satisfies both the exclusion and relevance conditions.

In the second prong of the approach, we estimate *predicted* bank flows from a gravity model adapted from the international trade literature. Building on prior studies (Houston, et al., 2012; Karolyi and Taboada, 2015), we model pre-determinants of cross-border bank flows for a sample of 26 source countries and 114 recipient countries over the period from 1995 through 2014. Specifically, we estimate predicted flows by estimating bilateral bank flows using a 5-year rolling window to obtain predicted flows for year *t* from information in year *t-1* to mitigate look-ahead bias. The predicted values from the model are extracted and then aggregated on a weighted-average basis for a given target country across all source countries using lagged foreign claims from source country *s* to recipient country *r* as weights.

The last third of the paper drills down to analyze the differential impact of these flows across individual banks that constitute the bank systems in the target countries. The basic idea of heterogeneous effects across banks is motivated in large part by the idea behind identifying global systemically important banks (G-SIBs) by the Basel Committee on Banking Supervision (BCBS) and the Financial Stability Board (FSB) globally.[2] Their G-SIB scores focus on size, interconnectedness, complexity, global activity and others. We are also influenced by recent theories of multinational banking, which predict that the increased competition and lower risk-taking stimulated by the activities of global banks arise from correlatedness of the potentially funded projects (Faia and Ottaviano, 2017). We test whether the link between bank flows and the contributions to systemic risk by individual banks vary by size, by their asset quality, cost efficiency, and leverage. Recipient country banks that are more exposed by their size or leverage to cross-border bank flows may be more likely to contribute to changes – whether positive or negative – in the systemic risk of the bank system. Analysis at the individual-bank level also allows us to examine the channels through which cross-border flows link to systemic risk changes by exploring potential changes in bank performance, risk-taking or other policy choices in the years that follow.

[2] See, for example, the Basel Committee on Banking Supervision's report, "Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems" (July 2011), FSB's report, "Reducing the Moral Hazard Posed by Systemically Important Financial Institutions: FSB Recommendations and Time Lines" (October 2010), and the Office of Financial Research's report, "Systemic Importance Indicators for 33 U.S. Bank Holding Companies: An Overview of Recent Data" (February 12, 2015).

There are several new measures of systemic risk (see, e.g., Bisias, Flood, Lo, and Valavanis, 2012, for a survey), but we focus on two that allow us to capture aggregate systemic risk at the country level: (1) *MES*, the marginal expected shortfall from Acharya, et al. (2017), and (2) *SRISK*, from Brownlees and Engle (2017).[3] *MES* measures the average bank return on days when the market is in the 5% left tail of its distribution. *SRISK* estimates the amount of capital needed during a crisis for a bank to maintain an 8% capital-to-assets ratio. These measures are gaining some traction as suitable measures of systemic risk (see e.g. Acharya, et al., 2017; Brunnermeier, et al., 2015; Engle, et al. 2014). The two measures are somewhat surprisingly not highly correlated. For us, the advantage of *MES* is that we compute the measure directly and can do so for individual banks in a given recipient country, which allows us to explore the heterogeneous impact of cross-border flows across different banks. We only have *SRISK* data at the recipient country level, but it allows us to calibrate across the two different measures. Reassuringly, they deliver very similar inferences.

1.3 What do we find?

The key finding in our study is that bank flows are reliably associated with economically large reductions in aggregate systemic risk. A one standard-deviation increase in flows is associated with a 0.088 reduction in *MES*, which represents 3.33% of the unconditional mean and 5.2% of its unconditional standard deviation across all recipient countries and years. The findings arise primarily for *inflows* (increases in *MES* following outflows are weak) and there is considerable variation across recipient countries and over time. To wit, the impact of bank flows on systemic risk is stronger in developed over emerging target markets, a surprising finding given the concerns of many policymakers. In addition, the reduction in bank-level systemic risk associated with bank flows is stronger for banks in countries with larger banking sectors and lower capital. We also examine whether the impact of bank flows differs based on recipient country *de jure* measures of regulatory quality. The impact of bank flows on *MES* is

[3] Given our large cross-section of countries, data availability prevents us from using another popular measure of systemic risk, *CoVaR* (Adrian and Brunnermeier, 2016). We discuss other stock-market based measures later in the robustness section.

marginally stronger for target countries with less stringent capital requirements, but surprisingly we find that the impact of bank flows differs little based on other measures of recipient country regulatory quality.

The second key finding stems from how differently an *individual* bank's contribution to systemic risk (*MES*) in a given target country is affected by foreign bank inflows. By exploring the impact on individual banks, we can provide further (and plausibly more direct) tests of the channel through which bank flows affect systemic risk. We find the reductions in *MES* following cross-border flows are concentrated among banks that are larger and more efficient (lower costs). We interpret this evidence as supportive of the main predictions of several models of the role of competition for bank-risk taking (Boyd and De Nicoló, 2005; Faia and Ottaviano, 2017). These models feature specific channels through which the cross-border flows could reduce systemic risk in recipient countries. Faia and Ottaviano (2017) predict that *MES* decreases could stem from a competitive response to the cross-border inflows that could arise from higher quality loan portfolios, improved cost efficiency, or a reduction in the potential for liquidity problems. Improvements may also stem from the monitoring role exercised by source banks in the interbank market (Iyer and Peydró, 2011). We track individual bank performance and risk-taking up to three years following bank inflows and find evidence of improved asset quality (lower levels of nonperforming loans) and improved profitability (return on assets, *ROA*), and some weaker evidence of improvements in efficiency (lower non-interest expense) and reductions in leverage.

1.4 How do we contribute to the literature?

Our study sheds light on the ongoing debate about the benefits and costs of cross-border lending and bank internationalization. Empirical evidence to date yields mixed results (Allen, et al., 2011; Schoenmaker and Wagner, 2011; Goetz, et al., 2016; Bruno and Shin, 2015). Several studies find that cross-border lending is less stable than local lending (Schnabl, 2012; Peek and Rosengren, 2000; De Haas and van Lelyveld, 2006; McCauley, McGuire, and von Peter, 2012). We believe our paper is among the first to focus on the link between multinational banking and the systemic risk of *target bank systems*. Gulamhussen, Pinheiro, and Pozzolo (2014), Berger, et al. (2016), and Jeon, et al. (2016) do consider bank risk taking, but not systemic risk. Berger, et al. find a positive link; internationalization, measured as the ratio of a bank's foreign to total assets, allows banks to increase risk due to market-based factors as opposed to taking advantage of opportunities for diversification, which reduce risk.

Our paper also connects to the literature on the economic consequences of banking regulations (Barth, Caprio, and Levine, 2004, 2006, 2008; Beck, Levine, and Levkov, 2010; Laeven and Levine, 2009; Morrison and White, 2009) and to the related literature examining regulatory arbitrage (Houston et al., 2012; Ongena, et al., 2013; Karolyi and Taboada, 2015). Cross-border studies about bank regulation have shown that tough regulatory restrictions on bank activities and barriers to foreign entry hurt banking sector performance (Barth, et al., 2006). Laeven and Levine (2009) find that tougher bank regulation reduces bank's risk-taking behavior, although the impact of regulations on risk-taking depends critically on each bank's ownership structure. Houston, et al. (2012), the closest paper to ours in this stream of papers, examine cross-border bank flows to find evidence of regulatory arbitrage as banks tend to predominantly transfer funds to countries with fewer regulations. Ongena, et al. (2013) find banks from countries with tighter restrictions on bank activities and higher capital requirements tend to make riskier loans abroad.[5] Our findings acknowledge these forces are at work, but suggest the presence of multinational banks in local markets on balance reduces risk-taking by promoting local competition.

Finally, we contribute to the newer literature on the determinants of systemic risk. Some studies focus on how non-traditional banking activities affect banks' systemic risk. Some find that higher levels of non-interest income lead to increases in systemic risk exposures (Brunnermeier et al., 2015; De Jonghe, 2010), or to increased risk-taking (DeYoung and Roland, 2001; Demirgüç-Kunt and Huizinga, 2010; Stiroh, 2004). Engle, et al. (2014) show the positive relation between non-traditional banking activities and systemic risk arises for banks in countries with less concentrated banking sectors.[6] What our study adds to this stream of the literature is global evidence on another important determinant of systemic risk; namely, cross-border international bank flows.

[5] Karolyi and Taboada (2015) test whether regulatory arbitrage is a motive behind cross-border bank acquisitions. They find market reactions to deal announcements are more in line with a benign form of regulatory arbitrage. Frame, et al. (2016) find U.S. bank holding companies are more likely to operate subsidiaries in countries with weak regulation and supervision and the activity, while more profitable, also increases bank risk and its contributions to systemic risk.

[6] Through the provision of non-traditional banking services, banks can obtain more information that helps reduce information asymmetry inherent in lending relationships (Boot, 2000; Degryse and Van Cayseele, 2000; Bhattacharya and Thakor, 1993).

2. Data.

Our data for this paper come from several sources. We obtain data on international bilateral bank flows from the Consolidated Banking Statistics (CBS) published by the Bank for International Settlements (BIS). We use the consolidated banking statistics (CBS) data following prior studies (e.g. Houston, et al., 2012; Cetorelli and Goldberg, 2011). The data provide details of the credit risk exposures of banks headquartered in up to 31 BIS reporting countries to all sectors of the economy in over 200 recipient countries. The number of reporting countries has changed over time. We are able to collect reliable historical data for 26 reporting countries and 198 recipient countries. The consolidated foreign claims (loans, debt securities, and equities) include: (1) cross-border claims − claims granted to non-residents; (2) international claims − local claims of foreign affiliates in foreign currency; and (3) local claims of foreign affiliates in local currency (BIS, 2009). The CBS data from the BIS does not provide a measure of bank flows, so we follow Houston et al. (2012) and construct our measure of bank flows, $\textit{Bank Flows}_{s,r,t}$ by computing the difference from *t-1* to *t* of the log of total foreign claims from source country *s* to recipient country *r*. In our main analysis, we aggregate across all source countries the annual bilateral flows at the recipient country-year level.

There are two potential issues with the CBS data: (1) unexpected breaks in the time series (e.g. cross-border bank acquisitions that lead to changes in the nationality of the reporting banks), and (2) the impact of exchange rate movements. CBS data are not adjusted for these factors and the data required to adjust for breaks in series are confidential. To ensure that issues associated with breaks-in-series or exchange rate movements are not driving our results, we follow Houston et al. (2012) and drop bilateral bank flows that exceed 100% in absolute value in a given year. In robustness tests, we winsorize bank flows at the top/bottom 1% of the distribution as an additional way to mitigate the impact of outliers. Finally, we also compute bank flows to a recipient country using the break-adjusted and exchange rate-adjusted changes in claims using the Locational Banking Statistics (LBS). These data provide information about the currency composition of banks' balance sheets, the geographical breakdown of their counterparties, and they capture the outstanding claims of banks located in BIS reporting countries including intragroup positions between offices of the same banking group. We do not use LBS data in our main bilateral regressions, because the LBS data do not provide the nationality of the lending banks (see, e.g., Avdjiev, Kuti, and Takáts, 2012), which is key to control for source country characteristics.

Our main measure of systemic risk is the marginal expected shortfall (*MES*) measure from Acharya, et al. (2017). We compute *MES* as the average bank return during the worst 5% of market return days in a year. We estimate *MES* for all banks with available data on stock prices from Thomson Reuters' DataStream. *MES* is then aggregated at the country level by computing the value-weighted average *MES* among all banks in the country in a given year. We are able to compute country-level measures of *MES* for 64 countries with at least three banks with available data. For ease of interpretation, we take the negative value of *MES* to ensure that both of our measures are increasing in systemic risk.

Our second measure of systemic risk, *SRISK*, comes from The Volatility Institute at New York University's Stern School of Business (V-LAB). Data on *SRISK* is available for 65 recipient countries in our final sample starting in 2000.[7] Coverage varies by country with 35 of our countries having data available since 2000.[8] *SRISK* is the expected capital shortfall of a bank conditional on a crisis event. Specifically, *SRISK* measures how much capital would be needed in a crisis for a bank to maintain a k% capital-to-assets ratio (e.g. where k is typically assumed to be 8%). *SRISK* is calculated at the bank level and then summed up to the country level. The components of *SRISK* are bank size, leverage, and long-run marginal expected shortfall (*LRMES*). *LRMES* is the expectation of the bank equity multi-period return conditional on a systemic event. Formally, *SRISK* is:

$$SRISK_{i,t} = kD_{it} - (1-k)W_{it}(1 + LRMES_{it}), \qquad (1)$$

where D is the book value of debt, W is the market value of equity, and k is the prudential capital fraction (Brownlees and Engle, 2017). Brownlees and Engle (2017) impose k to be 8%. The country-level data

[7] *SRISK* data is available for all but two (Australia and Panama) of the 26 BIS source countries.

[8] Data on *SRISK* starts in 2001 (three countries), 2002 (three added), 2003 (four more added), 2004 (seven), 2005 (four), 2006 (two), 2007 (two), 2008 (three), and 2009 (one). Data for Slovenia is only available since 2011. We include these last two countries in our main analyses for completeness, but our results are unaffected if we exclude them.

are available on a daily basis, and we use year-end values for each country. We scale this measure of systemic risk by the country's real Gross Domestic Product (*GDP*).

We also gather data for the key instrumental variable that we use in the two-stage least squares (2SLS) regression specifications. Data on the foreign ownership of banks comes from Claessens and van Horen (2014) together with financial data from Fitch Fundamentals to construct measures of foreign bank ownership across countries for each source country *s*. We obtain the total foreign banking assets owned by residents from source country *s* as the sum of total assets for all banks owned (50 percent or more) by foreigners from source country *s*. For a given country-pair, we aggregate the total bank assets owned by a source country across all regions of the world, excluding the region in which the recipient country *r* is located. We then aggregate the bilateral *Foreign ownership* variable at the recipient country-year level using the total distance (distance in kilometers between countries' capitals) between a source country *s* and recipient country r as the weight. Appendix D provides an example of the construction of our instrument for India in 2012. In 2012, there were 22 source countries with foreign claims on India. *Foreign ownership* shows heterogeneity in ownership of banks (outside of Asia) by source countries ranging from a low of 0.01% by Taiwan, to a high of 39.27% by Sweden. Column (5) shows distance (in kilometers) between each source country and India, which we use as a weight to aggregate *Foreign ownership* at the recipient country level. The product results in a value of 8.114 for India in 2012.

The identifying assumption is that the bank ownership by source country *s* in foreign countries is relevant for cross-border bank outflows, but should not have a direct effect on recipient country *r*'s systemic risk other than through its impact on bank flows. Since the measure excludes ownership of banks by the source country in the recipient country's region, our instrument has a reasonable chance at satisfying both the exclusion and the relevancy conditions.

We need measures of regulatory quality to assign cross-border bank flows as consistent with regulatory arbitrage and they are from Barth, et al. (2013). We use four measures. *Restrictions on bank activities* is an index that measures regulatory impediments to banks engaging in securities market activities (underwriting, brokering, dealing, mutual funds), insurance activities (underwriting and selling), and real estate (development or management). *Stringency of capital regulation* is an index measuring minimum bank capital ratios, as well as the sources of funds that count as regulatory capital. *Official supervisory power* is an index that measures whether supervisory authorities have the power to take actions to prevent or correct problems. And *Private monitoring* represents an index that measures whether there are incentives for the private monitoring of banks.[9] These are described in detail in Appendix A.

Finally, we obtain a number of country-level measures that have been shown to influence systemic risk (among others, Engle, Jondeau, and Rockinger, 2015; Brunnermeier, et al., 2015) from World Bank databases. To control for financial development and growth we use the growth in real GDP (*GDP growth*) obtained from the World Bank's *World Development Indicators* database. As a proxy for banking sector size, we use the log of total banking sector assets (*Bank sector assets*); we compute the latter as the total assets of all commercial banks, saving banks, and bank holding companies covered by Fitch Fundamentals. From the World Bank's *Global Financial Development* database (Beck, Demirgüç-Kunt, and Levine, 2009; Čihák et al., 2012) we obtain data on: non-interest income to total income (*Non-interest income*) to proxy for the extent of noncore banking activities; the proportion of banking assets held by the three largest banks (*Concentration*); stock market index returns (*Market return*); and, stock market volatility (*Volatility*), which is the annualized standard deviation of weekly stock market index returns. All variable definitions are found in Appendix A. Appendix B shows descriptive statistics of our measures of international bank flows and systemic risk for our final sample of 75 countries with available data on at least one of the measures of systemic risk.

Panels A and B of Table 1 show descriptive statistics of our main country-level variables for the 64 and 65 countries in our sample with available data on *MES* and *SRISK*, respectively. The average *MES* is 2.6%, while *SRISK* represents approximately 2.4% of GDP. In general, most of the variables are comparable across the two samples, although countries in the *MES* sample tend to have higher stock market return. The average market return is 10.2% for the *MES* sample, but only 8.9% for the *SRISK*

[9] Because the indices are not available annually, we use the value of the variables from the first survey (data as of 1999) for the period 2000 to 2001, those from the second survey (data as of 2002) for the period 2002 to 2004, those from the third survey (data as of 2005) for the period 2005 to 2010, and the value of the variables from the last survey for the period 2011 to 2014.

subsample. Panel A of Figure 2 exhibits the average *SRISK-to-GDP* and *MES* across countries by year. Both series sensibly peak during the global financial crisis period in 2008 and remain at elevated levels through 2011. In Panel B of Figure 2, we show the average *MES* (*SRISK*) by region. We observe that systemic risk, as measured by *MES* is highest in Europe and Central Asia, followed by South and East Asia, and then North America. *SRISK* is also highest in Europe and Central Asia, followed by North America and East Asia. Appendix C shows the correlation matrix for all variables used in our analyses. We observe a negative correlation between bank flows and our two systemic risk measures, as well as positive correlations between *MES* and *SRISK* and non-interest income and volatility.

3. Linking Cross-Border Bank Flows to Systemic Risk.

To assess the impact of bank flows on the recipient country's systemic risk, we run various specifications of the following regression model:

$$Systemic\ Risk_{r,t} = \alpha + \beta Flows_{r,t-1} + \gamma X_{r,t-1} + \delta_t + \theta_r + \varepsilon_{r,t}, \tag{2}$$

where *Systemic Risk* refers to our measures of systemic risk, *MES* and *SRISK-to-GDP*. $Flows_{r,t-1}$ refers to *actual* or *instrumented* bank flows into recipient country *r* in year *t-1*. $X_{r,t-1}$ is a vector of recipient country controls that have been shown to impact systemic risk of the financial system: *GDP growth, Volatility, Market return, Non-interest income, Bank sector assets,* and *Concentration*. *Volatility* and *Market return* are variables used to estimate the systemic risk of a country by Engle, et al. (2015); non-interest income has been shown to impact systemic risk at the bank-level (Brunnermeier, et al., 2015) especially in less concentrated banking sectors (Engle et al., 2014). Finally, δ_t and θ_r are year- and recipient-country fixed effects, respectively. In all regressions, we report robust standard errors clustered at the recipient country level.

Clearly, it is possible that improvements in financial system stability (e.g., a decline in systemic risk) in the recipient country attract bank flows, which introduces a form of reverse causality that can affect the interpretation of our findings. We attempt to address these concerns by implementing an instrumental variable approach: we project cross-border bank flows on an instrumental variable that is relevant for cross-border flows, but is uncorrelated with the recipient country's systemic risk proxy. In particular, we use a variable that captures the propensity of source country institutions to operate and lend abroad but that should not have a first-order effect on systemic risk in the recipient country. We use percentage ownership of banks in foreign countries by a given source country, *Foreign ownership*, as in the previous section.

Valid instruments must satisfy the relevance condition and the exclusion restriction. While no instrument is perfect, our instrument seems to satisfy both conditions. For the relevancy condition, our instrument is anchored in forces (ownership of banks abroad) that likely affect source country outflows, which in turn could affect bank outflows from source country *s* to recipient country *r*. Yet, while this instrument should have an impact on outflows from source country *s*, the instrument excludes the ownership of banks in the recipient country's region, a critical ingredient for our instrument to satisfy the exclusion restriction. Diagnostic tests confirm the validity of our instrument on a statistical basis.

We show our main results from the estimation of Eq. (2) in Table 2. The dependent variable in all regressions is the systemic risk of the *recipient* country's financial system. In Models (1) to (4), we use *MES* to measure systemic risk and, in Models (5) to (8), we use *SRISK-to-GDP*. Models (1) and (5) show results using the actual cross-border bank flows, *Flows* (difference in the log of total foreign claims to recipient country *r* from *t*-1 to *t*) as the key independent variable. This variable represents the sum of all flows entering a recipient country regardless of the source. In Models (2) and (4), we divide *Flows* into *Inflows* and *Outflows*, based on whether the log-difference in foreign claims is positive or negative in that year and zero, otherwise. Finally, in Models (3) - (4) and (7) - (8), we show first- and second-stage results from 2SLS regressions in which we instrument *Flows* using the variable *Foreign ownership.*

For each model, we find reliable evidence that cross-border bank flows are correlated with a reduction in *MES* (*SRISK-to-GDP)* in the recipient country. Across all model specifications in which flows are included, the coefficient of -0.417 on *Flows* is negative and statistically significant at the 5% level or lower. Economically, this effect appears large. Taking the coefficients in Model (1) as an example, a one-standard-deviation increase in *Flows* (0.21%) is associated with a reduction in *MES* of 0.088, which represents 3.3% of its mean (2.63%) and 5.2% of its standard deviation (1.67%) across all recipient countries and years.

Our results when using our other measure of systemic risk, *SRISK*, in Models (5) to (8) imply even larger economic effects. Taking the coefficient of -1.355 in Model (5), a one-standard-deviation increase in *Flows* (0.21 for this sample of target-country years) is associated with a reduction in *SRISK* of 0.285, which represents 12.1% of the unconditional mean and 6.8% of its standard deviation (4.21) across all recipient countries and years. Overall, our results using *SRISK* are of larger magnitudes, but are otherwise consistent with those using *MES* as our measure of systemic risk. In Models (2) and (6), we observe that the impact on systemic risk stems from bank inflows into a recipient country. For example, for *MES* in Model (2), the coefficient on inflows is reliably negative at -0.727 and that associated with outflows is weakly positive at 0.698, which implies that systemic risk increases when bank flows recede.

The control variables in the specifications are in general consistent with prior studies. There is a reliably positive coefficient with market return volatility for both *MES* and *SRISK*, and for market return for the *MES* regressions, though not so for *SRISK*. In Engle et al. (2015), their Granger-causality tests indicate only a weak and unreliable relationship with those variables. Brunnermeier et al. (2015) focus on the significant negative relationship between non-interest-income as a fraction of interest-income for their measure of *MES* at the individual bank level in the U.S. before, during and after the global financial crisis. We find a significant positive relation at the country level for non-interest-income and *MES*, although it is insignificant for *SRISK*. At the country level, we see that *SRISK* is inversely related to economic growth (as measured by GDP growth), although this relation is insignificant for *MES*. This is not easily comparable to Engle et al. (2015) as they only examine developed markets in Europe and individual U.S. banks. The adjusted R^2 is well above 60% for *MES* regressions and above 70% for *SRISK* regressions. Unobserved recipient country fixed effects comprise much of that explanatory power and year fixed effects do so to a much less extent.

While the results show that bank flows are associated with a reduction in systemic risk in the recipient country, these results still do not give us confidence that we have established grounds for causal interpretations because flows are not exogenous. To address these concerns, we show results from an instrumental variable approach in Models (4) - (5) and (7) - (8). The first-stage regression results in Models (3) and (7) show that our instrument exhibits reliable explanatory power for cross-border bank flows. The coefficient on our instrument is a weakly positive 0.011 for *MES* and more robustly positive 0.015 for *SRISK*. More ownership of banks in countries outside of the recipient country's region among the source countries that "matter" for a given recipient country (defined as ones that are geographically proximate) are associated with more bank flows to that recipient country. A one-standard-deviation increase in *Foreign ownership* (3.37%) is associated an increase in *Flows* of 0.0371, which is 53% higher than its unconditional mean (0.07) and it constitutes 17.65% of its unconditional variation. The partial *F*-tests (*p*-value of 0.053 and 0.005) reliably reject the null hypothesis that the instrument has no explanatory power for *Flows*.

Turning to the second-stage results, we find that the coefficients on the instrumented *Flows* remain negative and statistically significant in Models (4) and (8) for *MES* and *SRISK*, respectively. The magnitude of the estimated coefficients are, in fact, much larger than the analogous specifications for actual flows, and the implied economic magnitudes are larger notwithstanding the fact that the *Flows* variable is transformed due to its first-stage projection on the *Foreign ownership* instrumental variable. Using the significant negative coefficient of -8.338 in Model (4) for *MES*, a one-standard-deviation increase in instrumented *Flows* (0.12) is related to a 1.01% decrease in *MES* in the recipient country, which is a 38% decrease relative to its mean. Results are similar in magnitude when using our alternate measure of systemic risk (*SRISK-to-GDP*) in Model (8).

We perform a *post hoc* statistical test of the external validity of the instrumental variable by regressing residuals from second-stage regressions in Models (4) and (8) on the *Foreign ownership* variable. The *p*-values of the respective *F*-statistics for this overidentification test are well above any reasonable threshold for statistical significance, suggesting that the instrument is valid.[10]

A potential drawback of using the BIS's CBS data is the fact that breaks-in-series and exchange rate changes could create large outliers in our measure of bank flows, which may lead to incorrect inferences. To ensure that outliers or issues associated with the quality of the CBS data do not drive our results, in Panel B of Table 2, we replicate our results using data from the BIS Locational Banking Statistics (LBS).[11] Appendix E describes the different nature of the LBS and CBS data. Specifically, we use changes in the BIS break- and exchange-rate-adjusted foreign claims, scaled by total banking sector assets (*ΔClaims-to-assets)*. The results in Panel B validate our findings using CBS data in Panel A. Bank flows, measured as changes in foreign claims-to-assets are associated with lower systemic risk. The magnitude of the results is slightly larger than those we reported earlier in Panel A. As an example, from Model (1) in Panel B of Table 2, a one-standard-deviation increase in *ΔClaims-to-assets*, (5.79%) is associated with a reduction of 0.162 in *MES*, which represents 6.2% (9.7%) of its unconditional mean (standard deviation). Importantly, the results using the LBS data continue to hold even after we instrument *ΔClaims-to-assets* using *Foreign ownership.* That our findings continue to hold with the CBS data notwithstanding the breaks-in-series and exchange rate fluctuations that it fails to control gives us additional confidence in the main findings.

3.1 Systemic risk and predicted *cross-border bank flows.*

As mentioned in the introduction, identifying the impact of cross-border bank flows on the aggregate systemic risk of recipient countries is difficult because changes following inflows or outflows can be attributed to other changes in the macro-economy or capital markets around the same time. In this

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[10] We perform these tests in lieu of a Hansen's *J*-statistic overidentification test because our equation is exactly identified since we only have one instrument. We cannot perform a formal test of the over-identifying restrictions. In earlier tests, we explored combinations of instrumental variables based on multiple combinations of source-country capital export restrictions from Fernandez et al. (2015) and source country regulatory variables from Barth et al. (2013). In these cases, we were able to employ Hansen's overidentification test and our inferences were similar.

[11] LBS data provide outstanding claims of internationally active banks, but it does not allow us to identify the source country of the claims, which prevents us from using it for our bilateral regressions in the next section. As an example, if a U.S. bank's Italian subsidiary makes a loan to a German firm, the LBS data would record this as an Italian claim on Germany, while the CBS data would more correctly record this as a U.S. claim on Germany. Both data correctly identify the recipient country.

section, we pursue an alternate approach to address this identification challenge. That is, we estimate *predicted* bank flows using a gravity model across source-recipient country-pair-years. Building on prior studies (Houston, et al., 2012; Karolyi and Taboada, 2015), we model pre-determinants of cross-border bank flows for a sample of 26 source countries and 114 recipient countries over the period from 1995 through 2014 using a gravity model adapted from the international trade literature. The predicted values from the model are extracted and then aggregated on a weighted average basis for a given recipient country from across all source countries in which the weights capture different measures of economic links to the recipient country. The goal of this alternative approach is that we can isolate the most salient components of the flows by separating out other confounding macroeconomic and capital market forces as well as institutional forces that are at work.

We first estimate bank-flows by country-pair-years using various specifications of the following gravity model using all available data from 1995 to 2014:

$$Bank\ Flow_{s,r,t} = \alpha + \beta_1 \Delta X_{s,r,t} + \beta_2 Z_{s,r} + \gamma_t + \delta_s + \theta_r + \varepsilon_{s,r,t}. \tag{3}$$

Bank Flow$_{s,r,t}$ is the difference in the log of total foreign claims from *t-1* to *t* from source country *s* to recipient country *r*. ΔX is a vector of controls that have been shown to influence bank flows, measured as differences between source county *s* and recipient country *r*, which includes: (1) *Foreign ownership*, our instrumental variable; (2) the creditor rights index (*Creditor rights*) from Djankov et al. (2007) to control for the power of secured creditors; (3) the depth of credit information (*Credit depth*) from the World Bank's Doing Business database to control for the information content of credit information; (4) the property rights index (*Property rights*) from the Fraser Institute as a proxy for the quality of legal institutions; (5) the *log of GDP per capita*; (6) real *GDP growth;* (7) the natural log of population (*Population*), (8) *Real exchange rate return*, the annual real bilateral U.S. dollar exchange rate return; and, (9) *Bilateral trade*, the maximum of bilateral imports and exports scaled by recipient country GDP. *Z* is a vector of variables commonly used in the trade literature to explain resistance to greater cross-border trade flows, which we obtain from Mayer and Zignago (2011). These include the log of the circle distance in kilometers between countries' capitals (*Distance*), an indicator variable for countries that share the same language (*Same Language*), and indicators for countries that belonged to the same colony (*Colony*), and those that share a border (*Contiguous*). Finally, γ_t, δ_s, and θ_r refer to year, source, and recipient country fixed effects, respectively.

The results from these regressions are in Table 3. Models presented here replicate the prior work of Houston, et al. (2012), and we find our results to be mostly consistent.[12] The coefficients on *GDP growth*, and *Property rights* are reliably significant and negative. Cross-border bank flows are stronger in the direction of relatively faster growing economies with stronger property rights. Also consistent with Houston et al. (2012) we find negative coefficients on differences in *Creditor* rights, and *log of GDP per capita*, although the coefficients lose their statistical significance in certain specifications. The positive and reliably significant coefficients on *Same Language* and *Colony* and the negative and significant coefficient on *Distance* in all regressions confirm what is found in many gravity models involving economic flows: the greater the distance between two countries (geographically or by common language), the lower are the cross-border flows.

In Models (1) through (5), we present results from panel regressions using various specifications and alternate set of control variables. In Model (3), we include *Financial Liberalization*, an index of financial liberalization from Abiad, Detragiache and Tressel (2010). The inclusion of *Financial Liberalization* significantly reduces the sample from 21,277 country-pair-year observations to only 16,342 and the coefficient on that variable, while negative, is statistically insignificant. Model (4) introduces regulatory variables that allow us to test whether cross-border bank flows are influenced by differences in the quality of the regulatory environment. We find that the coefficient on *Restrictions on bank activities* is positive and statistically significant, thus confirming the findings in Houston et al. (2012) that banks transfer funds from (to) countries with more (fewer) regulations. Just as interesting to us is the fact that many of these measures of regulatory quality have no explanatory power, such as the

[12] Our results replicate Table 4 of the Internet Appendix from Houston, et al. (2012). We explored alternative specifications to deal with the large proportion of zeros among the country-pair-year observations in the flows and the potential biases that can arise. The primary alternative estimation approaches drawn from the international trade literature to deal with include Poisson pseudo-maximum likelihood (PPML) of Santos-Silva and Tenreyro (2006), and Irrarazabal, Moxnes, and Opromolla (2013) and simulated method of moments (SMM) following Bernard et al. (2003), and Simonovska and Waugh (2014). Karolyi and Taboada (2015) examine the tradeoffs in these three different estimation approaches for cross-border bank acquisition flows.

degree of independence of supervisory authorities, the stringency of capital requirements, the extent of private monitoring and the strength of external auditing for banks. In Model (5), we over-saturate our panel regression model with a full set of recipient-country-year, and source-country-year fixed effects, excluding the controls. The goal here to control for additional unobservable time-varying factors at the country level that may explain flows. Indeed, there is a significant increase in the explanatory power from Model (4) to Model (5) with the adjusted R^2 reaching as high as 19.6%. This means that our pre-specified explanatory variables capture only one-third of the potential variation in country-pair-year flows.

Finally, in Model (6), we show average coefficients from regressions using a five-year rolling window, our preferred approach to estimate predicted flows. Our estimation window to obtain predicted flows for year *t* ends in year *t-1* to avoid introducing any look-ahead bias. The predicted values from the model are extracted and aggregated on an average basis for a given recipient country across all source countries using lagged foreign claims from source country *s* to recipient country *r* as weights. To aggregate predicted flows to the recipient country-year level, we compute:

$$Predicted\ Flows_{rt} = \sum_{s=1}^{N} \hat{y}_{s,r,t} \times \frac{Foreign\ claims_{s,r,t-1}}{Total\ foreign\ claims_{r,t-1}}\ . \tag{4}$$

Subscript *r* refers to recipient country, *s* refers to source country, and $\hat{y}_{s,r,t}$ are the predicted values from estimating Equation (3) using a 5-year rolling-window approach. $Foreign\ claims_{s,r,t-1}$ are the total foreign claims by source country *s* on recipient country *r* as of *t-1*, and $Total\ foreign\ claims_{r,t-1}$ are the total foreign claims from all source countries on recipient country *r* in year *t-1*. Note that we aggregate across all 26 BIS-reporting source countries in Eq. (4).[13] Table 1 also reports summary statistics associated with the predicted flows computed using this approach. We find that, for our *MES* sample (Panel A), the mean *Predicted flows* is 0.17 with a standard deviation of 0.55, and for the *SRISK* subsample (Panel B), the mean *Predicted flows* is 0.17 with a standard deviation of 0.54. There is an increase in the unconditional variation in the predicted flows relative to the actual flows.

[13] In robustness tests, we aggregate predicted flows using equal weights as an alternative weighting scheme.

Table 4 next exhibits the results of the second-pass regressions using the predicted flows and our systemic risk proxies. In Models (1) and (2) we show results using *MES* and Model (3) and (4) show results for *SRISK*. These are the analogous specifications of Models (1) and (5) in Table 2 using the actual cross-border bank flows. For *MES*, the coefficient of -0.305 for *Predicted Flows* is statistically reliable and economically as large as implied in Table 2. A one-standard-deviation increase in *Predicted Flows* (0.55) is related to a 0.168% decrease in *MES* in the recipient country, which is 6.4% of its unconditional mean and 10.1% of its standard deviation (1.66 for this subsample). Likewise, using the coefficient from Model (3), a one-standard-deviation increase in *Predicted Flows* (0.54) is related to a 0.395% decrease in *SRISK* in the recipient country, which is equivalent to 16.2% of its mean (2.43 for this sample) or 9.8% of its standard deviation (4.02). These are comparable comparative statics to what we showed in Table 2. The results using *Predicted* Flows aggregated using equal weights in Models (2) and (4) are similar to those using the value-weighted *Predicted Flows*. The results for *Actual Flows* were economically similar in magnitudes to those for *Predicted Flows*. A focus on predicted flows from specifications that control for known determinants of bank flows, while far from perfect, should alleviate some concerns that bank flows are contaminated by contemporaneous macroeconomic or capital market forces at work that can influence changes in systemic risk in the recipient country.

3.2 Cross-border bank flows, systemic risk and a couple of financial crises.

In this section, we explore whether and how the impact of bank flows on systemic risk is affected by countries' financial development, and by two major financial crises during our sample period: the global financial crisis (*GF crisis*) and the European sovereign debt crisis (*Euro crisis*). To do so, we run regressions using interactions between our instrumented bank flows measure, (which we denote from here on *Flows - IV*) and three indicator variables. Specifically, we use three indicators: (1) *Developed* – an indicator that equals one for developed markets, using the MSCI Developed markets definition; (2) *GF Crisis*, an indicator that is equal to one for years 2008 and 2009 and 0 otherwise, and (3) *Euro crisis*, an indicator variable that is equal to one for years 2010-2012 and zero otherwise.

Table 5 shows the results from these regressions. In Models (1) - (4), we show results using *MES* as our dependent variable, while Models (5) - (8) show results for *SRISK*. The results from Model (1) suggest that the reduction in *MES* that is associated with bank flows is stronger in developed target markets. A one-standard deviation increase in *Flows - IV* is associated with a decrease of 0.793% in MES in emerging markets, which represents a decrease of 30.2% relative to its mean. For developed markets, a one-standard deviation increase in *Flows - IV* is associated with a larger 1.04% reduction in *MES*, or 39.5% relative to its unconditional mean. Results are similar for *SRISK* (Model 5).

In Model (2), we assess the impact of the global financial crisis in 2008-2009. The results show that the impact of bank flows on systemic risk is mostly unchanged or modestly abates during the global financial crisis. During crisis years, a one-standard deviation increase in *Flows - IV* is associated with a -0.648% reduction in *MES*, or a 24.6% reduction relative to its mean. In non-crisis years, the impact is significantly stronger, implying a 35.8% reduction in *MES* relative to its unconditional mean.[14] From Model (3), we observe that the impact of bank flows on systemic risk across our full sample of recipient countries was not different during the European debt crisis (2010-2012. However, for European countries in Models (4) and (8), we observe that bank flows are only weakly associated with systemic risk, and there is no differential impact during the European sovereign debt crisis. We conclude from these findings that our overall results are not driven by Europe or perturbed unusually during the Euro debt crisis.

4. Understanding the potential mechanisms at the bank level.

Our results thus far show that bank flows are associated with positive consequences (lower systemic risk) for the recipient countries. But all of the analysis to now takes place at the country level. Of course, a large fraction of these bank flows is comprised of bank-to-bank lending activities. To examine more closely how bank flows are affecting systemic risk in the recipient countries, we now turn our

[14] From Model (2) in Table 5, a one-standard deviation increase in *Flows-IV* is associated with a -0.943 (-7.857 × 0.12) reduction in MES in non-crisis years, or a 35.8% reduction relative to its mean (-0943/2.63). During crisis years, a one-standard deviation increase in *Flows-IV* is associated with a -0.648 ([-7.857+2.459] × 0.12) reduction in *MES*, or a 24.6% reduction relative to its mean (-0.648/2.63).

attention to the banks within the recipient countries. To this end, we obtain bank-level financial data from Fitch Solutions' *Fundamental Financial Database*. Fitch Solutions provides comprehensive financial bank data covering over 33,000 banks in more than 200 countries. We obtain fundamental data for those banks with market data available in *DataStream* that we used to construct our main systemic risk measure at the bank level, or *MES*. After dropping banks with missing data on total assets and those with a negative book value of equity, we end with a final sample of 1,661 banks in 61 countries, totaling 14,008 bank-year observations.

Our goal for this analysis is to examine how an individual bank's *contribution to* systemic risk is associated with cross-border bank flows. By exploring the impact of bank flows on individual banks, we can provide tests of predictions from theories of multinational banking about the impact of globalization of bank systems on risk-taking, in general, and on bank-level systemic risk, in particular. This part of our study is also motivated by the emerging literature on how banks adjust their performance, their risk-taking and other policies, as they become more globalized. There is some recent research on this question that suggests that the riskiness of banks increases as they expand globally (Gulamhussen, et al., 2014; Berger, et al., 2016; and, Jeon, et al., 2016), while other studies suggest that international expansion reduces bank and systemic risk (Faia et el., 2017). However, these papers do not directly address the systemic risk consequences of globalization for the recipient countries, nor do they examine the potential role of cross-border bank flows as the mechanisms through which risk-taking propagates.

The BIS consolidated foreign claims data do not allow us to identify which banks are the recipients of the cross-border bank flows. But, our bank-level market-based measure of systemic risk is obtained from *DataStream*, which covers large banks, so it seems sensible to assume that some of these large banks should be directly or indirectly affected by cross-border bank flows. We measure systemic risk using *MES* at the bank level, where *MES* is defined as the bank's average stock return when the stock market is in the 5% left tail of its return distribution in that year. As before, we take the negative value of *MES* as our measure so that it is increasing in systemic risk. The next step is to describe the characteristics and attributes of our global sample of banks.

4.1. A global sample of individual banks.

Table 6 provides summary statistics for the bank-level variables we use in the bank-level analysis. Our sample consists of large banks, with average (median) total assets of $3.3 billion ($2.5 billion). For the average bank, income from nontraditional banking activities (non-interest income) represents about 26.2% of total income, while non-deposit short-term funding represents about 5.5% of total liabilities. Not surprisingly, since our sample period covers the financial crisis, banks' ROA is relatively low at 0.65%. About 4.8% of the banks in our sample are foreign-owned.

We first examine the average effect of bank flows across all banks in the country. Table 7 presents our main bank-level results. We report results from OLS as well as two-stage least squares (2SLS) regressions that include individual bank and year fixed effects. Standard errors are robust and clustered at the country level, as before. We include several country and bank-level variables that have been shown to impact systemic risk (see, e.g., Laeven, Ratnovski, and Tong, 2016; Anginer, Demirgüç-Kunt, and Zhu, 2014). Firm-level controls include: *Size* (log of assets in US$ million); the proportion of income generated from nontraditional commercial bank activities (*Non-interest income*); reliance on non-deposit short-term funding (*ST funding*), *Leverage* (measured as book value of assets-to-equity); profitability (*ROA*); and, proxies for cost efficiency (*Non-interest expense*) and asset quality (*NPL-to-loans*). We also incorporate country-level controls: *GDP growth*, *Volatility*, *Market return*, *Non-interest income*, *Bank sector assets (*log of total banking sector assets*)*, and a proxy for bank concentration (*Concentration*) to account for the impact of competition on banks' systemic risk (Anginer, et al., 2014).

In Model (1) of Table 7, we show results from OLS regressions for actual bank flows. The coefficient for *Flows*, -0.440 is reliably different from zero. The economic effect of total flows is significant. We estimate, using the coefficient in Model (1), that a one-standard-deviation increase in *Flows* (0.153) is associated with a 0.067 decrease in *MES*, which represents about a 4.2% decrease relative to its mean (1.61). This magnitude accords well with what we reported in Table 2. Model (2) repeats the same regression except that actual *Flows* is separated into *Inflows* (positive changes in foreign claims from *t-1* to *t* and zero otherwise) and *Outflows*. As we saw in Table 2 at the country level, the negative coefficient on *Flows* is concentrated on the subset associated with inflows. We find that, on average, cross-border bank flows are negatively associated with the contributions to systemic risk of individual banks.

It is perhaps not surprising that unobservable bank- and year-fixed-effects capture a significant fraction of the overall explanatory power of *MES* across our bank-year sample of 14,008 observations. Beyond these fixed effects, the only bank-level variables that have reliable explanatory power in this setting are the log of bank assets, and the *NPL-to-loans*, which are positive. Larger banks, and banks with weaker loan quality, as expected, contribute more to systemic risk. Brunnermeier, et al. (2015, their Table V) confirm the former finding for their measure of realized systemic expected shortfall for U.S. banks during the global financial crisis. In this bank-level sample, we confirm the findings in Table 2 that market index returns and market volatility are reliably positively correlated with *MES*, but, unlike for the recipient country-year sample in the earlier table, we no longer find reliable evidence that *MES* is larger for banking sectors with higher levels of non-interest income.

In Models (3) - (4) of Table 7, we show results from first- and second-stage 2SLS regressions using the *Foreign ownership* instrumental variable constructed at the recipient country level. The first-stage regression projects the actual *Flows* on the instrumental variable including the bank and country level controls. The coefficient on *Foreign ownership* is reliably positive as before. The economic effect is noteworthy: a one-standard-deviation increase in *Foreign ownership* is associated with a 0.113 increase in *Flows*, or about 73% of its unconditional standard deviation. The first-stage *F*-statistics allow us to reject the null hypothesis that it is uncorrelated with bank flows. In Model (4), the coefficient on instrumented *Flows* for an individual bank's *MES* is -1.172 and it is statistically significantly different from zero. A one-standard-deviation increase in instrumented *Flows* (0.275) is associated with a 0.322 decrease in *MES*, or 19.9% of its unconditional mean at the individual bank-year level. The relationship implied by these coefficients are larger than those implied at the country level. Finally, in Model (5) we show results using interactions between *Flows - IV* and our *Developed* indicator. The results confirm those from our country-level analysis and suggest that the impact of *Flows* on *MES* is concentrated among developed markets as target countries. The coefficient on *Flows – IV* is insignificantly different from zero and all the explanatory power shifts to its interaction with *Developed*.

4.2. Bank flows and systemic risk by individual bank exposures.

We next examine how bank flows affect different types of banks. Specifically, we assess the differential impact of bank flows on banks with different size, leverage, asset quality, and cost efficiency. To this end, we first sort banks in each country into quintiles based on: (1) *Size*, or log assets; (2) *Leverage*; (3), asset quality (*NPL-to-loans*), and (4) cost efficiency *(Non-interest expense,* as a fraction of gross revenues). Using these quintile indicators, we run regressions including interactions between our instrumented bank flows measure (*Flows - IV*) and each bank characteristic quintile. In all regressions, we include bank and year fixed effects and cluster the standard errors at the country level.

Figure 3 reports the coefficients on the interactions terms (*Flows –IV × Quintile*) along with the 95% confidence interval, represented by the shaded region in the graphs. In Panel A, the graph shows results using bank size (log of assets). Although the impact of bank flows on bank-level *MES* is significantly negative across size quintiles, the impact is notably stronger for larger banks (top quintile) banks. The *F*-test (*p*-value of 0.003) confirms that the coefficients on the interaction terms are reliably different across size quintiles. In Panel B, the graph shows results using bank leverage. The impact of bank flows on bank-level *MES* is weakly significant across quintiles of leverage (*p*-value of *F*-test is 0.109), but visually it is hard to find differences across them.

In Panel C of Figure 3, we show equivalent results using quintiles based on *NPL-to-loans* ratio as a measure of asset quality. The results show that the impact of bank flows on *MES* does not differ based on banks' asset quality (*p*-value of *F*-test is 0.191). Finally, in Panel D we show results using non-interest expense-to-gross revenues as a proxy for cost efficiency. The results reveal that the magnitude of the impact of bank flows is larger for banks that are more efficient (bottom quintile of non-interest expense). The *F*-test (*p*-value of 0.019) confirms that the coefficients on the interaction terms are different across cost efficiency quintiles. Overall, cross-border bank flows appear to be associated with a decrease in *MES* and these bank flows are associated with a decrease in *MES* through a bank channel involving those that are larger and more efficient. We interpret these preliminary findings as consistent with the competitive channel delineated by Boyd and De Nicoló (2005) and Faia and Ottaviano (2017) in their respective models. Direct involvement of global banks in local activities in their model can reduce risk-taking by promoting local competition. Indeed, the larger, more efficient banks in a target market are more likely to have correlated projects with those of the multinational banks and it is they that appear to be most acutely treated by the increased in cross-border bank flows.

4.3. Does the link between bank flows and systemic risk matter by country?

With these bank-level regressions available to us, we now turn to examine how the impact of bank flows on bank-level systemic risk might differ based on country characteristics. We first explore *de facto* characteristics of the banking sector in the target markets. Banks in countries with weaker banking sectors may benefit more from bank flows into the country. Banks in such countries may not have as much access to capital in the domestic market and thus rely more on cross-border bank flows (e.g. loans obtained from a foreign bank). On the other hand, if banks in weaker countries obtain access to capital through cross-border bank flows, they may in turn misuse those funds and invest in excessively risky or poor projects, which may adversely affect their performance and in turn, destabilize the banking sector.

To examine this hypothesis, we first sort countries into quintiles based on four *de facto* characteristics: *Bank sector assets (scaled by GDP)*; *Bank sector capital*; *Bank sector NPL-to-loans*, and, *Bank sector ROA*. We then run panel regressions with bank and year fixed effects using bank-level *MES* as our dependent variable and include interactions between our instrumented bank flows measure (*Flows - IV*) and each *de facto* quintile indicator. We show these results in Panel A of Figure 4, where we plot the coefficients on the interaction term (*Flows - IV* × *Quintile*) along with the 95% confidence interval, represented by the shaded region in the graphs.

Results in Panel A of Figure 4 show that bank flows lead to a more significant reduction in *MES* for banks in countries with larger banking sectors. The *F*-test (*p*-value is 0.021) confirms that the magnitude of the coefficients on the interaction term (*Flows IV* × *Quintile*) differs across bank sector size quintile. The reductions in *MES* are larger in target markets with larger bank sectors as a percentage of the country's GDP. More dramatic reductions in *MES* are also noted for target markets with less capitalized banking sectors (*p*-value of *F*-test is 0.085). We observe no difference in the impact of bank flows by the asset quality or the profitability of the banking sector.

Houston et al. (2012) show that the direction of bank flows is in line with regulatory arbitrage, which they interpret as having adverse consequences on recipient countries. To address this question in our setting, we examine the impact of bank flows on bank-level *MES* based on recipient countries' *de jure* regulatory quality. We use four *de jure* regulatory quality variables from Barth, Caprio, and Levine (2013): *Restrictions on bank activities*; *Official supervisory powers*; *Stringency of capital requirements*; and, *Private monitoring*. In line with our prior analysis based on *de facto* country characteristics, we use our four *de jure* measures to sort recipient countries into quintiles based on each measure. We then run regressions and include interactions between our instrumented flows measure and each quintile indicator. The results are in Panel B of Figure 4.

These results show that the impact of cross-border bank flows on *MES* is stronger for banks in countries with less stringent capital requirements (*p*-value of *F*-test is 0.034). In fact, the top-left figure suggests that the impact is larger for all but those banks in countries with the most stringent restrictions on capital (highest quintile). The impact of bank flows on bank-level *MES* does not appear to differ based on any other *de jure* measures of regulatory quality, which is surprising given the findings in Houston et al. (2012). The *F*-tests for the equality of the interaction terms across quintiles is insignificant in all other regressions.

We can push our inferences one step further based on these figures in Panel B of Figure 4. The results do show consistent evidence against what some regard as the destructive view of regulatory arbitrage in cross-border bank flows. Using all four measures of regulatory quality, we observe that bank flows are associated with *declines* in *MES* for individual banks even in countries with the weakest (bottom quintile) levels of regulatory quality. If anything, our evidence here suggests that bank flows (that tend to come from countries with better regulatory quality than that of the typical recipient country) have positive stabilizing effects on banks and banking sectors of the weakest countries.

4.4. Long-run impact of bank flows on MES, performance and risk-taking.

We next explore whether the impact of bank flows has a long-lasting effect on bank-level *MES*, performance, and risk-taking. We first examine the long-term impact of bank flows on *MES* by exploring the impact of our instrumented bank flows measure (*Flows - IV*) in years *t*, *t-1*, *t-2*, and *t-3*. We report the coefficients from regressions of bank-level *MES* with bank and year fixed effects and control variables on contemporaneous and lagged *Flows - IV* in Figure 5. As before, we show the coefficients as well as the 95% confidence intervals. The results suggest that the impact of bank flows on *MES* is relatively short-lived. The impact becomes insignificant after the first year. It should be noted that the magnitude of the 95% confidence interval also widens with the longer duration tests of impact which reflects back that there are ever increasingly fewer observations and less precision in estimation.

Next, we investigate the channels through which systemic risk can be reduced as a result of heightened cross-border bank flows. In this analysis, we focus on the longer-term impact of bank flows into a recipient country at the individual bank level. With the additional flows into a recipient market, our goal is to assess how banks in the recipient country change their performance, risk-taking, or other policies in the years following. One important caveat is that the BIS data does not allow us to identify the banks that are treated ("receive" the funds) by the bank flows. We thus rely more coarsely on assessing the *average* impact for individual banks in the recipient country.

We examine the long-term impact of bank flows by exploring the impact of *Flows - IV* in years *t*, *t-1*, *t-2*, and *t-3* on various measures of bank performance, risk-taking and other policy choices. Specifically, we analyze the impact of bank flows on profitability (*ROA*), cost efficiency (*Non-interest expense* as a fraction of total income), *Leverage*, and asset quality (*NPL-to-loans*). The results are presented in Figure 6. They reveal that bank flows are associated with improvements in annual profitability. Consider, for example, the *ROA* results (Panel A), for which the contemporaneous (year *t*) regression coefficient on *Flows - IV* is 2.426. A one-standard-deviation increase in *Flows - IV* (0.262) is associated with a 0.636 increase in *ROA*, which represents a 97.4% increase relative to its mean. Table 6 shows that the average bank's net income as a fraction of total assets is 0.653%, thus a 97.4% increase represents an increase in *ROA* to 1.29%. The figure shows that the effect dissipates dramatically within one year of the cross-border inflows – the 97% confidence interval band straddles zero for years *t-1*, *t-2*, and *t-3*.

How this gain in profitability is realized may be through greater cost efficiency. The results in Panel B of Figure 6 show that the long-run impact of bank flows is associated with a decrease in non-interest expenses as a fraction of gross revenues reaching by the second year (top right in Figure 6). There is some reliable evidence of long-term improvements in asset quality as well (Panel D). The impact here appears statistically and economically significant. We find that a one-standard deviation increase in *Flows - IV* (0.262 for this sample) is associated with a 3.132 decline in *NPL-to-loans* in year *t*, or an 85.14% decline relative to its mean. The average bank's *NPL-to-loans* ratio is 3.679%; thus, an 85.14% decrease represents a decrease in *NPL-to-loans* to 0.547%. This could be a result of better lending decisions, which may be influenced by lending banks' (banks from countries with better regulatory quality) oversight of the recipient country banks' activities. The impact is statistically significant, but of lower magnitude in the three years subsequent to the flows. The impact on leverage is negligible.

The observed improvements in asset quality, profitability, and cost efficiency associated with bank flows appear to be inconsistent with the risk-taking view of bank globalization (Detragiache, et al., 2008) and more consistent with the competition view of globalization (Faia and Ottaviano, 2017). Rather than increasing risk-taking by banks, which would lead to poorer asset quality, we observe such flows are associated with improvements in asset quality. Perhaps the greater presence of source banks in the recipient market by means of these flows serves as a greater monitoring role or one that stimulates better risk management processes. By greater monitoring or by stimulating more discipline toward risk management in target country bank activities, the global banks that represent the source flows are typically from countries with more stringent regulatory regimes (Houston et al., 2012). And they do appear to help recipient banks lower their exposure to riskier activities, improve their asset quality, cost efficiency, and profitability, which, in turn, may lead to the improvements in the stability of the banks and the banking sector.

4.5. Assessing the Channel of Reductions in MES.

Our results show that bank flows are associated with a reduction in bank-level *MES*. These flows are also associated with long-term improvements in profitability, asset quality, and cost efficiency. As a final experiment, we will examine how banks that reduce *MES* during large inflows of capital respond in terms of their performance. Here we focus on the differential impact of large (small) bank inflows into a recipient country at the individual bank level. Specifically, each year we create indicator variables of *High* (*Low*) *Inflows* that is equal to one if bank inflows in year *t* are above (below) the cross-country median. In addition, we sort banks into groups based on the change in *MES* in year *t*. We create two indicator variables. *ΔMES<0* (*ΔMES>0)* is an indicator variable that is equal to one if a bank experienced a reduction (increase) in *MES* in year *t* and zero otherwise. Using these indicator variables, we run regressions using four measures of bank performance as the dependent variable: *ROA*; *Non-interest expense*; *Leverage*; and, *NPL-to-loans*. In the regressions we include interactions between the *High* (*Low*) *Inflows* and the *ΔMES<0* (*ΔMES>0)* indicators.

We present results from these regressions in Table 8. Bank level controls include: *Size*; *Non-interest income*; *ST funding; Leverage*; *ROA*; *Non-interest expense*, and *NPL-to-loans*. We also incorporate country-level controls that include *GDP growth*, *Volatility*, *Market return*, *Non-interest income*, *Bank sector assets,* and *Concentration.* In Table 8, we only report the coefficients from the interaction terms. In Panel A we report results using *ROA* and *Non-interest expense* as the dependent variable, while Panel B reports results from regressions of *Leverage* and *NPL-to-loans*.

The results in Panel A of Table 8 suggest that banks in countries that experienced large inflows experienced significant improvements in *ROA*. In countries that experienced large inflows, the impact was stronger for banks that decreased *MES (p*-value of *F-test* is 0.035). The impact on *ROA* was smaller in magnitude for countries that experienced low inflows. We find similar results using non-interest expense. Banks in countries with large inflows experienced a large reduction in non-interest expense. The impact was strongest in banks that experienced a reduction in *MES*. The results in Panel B of Table 8 show significant reductions in leverage for banks in countries that experienced large inflows, but the impact is significant only for banks that decreased *MES*. Similarly, the results show a reduction in non-performing loans only for banks in countries with large inflows. The impact is stronger for banks that decreased (relative to those that increased) *MES* in those countries (*p*-value of *F-test* is 0.000). Overall, the results show that the reduction in *MES* was followed by improvements in profitability cost efficiency, and asset quality. Banks in countries that experienced large inflows experienced larger improvements in performance. Finally, the improvements in performance were stronger for banks that decreased *MES*.

5. Robustness tests.

We perform various tests to examine the robustness of our results. First, we test the robustness of our results to alternate measures of systemic risk and report these in our online appendix. Specifically, we use four alternate proxies for systemic risk: *SRISK-to-assets– SRISK* scaled by total banking system's assets instead of country GDP; *CatFin* (Allen, Bali, and Tang (2012); *Turbulence* (Kritzman and Li (2010)), and *Systemic PCA–* the first principal component of *SRISK-to-GDP*, *MES, CatFin,* and *Turbulence.*[15] With the exception of *Catfin* and *Turbulence*, we find that our results are robust to these alternate measures of systemic risk.[16] One additional concern with our results is that our *MES* measure is correlated across countries. To assess how this may affect our results, we orthogonalize the unique country-specific dimension of *MES* and use the orthogonalized measure as our dependent variable. Specifically, we first run regressions of country-level *MES* on the average cross-country *MES*, excluding country *i*. We extract the residuals from these regressions and use them as our dependent variable. We report the results in our online appendix. The results using the orthogonalized *MES* are similar in magnitude and statistical significance as our main results.

[15] *Turbulence* measures excess volatility and compares the realized squared returns of financial institutions with their historical volatility. *CatFin* measures the time-varying value at risk at the 99% confidence level. We follow Giglio, et al., (2015), who calculate this measure as the average of the empirical distribution VaR and the Generalized Pareto Distribution VaR for all banks in a given country.

[16] The coefficient on *Flows* remains negative, but is statistically insignificant in regressions using *CatFin* and *Turbulence*. Our sample size is reduced to 503 (427) when using these measures, which may explain the lack of significance.

We also conduct robustness tests for our main bank-level results (Table 7). First, we also replicate our bank-level results (specifically, those in Table 7) using LBS data, which allow us to correct for breaks in series and for the impact of exchange rates. As before, we use the percent changes in claims to assets (claims-to-total assets) as our measure of flows. In addition, given that U.S. banks make up the majority of banks in our sample, we run regressions excluding U.S. banks. Overall, our main findings are robust to these alternate regression specifications. We report these results in our online appendix.

4 Conclusions.

This paper examines the link between cross-border bank flows and the financial stability of recipient countries by assessing how bank flows affect the country's systemic risk, measured by *MES* and *SRISK-to-GDP*. The goal of the study is to shed new light on the ongoing debate on whether bank globalization, and cross-border lending activity, in particular, is detrimental or potentially beneficial to recipient countries. Overall, these bank flows are associated with improved financial stability (i.e. lower systemic risk) in the recipient country. The relationship is stronger in developed markets. In addition, the reduction in bank-level systemic risk associated with bank flows is larger in magnitude for banks in countries with larger banking sectors and lower capital. We also find some evidence that the impact of bank flows on *MES* is stronger in countries with weaker regulatory quality (less stringent capital requirements). . Overall, our findings suggest that bank flows are beneficial to the recipient country. We also find that the impact of bank flows differs across banks in the recipient country. Specifically, we find a reduction in systemic risk for larger and more efficient (lower non-interest expense) banks. Furthermore, the bank flows appear to affect systemic risk in the recipient country by improving banks' profitability, asset quality and cost efficiency.

Overall, our findings shed light on the long-standing debate about the benefits and costs of cross-border lending and bank internationalization, in general. Our results suggest that recipient countries benefit from cross-border bank lending through improved financial stability. The evidence should be of particular interest to regulators who may be concerned with the impact of cross-border lending activities.

For scholars, we present what we believe is the first evidence in the finance literature of the effect of cross-border flows on the stability of a country's financial system. In doing so, we open the door to further research questions which may include studying the effects of cross-border bank flows more extensively at the bank-level or examining other measures of cross-border systemic risk and financial system linkages.

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Table 1. Summary Statistics.

This table presents summary statistics for the variables used in the analysis below. The sample period for our analysis is 2000-2014. Panel A presents summary statistics for all countries in our sample with available data on our main systemic risk measure (Marginal Expected Shortfall, *MES*). Panel B presents summary statistics for countries for which we have *SRISK* data. All variables are defined in Appendix A.

Panel A. Main sample (64 countries). 2000-2014.						
	N	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
MES (%)	758	2.63	1.39	2.29	3.47	1.67
Flows	758	0.07	-0.04	0.06	0.19	0.21
Δ Claims-to-assets (%)	758	1.68	-0.78	0.84	3.39	5.79
Flows - IV	758	0.07	-0.02	0.07	0.15	0.12
Predicted Flows	692	0.17	0.02	0.10	0.20	0.55
GDP growth (%)	758	8.14	1.30	8.01	15.56	12.15
Market return (%)	758	10.17	-9.33	8.51	23.84	32.11
Volatility (%)	758	21.98	14.98	20.69	26.61	9.43
Non-interest income (%)	758	35.15	27.50	33.48	40.94	12.22
Bank sector assets (log)	758	13.22	11.77	13.09	14.55	1.89
Concentration (%)	758	66.53	49.14	66.88	84.41	20.42
Foreign ownership (%)	758	6.84	3.65	7.41	9.50	3.37
Panel B. SRISK subsample (65 countries). 2000-2014.						
	N	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
SRISK-to-GDP (%)	809	2.35	0.00	0.11	3.18	4.21
Flows	809	0.08	-0.04	0.06	0.20	0.21
Δ Claims-to-assets (%)	809	2.23	-0.68	1.07	3.97	6.87
Flows - IV	809	0.08	-0.05	0.07	0.20	0.18
Predicted Flows	706	0.17	0.02	0.11	0.21	0.54
GDP growth (%)	809	8.03	1.32	7.97	15.23	11.88
Market return (%)	809	8.94	-9.33	8.07	23.31	28.04
Volatility (%)	809	21.74	15.04	20.46	26.35	9.48
Non-interest income (%)	809	35.30	27.36	33.73	41.33	12.23
Bank sector assets (log)	809	13.19	11.83	12.98	14.47	1.83
Concentration (%)	809	67.60	51.26	69.21	85.25	20.66
Foreign ownership (%)	809	6.72	3.56	7.13	9.54	3.50

Table 2. Systemic Risk Baseline Regressions using Marginal Expected Shortfall and SRISK.

This table presents OLS and 2SLS results from estimating systemic risk using known determinants including volatility and non-traditional income as well as cross-border banking flows. Models (1) - (4) examine Marginal Expected Shortfall (MES) and Models (5) - (8) examine SRISK (normalized by the country's GDP). In Panel A, we report results using the BIS consolidated banking statistics (CBS) to compute bank flows as the log difference in total foreign claims from t-1 to t. In Panel B, we use data from the Locational Banking Statistics (LBS) to compute flows as the change in BIS-adjusted claims scaled by total banking sector assets. In Models (1) and (5), we use the actual bank flows. In Models (2) and (6) we separate positive (Inflows) and negative (Outflows) bank flows for recipient countries. In Models (3) - (4) and (7) - (8), we show first- and second-stage results from regressions in which we instrument bank flows using the average source countries' ownership of banks in foreign countries, excluding the recipient country (*Foreign ownership*). We aggregate the average foreign bank ownership across source countries at the recipient county-year level using the total distance between a source-recipient country-pair as a weight. Controls include *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank sector assets*, and *Concentration*. The sample period is 2000-2014, and robust *t*-statistics based on standard errors clustered at the country level are in parentheses. We report *F*-statistics and *p*-values from the first-stage regressions. The last two rows report *F*-statistics and *p*-values for external validity test, in which we estimate a second pass regression of the residuals from Models (4) and (8) as our dependent variable on our instrument. All variables are defined in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Consolidated Banking Statistics Data

Dependent variable:	Marginal Expected Shortfall (MES)		$Flows_{t-1,t}$	MES	SRISK-to-GDP		$Flows_{t-1,t}$	SRISK
			1st stage	2nd stage			1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flows $_{t-1, t}$	-0.417**			-8.338**	-1.355***			-30.007***
	(-2.28)			(-2.47)	(-3.03)			(-4.27)
Inflows $_{t-1, t}$		-0.727**				-1.778**		
		(-2.64)				(-2.64)		
Outflows $_{t-1,t}$		0.698*				0.683		
		(1.69)				(0.75)		
Foreign ownership $_{t-1}$			0.011*				0.015***	
			(1.89)				(2.80)	
GDP growth $_{t-1,t}$	-0.001	-0.003	0.005***	0.035**	-0.017**	-0.020**	0.005***	0.122***
	(-0.28)	(-0.49)	(3.13)	(2.09)	(-2.31)	(-2.60)	(3.48)	(3.73)
Market return $_{t}$	0.004***	0.004***	0.001***	0.010***	-0.008	-0.008	0.001**	0.018
	(3.13)	(2.89)	(2.76)	(3.73)	(-0.91)	(-0.98)	(2.36)	(1.50)
Volatility $_{t}$	0.093***	0.092***	-0.001	0.082***	0.092***	0.094***	-0.000	0.075***
	(8.09)	(8.02)	(-0.71)	(6.52)	(3.78)	(3.83)	(-0.29)	(3.20)
Non-interest income $_{t}$	0.014**	0.013**	0.000	0.016**	-0.013	-0.013	0.001	0.004
	(2.03)	(2.00)	(0.48)	(2.49)	(-0.63)	(-0.62)	(0.68)	(0.23)
Bank sector assets $_{t}$	-0.189	-0.208	0.101***	0.624	-0.346	-0.388	0.080**	2.047**
	(-0.90)	(-0.92)	(3.09)	(1.46)	(-0.59)	(-0.66)	(2.61)	(2.62)
Concentration $_{t}$	0.007*	0.007*	0.000	0.010**	0.011	0.012	-0.000	0.003
	(1.75)	(1.80)	(0.39)	(2.41)	(0.90)	(0.92)	(-0.37)	(0.24)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	758	758	758	758	809	809	809	809
Adjusted R^2	0.670	0.671	0.257	0.671	0.728	0.727	0.297	0.736
# countries	64	64	64	64	65	65	65	65
Partial R^2				0.004				0.008
1st stage *F*-statistic				3.899				8.521
1st stage *p*-value				0.053				0.005
External validity *F*-stat.				0.080				0.100
External validity p-value				0.775				0.749

Table 2. (continued)

Panel B: Locational Banking Statistics Data.

Dependent variable:	Marginal Expected Shortfall (MES)		ΔClaims-to-assets$_{t-1,t}$	MES	SRISK-to-GDP		Δ Claims-to-assets	SRISK-to-GDP
			1st stage	2nd stage			1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Claims-to-assets $_{t-1,\ t}$	-0.028***			-0.450***	-0.039**			-1.633***
	(-3.32)			(-4.27)	(-2.11)			(-4.94)
Inflows $_{t-1,\ t}$		-0.034***				-0.040		
		(-3.17)				(-1.60)		
Outflows $_{t-1,t}$		0.551				0.259		
		(1.46)				(0.30)		
Foreign ownership$_{t-1}$			0.348**				0.387**	
			(2.10)				(2.03)	
GDP growth $_{t-1,t}$	-0.001	-0.002	0.092***	0.039***	-0.021**	-0.022***	0.089**	0.126***
	(-0.16)	(-0.44)	(2.83)	(3.49)	(-2.63)	(-2.68)	(2.65)	(4.44)
Market return $_t$	0.004***	0.004***	0.016**	0.010***	-0.008	-0.009	0.023**	0.026**
	(3.26)	(2.94)	(2.17)	(5.73)	(-0.95)	(-0.98)	(2.03)	(2.32)
Volatility $_t$	0.090***	0.091***	-0.113**	0.040**	0.090***	0.092***	-0.060	-0.008
	(8.02)	(7.97)	(-2.11)	(2.37)	(3.86)	(3.83)	(-0.93)	(-0.28)
Non-interest income $_t$	0.013**	0.014**	-0.002	0.011*	-0.014	-0.013	0.001	-0.015
	(2.01)	(2.03)	(-0.09)	(1.78)	(-0.68)	(-0.66)	(0.04)	(-0.79)
Bank sector assets $_t$	-0.161	-0.200	2.574***	0.904***	-0.363	-0.408	2.521**	3.625***
	(-0.73)	(-0.87)	(3.12)	(2.75)	(-0.60)	(-0.68)	(2.29)	(3.32)
Concentration $_t$	0.006	0.007	-0.020	-0.001	0.011	0.011	-0.020	-0.020*
	(1.59)	(1.66)	(-1.22)	(-0.28)	(0.87)	(0.90)	(-1.24)	(-1.88)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	758	758	758	758	809	809	809	809
Adjusted R^2	0.674	0.673	0.335	0.676	0.727	0.726	0.303	0.745
# countries	64	64	64	64	65	65	65	65
Partial R^2			0.005				0.004	
1st stage *F*-statistic			4.845				4.483	
1st stage *p*-value			0.032				0.038	
External validity *F*-stat.			0.020				0.000	
External validity p-value			0.885				0.981	

Table 3. Gravity Model Regressions for Cross-Border Bank Flows.

This table presents results from OLS regressions of cross-border bank flows on a country pair-year level. Bank flows refer to the log difference (difference in log from t-1 to t) of total foreign claims from source country s to recipient country r. In Models (1) - (5), we show results from panel regressions for the full sample period 1995-2014. In Model (6), we report the average coefficients from the estimation of five-year rolling window regressions. We use the results from the rolling window regressions to estimate predicted bank flows for year t using all available information through year t-1. The sample period is 1995-2014 and robust t-statistics based on standard errors clustered at the country level are in parentheses. All variables are defined in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Cross-border Bank Flows$_{s,r,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
						Rolling Window Estimates
Foreign ownership	0.002**	0.002**	0.002**	0.002**		0.004
	(2.29)	(2.09)	(2.54)	(2.26)		(1.57)
Δ Creditor rights	-0.042*	-0.040	-0.059**	-0.039		-0.036
	(-1.70)	(-1.54)	(-2.06)	(-1.03)		(0.96)
Δ Credit depth	-0.001	-0.000	-0.003	0.000		0.009
	(-0.10)	(-0.01)	(-0.51)	(0.03)		(0.81)
Δ Property rights	-0.019***	-0.022***	-0.033***	-0.019***		-0.041
	(-3.22)	(-3.37)	(-5.09)	(-2.76)		(1.19)
Δ Log GDP per capita	-0.058	-0.077*	-0.049	-0.050		-0.159
	(-1.32)	(-1.90)	(-1.05)	(-1.11)		(1.56)
Δ GDP growth	-0.001***	-0.001***	-0.001***	-0.001***		0.000
	(-3.31)	(-2.72)	(-4.00)	(-3.84)		(1.01)
Δ Population (log)	-0.073	-0.070	-0.184**	-0.072		-0.218
	(-1.05)	(-1.16)	(-2.15)	(-0.82)		(1.03)
Same language	0.030***	0.029***	0.023**	0.032***		0.035*
	(2.93)	(2.82)	(1.98)	(2.68)		(1.81)
Distance	-0.026***	-0.023***	-0.017***	-0.024***		-0.021*
	(-5.32)	(-3.77)	(-2.90)	(-4.06)		(1.86)
Contiguous	-0.023*	-0.021*	-0.015	-0.023**		-0.028
	(-1.81)	(-1.70)	(-1.10)	(-1.96)		(1.11)
Colony	0.039***	0.039***	0.038***	0.031**		0.040**
	(3.27)	(3.12)	(2.66)	(2.32)		(1.98)
Δ Real exchange rate return		-0.008	0.016	0.020		-0.010
		(-0.30)	(0.54)	(0.67)		(1.02)
Bilateral trade (% GDP)		0.001	0.001	0.001		0.002
		(0.91)	(0.68)	(0.47)		(0.88)
Δ Financial liberalization			-0.010			
			(-1.36)			
Δ Restrictions on bank activities				0.006**		
				(2.45)		
Δ Independence of supervisors				0.002		
				(1.13)		
Δ Stringency of capital regulation				-0.002		
				(-0.33)		
Δ Private monitoring				-0.004		
				(-1.46)		
Δ Strength of external audit				0.006		
				(1.45)		
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Source country fixed effects	Yes	Yes	Yes	Yes	No	Yes
Recipient country fixed effects	Yes	Yes	Yes	Yes	No	Yes
Source country-Year fixed effects	No	No	No	No	Yes	No
Recipient country-Year fixed effects	No	No	No	No	Yes	No
Observations	21,277	19,432	16,342	17,048	19,432	5,264
Adjusted R^2	0.064	0.066	0.074	0.072	0.196	0.092
# of recipient countries	114	109	83	100	109	100

Table 4. Predicted Flows Regressions using Marginal Expected Shortfall and SRISK.

This table presents results related to a two-stage estimation process. In Models (1)-(2) we report results using *MES* (%) as the dependent variable. We multiply *MES* by negative one to ensure that both measures are increasing in systemic risk. We estimate predicted flows from regressions of cross-border bank flows on a country pair-year level. We use a five-year rolling-window approach. Predicted flows for year *t* are obtained from regressions using all available data through year *t-1*. We aggregate predicted bilateral flows at the recipient-country-year level using two approaches: (1) value-weighted using the lagged bilateral foreign claims between source country *s* and recipient country *r* as weights - *Predicted Flows (VW)*, and (2) equally weighed - *Predicted Flows (EW)*. Models (1) and (2) report results using *MES* and Models (3) and (4) show results using *SRISK-to-GDP* as the dependent variable. Controls include *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank sector assets*, and *Concentration*. The sample period is 2000-2014 and robust *t*-statistics based on standard errors clustered at the country level are in parentheses. All variables are defined in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	*MES (%)*	*MES (%)*	*SRISK/GDP*	*SRISK/GDP*
Predicted Flows $_{t-1, t}$ (VW)	-0.305**		-0.731**	
	(-2.57)		(-2.20)	
Predicted Flows $_{t-1, t}$ (EW)		-0.296**		-0.731**
		(-2.55)		(-2.20)
GDP growth $_{t-1,t}$	-0.001	-0.001	-0.022**	-0.022**
	(-0.25)	(-0.24)	(-2.26)	(-2.27)
Market return $_t$	0.004**	0.004**	0.000	0.000
	(2.44)	(2.41)	(0.11)	(0.09)
Volatility $_t$	0.093***	0.093***	0.079***	0.080***
	(6.47)	(6.48)	(3.66)	(3.68)
Non-interest income $_t$	0.010	0.010	-0.012	-0.012
	(1.58)	(1.57)	(-0.58)	(-0.57)
Bank sector assets $_t$	-0.218	-0.225	-0.237	-0.252
	(-0.94)	(-0.97)	(-0.40)	(-0.42)
Concentration $_t$	0.007*	0.007*	0.008	0.008
	(1.71)	(1.69)	(0.66)	(0.65)
Recipient country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	692	692	706	706
Adjusted R^2	0.689	0.688	0.759	0.759
# of recipient countries	57	57	57	57

Table 5. The Impact of Financial Development and Financial Crises

This table presents results from regressions of systemic risk on instrumented bank flows (*Flows - IV*). Specifically, we instrument $Flows_{t-1,t}$ using the total foreign banking assets owned by residents of source country s, scaled by total banking sector assets. For a given country-pair, we aggregate the total bank assets owned by a source country across all regions of the world, excluding the region in which the recipient country r is located. We aggregate the instrument at the recipient county-year level using the total distance between source and recipient countries' capitals as weights. We interact *Flows - IV* with three indicator variables: (1) *Develope*d- an indicator variable for developed countries based on the MSCI developed market index definition; (2) *GF Crisis* - an indicator variable that is equal to one for the years 2008 and 2009 and zero otherwise; and, (3) *Euro Crisis*- an indicator variable that is equal to one for the years 2010-2012 that coincide with the European sovereign debt crisis. In Models (1) - (4), we show results using Marginal Expected Shortfall (MES), and, in Models (5) - (8), we show results using SRISK-to-GDP as our dependent variable. In Models (4) and (8) we show results for the subsample of recipient countries in Europe. Controls (not reported to conserve space) include *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank sector assets*, and *Concentration*. The sample period is 2000-2014, and robust t-statistics based on standard errors clustered at the country level are in parentheses. All variables are defined in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Marginal Expected Shortfall (MES %)				SRISK-to-GDP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Europe only				Europe only
Flows - IV	-6.608**	-7.857**	-8.748**	15.413*	-25.516***	-30.035***	-28.757***	-27.996*
	(-2.07)	(-2.43)	(-2.60)	(1.86)	(-3.99)	(-4.29)	(-4.32)	(-1.86)
Flows - IV × Developed	-2.042**				-5.486**			
	(-2.00)				(-1.98)			
Flows - IV × GF crisis		2.459***				4.063**		
		(2.95)				(2.16)		
GF crisis		0.321				0.811		
		(0.84)				(1.01)		
Flows -IV × Euro crisis			-0.438	0.138			3.712*	5.367*
			(-0.73)	(0.13)			(1.76)	(1.70)
Euro crisis			-0.714	5.821***			-0.044	0.994
			(-1.02)	(3.41)			(-0.04)	(0.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	758	758	758	301	809	809	809	356
Adjusted R^2	0.674	0.680	0.671	0.771	0.740	0.739	0.739	0.767
# countries	64	64	64	27	65	65	65	28

Table 6. Bank-Level Summary Statistics.

This table presents summary statistics for the variables used in the *bank-level* analysis below. *MES* –is the negative of the average bank returns during the worst 5% market return days in a year. *Size* is the natural logarithm of total assets (in US$ million); *Non-interest income-to-income* is non-interest income divided by the sum of-interest and non-interest income; *ST funding* is non-deposit short-term funding divided by total liabilities; *Leverage* is total assets divided by the book value of equity; *NPL-to-loans* is the ratio of non-performing loans-to-total loans; *ROA* is net income divided by average total assets; *Non-interest expense* is the ratio of non-interest expense-to-gross revenues, and *Foreign* is an indicator variable that is equal to one if 50 percent or more of a bank's shares are owned by foreigners and zero otherwise (Claessens and Van Horen, 2014). *Flows* is the log difference of total foreign claims from *t-1* to *t* to recipient country *r*; *Flows - IV* are bank flows instrumented using the average source countries' ownership of banks in foreign countries, excluding those countries in the same region as the recipient country (*Foreign ownership*). We aggregate the instrument at the recipient county-year level using the total distance between source and recipient countries' capitals as weights. *Inflows* are equal to *Flows* (log difference in foreign claims between *t-1* and *t*) when there is an inflow of funds into a country, and zero otherwise; *GDP growth* is the year-over-year change of the country's real GDP; *Volatility* is the annual stock market volatility for the country; *Market return* is the annual stock market return for the country; *Non-interest income* is the annual value for aggregate non-interest income relative to total income for the country's banking system; *Bank sector assets* is the log of total banking sector assets; and *Concentration* is the assets of three largest commercial banks as a share of total commercial banking assets. *Foreign ownership* is the sum of the assets of majority-owned banks in foreign countries by source country *s* (in regions outside of recipient country *r's*), as a proportion of source country banking sector assets. We aggregate the foreign ownership by recipient country-year using the distance between source and recipient country capitals as a weight. The sample period for our analysis is 2000-2014. We obtain returns and market-based data from DataStream. We obtain financial data from Fitch Fundamentals financial data.as of December of each year. Country level data are from the World Bank Development Indicators and the Global Financial Database. Banks are defined as firms with SIC codes 6000, 6020, 6021, 6022, 6029, 6081 6082, or 6712. All variables are defined in Appendix A.

Bank Sample - All Countries						
	N	Mean	25^{th}	Median	75th	Std. deviation
Bank level variables:						
MES	14,008	1.614	0.197	1.247	2.492	1.867
Flows	14,008	0.068	-0.029	0.103	0.163	0.153
Δ Claims-to-assets	14,008	0.336	-0.642	0.321	1.090	1.251
Flows - IV	14,008	0.068	-0.161	0.168	0.303	0.275
Size	14,008	8.106	6.393	7.819	9.699	2.251
Non-interest income	14,008	26.153	15.400	23.990	34.255	16.293
ST funding	14,008	5.466	0.193	2.917	7.567	7.450
Leverage	14,008	13.744	9.470	11.736	15.453	8.365
NPL-to-loans	14,008	3.679	0.600	1.900	4.660	5.170
ROA	14,008	0.653	0.202	0.500	1.110	1.144
Non-interest expense	14,008	65.806	54.700	63.700	73.035	22.103
Foreign	14,008	0.048	0.000	0.000	0.000	0.214
Country- level variables:						
GDP growth	14,008	5.573	3.277	4.487	6.771	8.259
Market return	14,008	5.620	-9.906	7.526	17.138	21.508
Volatility	14,008	20.543	14.964	20.749	23.971	7.699
Non-interest income (%)	14,008	36.337	31.358	37.133	40.802	8.538
Banking sector assets	14,008	15.630	14.029	16.803	17.163	2.102
Concentration	14,008	43.702	29.870	35.409	52.525	20.610
Foreign ownership	14,008	7.900	6.305	8.243	9.265	2.824

Table 7. Bank-Level Tests of Cross-Border Bank Flows and Systemic Risk.

This table presents results from OLS and two-stage least squares (2SLS) regressions. The dependent variable is *MES* – the negative of the average bank returns during the worst 5% market return days in a year. Bank flows are the log difference in total foreign claims from *t-1* to *t* ($Flows_{t-1,t}$). Models (1) and (2) show results from OLS regressions. In Model (2) we separate positive (*Inflows*) and negative (*Outflows*) bank flows for recipient countries. In Models (3) - (4), we show first- and second-stage results from regressions in which we instrument *Flows* using the average source countries' ownership of banks in foreign countries, excluding the recipient country (*Foreign ownership*). In Model (5) we interact *Flows - IV* with an indicator variable, *Developed*, that is equal to one for developed countries based on the MSCI developed market index definition. Bank-level controls include *Size* (log of assets); *Non-interest income*; *ST funding*; *Leverage*; *NPL-to-loans*; *ROA*; *Non-interest expense*, and *Foreign.* We also incorporate country-level controls, including: *GDP growth, Volatility, Market return, Non-interest income, Bank sector assets*, and *Concentration*. We obtain bank financial data from Fitch Fundamentals financial data. The sample period is 2000-2014 and *t*-statistics based on standard errors clustered at the country level are in parentheses. Bank and year fixed effects are included in all regressions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	*MES (%)*	*MES (%)*	$Flows_{t-1,t}$	*MES (%)*	*MES (%)*
	OLS	OLS	First-Stage	Second-Stage	
	(1)	(2)	(3)	(4)	(5)
Flows t-1,t (Flows - IV)	-0.440***			-1.172***	0.514
	(-2.83)			(-2.83)	(0.62)
Inflows t-1,t		-0.671**			
		(-2.32)			
Outflows t-1,t		-0.039			
		(-0.10)			
Foreign Ownership t-1			0.040***		
			(3.63)		
Flows - IV × Developed					-2.207***
					(-2.95)
Size t	0.238***	0.238***	-0.012	0.234***	0.254***
	(3.36)	(3.34)	(-1.17)	(3.46)	(4.96)
Noninterest income-to-income t	0.000	0.000	0.000	0.000	0.000
	(0.12)	(0.09)	(0.53)	(0.22)	(0.08)
S-T funding t	0.004	0.004	-0.000	0.004	0.004
	(1.07)	(1.03)	(-0.46)	(0.97)	(0.92)
Leverage t	0.002	0.002	-0.000	0.002	0.002
	(0.55)	(0.58)	(-0.73)	(0.59)	(0.43)
NPL-to-loans t	0.020***	0.020***	-0.004***	0.017***	0.018***
	(3.11)	(3.14)	(-2.74)	(3.04)	(2.88)
ROA t	-0.075	-0.075	0.002	-0.072	-0.076
	(-1.51)	(-1.51)	(1.01)	(-1.54)	(-1.60)
Non-int. expense t	0.000	0.000	0.000	0.000	0.000
	(0.24)	(0.24)	(0.50)	(0.31)	(0.19)
Foreign	-0.240	-0.259	0.080**	-0.196	-0.298
	(-1.22)	(-1.31)	(2.36)	(-1.09)	(-1.57)
GDP growth t-1,t	-0.008	-0.007	0.003***	-0.005	-0.009
	(-1.49)	(-1.44)	(2.87)	(-1.00)	(-1.66)
Volatility t	0.062***	0.062***	-0.001	0.061***	0.057***
	(7.00)	(7.14)	(-0.59)	(7.90)	(6.71)
Market return t	0.005**	0.005**	0.001**	0.005***	0.003*
	(2.58)	(2.60)	(2.14)	(3.19)	(1.92)
Non-interest income (%)	0.008	0.008	0.001	0.008	0.007
	(1.13)	(1.17)	(0.94)	(1.23)	(1.01)
Bank Sector Assets t	-0.267*	-0.266*	0.097**	-0.242*	-0.249*
	(-1.71)	(-1.69)	(2.28)	(-1.65)	(-1.80)
Concentration t	0.003	0.003	-0.001	0.003	0.003
	(1.14)	(1.20)	(-0.86)	(1.06)	(1.27)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	14,008	14,008	14,008	14,008	14,008
Adjusted R^2	0.594	0.594	0.385	0.228	0.596
Partial R^2			0.102		
1st stage *F*-statistic			13.173		
1st stage *F*-statistic *p*-value			0.001		

Table 8. Impact of Large Inflows on Bank Performance.

This table presents results from OLS regressions of measures of bank performance. We report the coefficients from interactions of indicator variables *High (Low) Inflows* that is equal to one if inflows into a recipient country in year *t* are above (below) the cross-country median and indicators for banks that decreased (increased) *MES* in year *t*. Specifically, Δ*MES<0* (Δ*MES>0*) is an indicator that is equal to one if a bank experienced a(n) decrease (increase) in *MES* in year *t* and zero otherwise. The dependent variables are: 1) *ROA*; 2) *Non-interest expense*; 3) *Leverage* and 4) *NPL-to-loans*. Bank-level controls (not shown to conserve space): include *Size* (log of assets); *Non-interest income*; *ST funding*; *Leverage*; *NPL-to-loans*; *ROA*; and *Non-interest expense*. Country-level controls include *GDP growth, Volatility, Market return, Non-interest income, Bank credit*, and *Concentration*. We obtain bank financial data from Fitch Fundamentals financial data. We include bank and year fixed effects in all regressions. We report F-tests and p-values for tests of differences in coefficients. The sample period is 2000-2014 and *t*-statistics based on standard errors clustered at the country level are in parentheses. All variables are defined in Appendix A.

Panel A. ROA and Non-Interest Expenses.

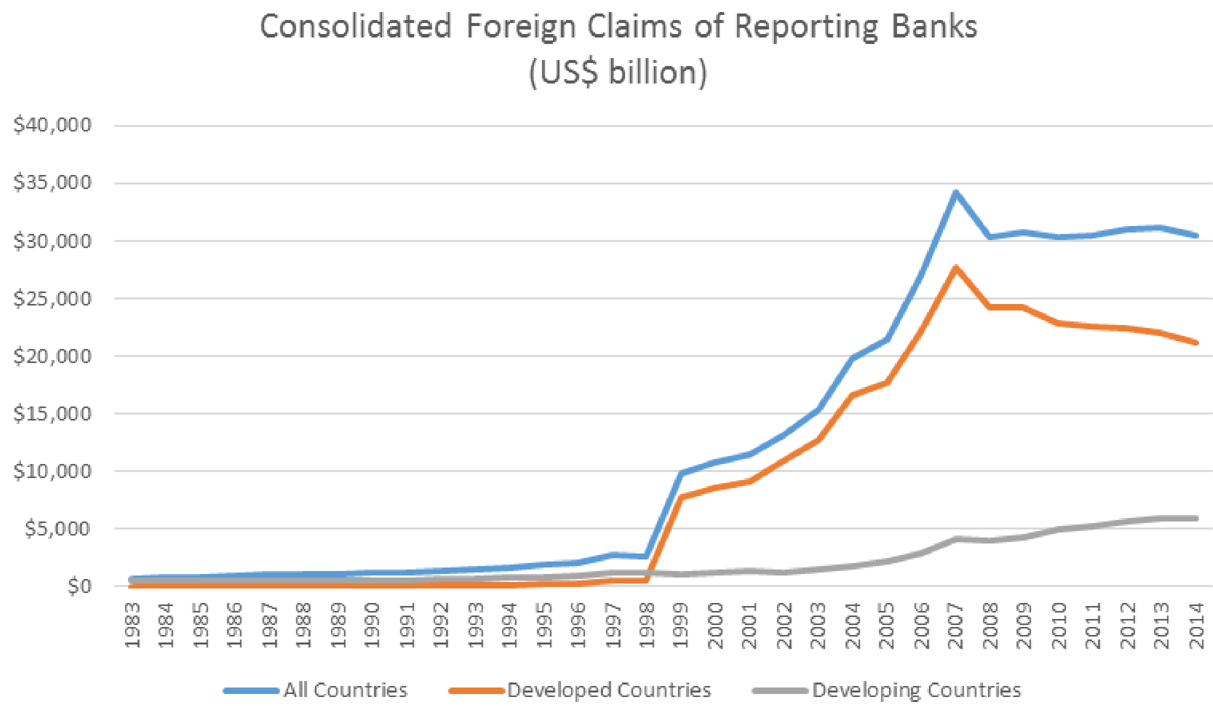
Dependent variable:	ROA			Non-interest expenses (%)		
	Inflows $_{t-1,t}$		F-test (H_0: High=Low) (p-value)	Inflows $_{t-1,t}$		F-test (H_0: High=Low) (p-value)
	High	Low		High	Low	
ΔMES t-1,t <0	0.306***	0.224**	*2.48*	-4.442**	-3.532**	*4.36***
	(2.83)	(2.60)	*(0.121)*	(-2.38)	(-2.25)	*(0.041)*
ΔMES t-1,t >0	0.227**	0.220**	*0.02*	-3.345*	-3.512**	*0.09*
	(2.11)	(2.62)	*(0.878)*	(-1.78)	(-2.20)	*(0.766)*
F-test (H_0: ΔMES<0=ΔMES>0)	*4.67***	*0.09*		*4.89***	*0.01*	
p-value	*(0.035)*	*(0.762)*		*(0.031)*	*(0.918)*	
Controls	Yes	Yes		Yes	Yes	
Bank fixed effects	Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes	
Observations	13,260			13,443		
R^2	0.532			0.530		
Adjusted R^2	0.466			0.466		
# countries	61			61		

Panel B. Leverage and Non-Performing-to-Gross-Loans.

Dependent variable:	Leverage			Non-Performing -to-Gross-Loans		
	Inflows $_{t-1,t}$		F-test (High=Low) (p-value)	Inflows $_{t-1,t}$		F-test (High=Low) (p-value)
	High	Low		High	Low	
ΔMES t-1,t <0	-0.963**	-0.861***	0.20	-1.373***	-0.157	17.66***
	(-2.20)	(-2.77)	(0.650)	(-4.11)	(-0.54)	(0.000)
ΔMES t-1,t >0	-0.487	-0.757*	0.88	-0.694*	-0.182	2.35
	(-1.33)	(-1.76)	(0.352)	(-1.80)	(-0.64)	(0.130)
F-test (H_0: ΔMES<0=ΔMES>0)	*3.46**	*0.40*		*14.51****	*0.14*	
p-value	*(0.068)*	*(0.529)*		*(0.000)*	*(0.714)*	
Controls	Yes	Yes		Yes	Yes	
Bank fixed effects	Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes	
Observations	13,451			13,198		
R^2	0.630			0.695		
Adjusted R^2	0.579			0.653		
# countries	61			61		

Figure 1. Consolidated Foreign Claims By Year.

The figure shows the total foreign claims for reporting banks in 26 source countries to all recipient countries from 2000 through 2014. The top panel divides the total bank flows by recipient country financial development. The bottom panel shows the total foreign claims by source country/region. Source: Bank for International Settlements Quarterly Review.



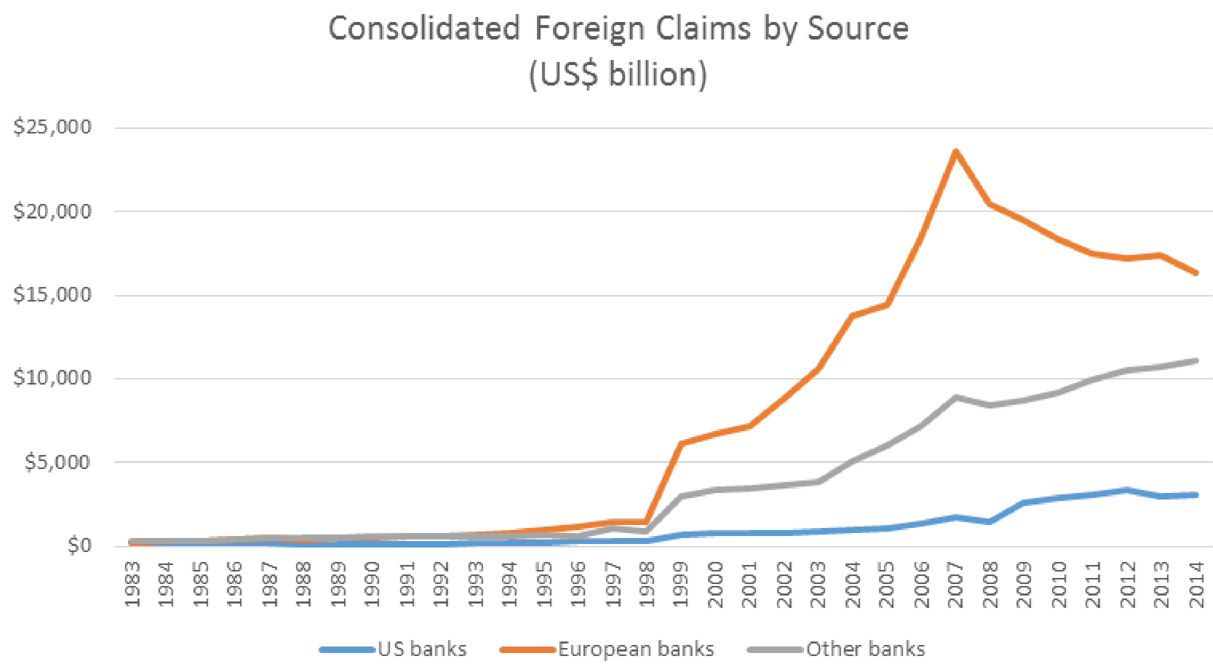
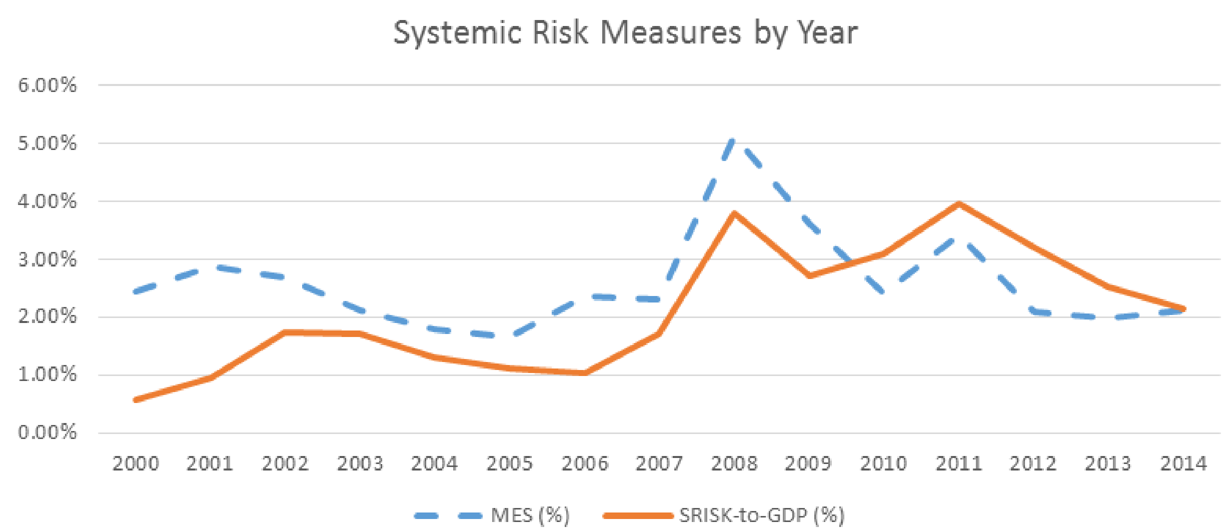


Figure 2. Systemic Risk Measures by Year and Region.

The figure shows the evolution of our two measures of systemic risk: 1) *SRISK-to-GDP* -year-end value of *SRISK* for the country divided by the annual GDP of the country, and 2) *MES* - the annual value-weighted average *MES* of all banks in a country. *MES* is the average stock return of the bank when the country's stock market is in the 5% left tail of returns. We take the negative value of *MES* as our measure so that both measures are increasing in systemic risk. Panel A shows the cross-country average of each measure by year, and Panel B shows the average by region, as defined by the World Bank. In Panel B, we first compute the average systemic risk measure across all countries in a region by year, and report the time-series average.

Panel A. Systemic Risk Measures by Year



Panel B. Systemic Risk Measures by Region

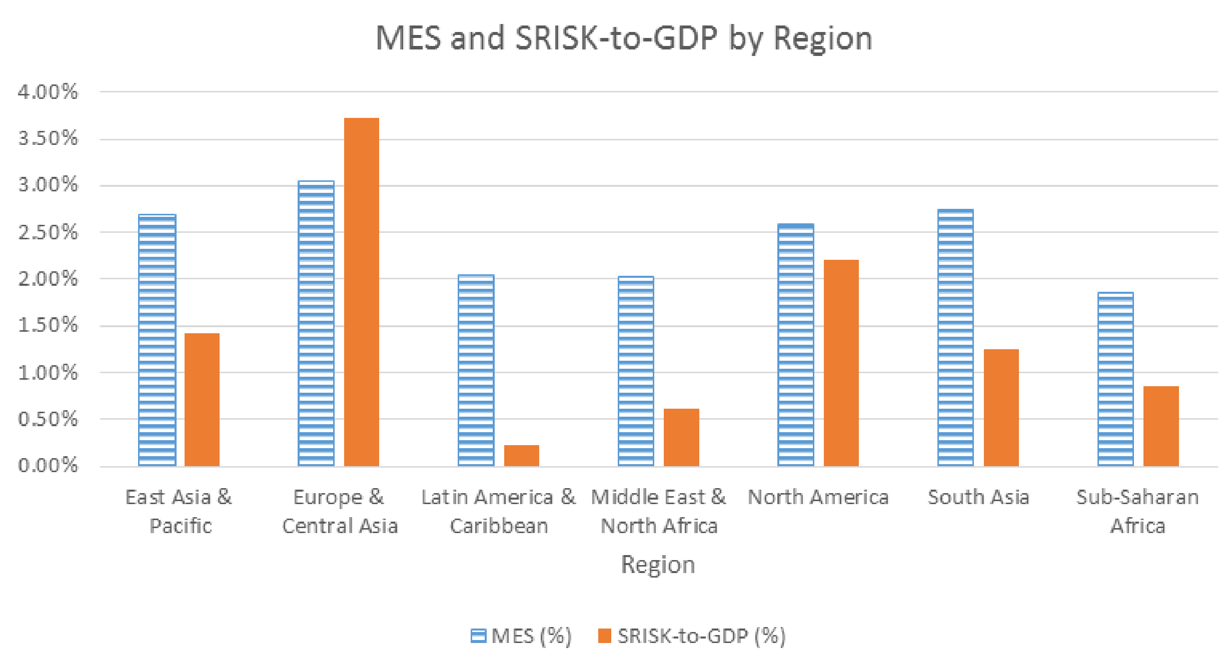
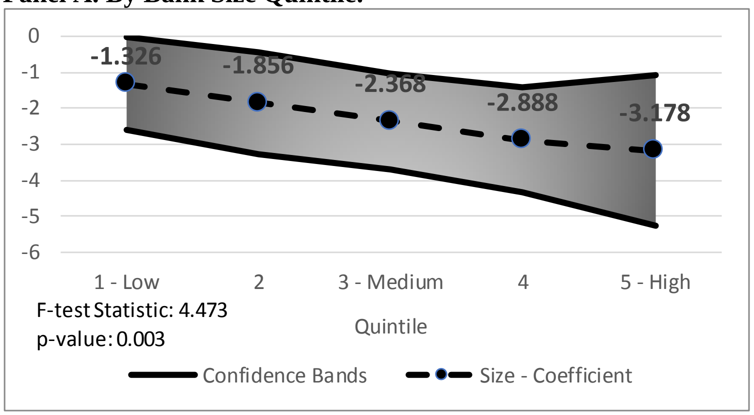


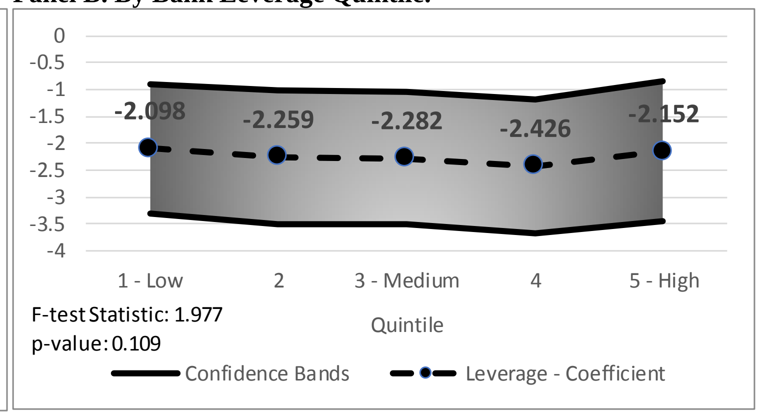
Figure 3. Impact of Flows by Bank Characteristics.

The figure shows coefficients from regressions of marginal expected shortfall (*MES*) on instrumented bank flows (*Flows - IV*) interacted with indicator variables for quintiles of bank characteristics. Specifically, each year we sort banks in each country by quintiles based on 1) *Size*; 2) *Leverage*; *NPL-to-loans*, and 4) *Non-interest expense %*. We report the coefficients on the interactions between *Flows - IV* and each bank characteristic quintile indicator. All regressions include bank and year fixed effects and the standard errors are clustered at the country level. The shaded regions show the 95% confidence interval bands. The F-statistics and *p*-values are for *F*-tests of the equality of all interaction terms.

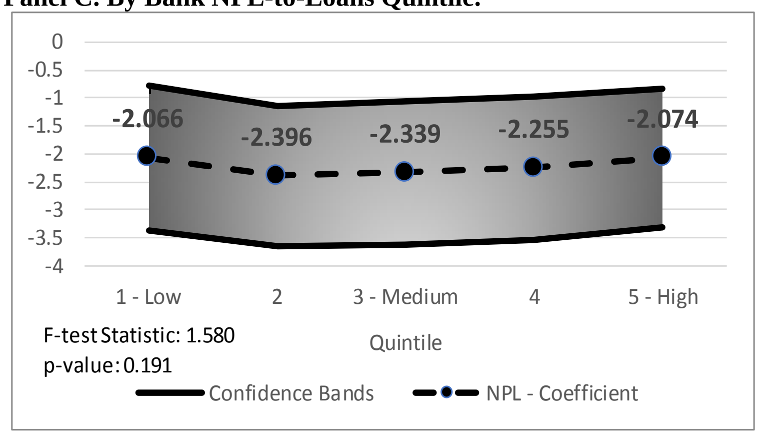
Panel A. By Bank Size Quintile.



Panel B. By Bank Leverage Quintile.



Panel C. By Bank NPL-to-Loans Quintile.



Panel D. By Bank Non-Interest Expense Quintile.

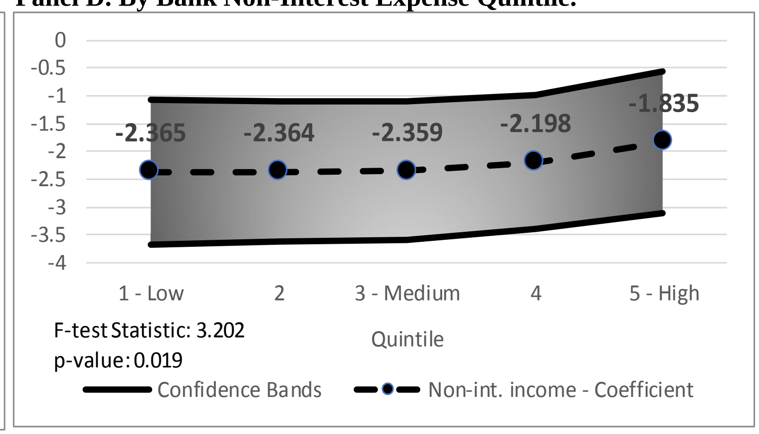
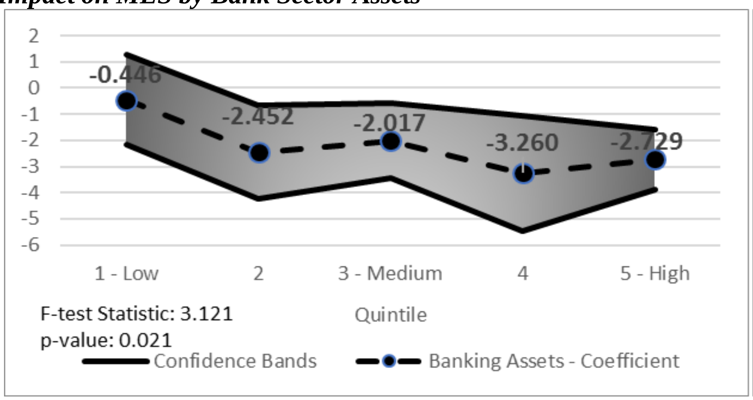


Figure 4. Impact of Flows by Recipient Country's *De Facto* and *De Jure* Characteristics.

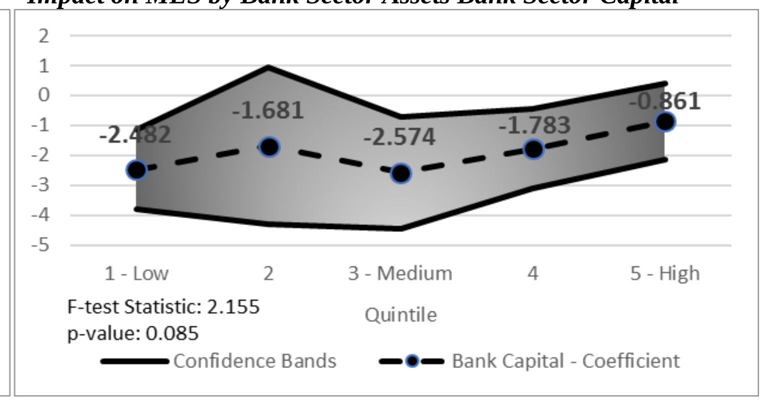
The figure shows coefficients from regressions of marginal expected shortfall (*MES*) on instrumented bank flows (*Flows - IV*) interacted with indicator variables for quintiles of recipient country *de facto* and *de jure* characteristics. Specifically, each year we sort countries by quintiles based on four *de facto* measures: 1) *Bank sector assets*; 2) *Bank sector capital*; 3) *Bank sector NPL-to-loans*, and 4) *Bank sector ROA*. We repeat the sorting procedure using four de jure measures of regulatory quality: 1) *Restrictions on bank activities*; 2) *Official supervisory power*; 3) *Stringency of capital regulations*, and 4) *Private monitoring*. We report the coefficients on the interactions between *Flows - IV* and each *de facto* (*de jure*) characteristic quintile indicator. All regressions include bank and year fixed effects and the standard errors are clustered at the country level. The shaded regions show the 95% confidence interval bands. The F-statistics and *p*-values are for *F*-tests of the equality of all interaction terms.

Panel A: De Facto Measures

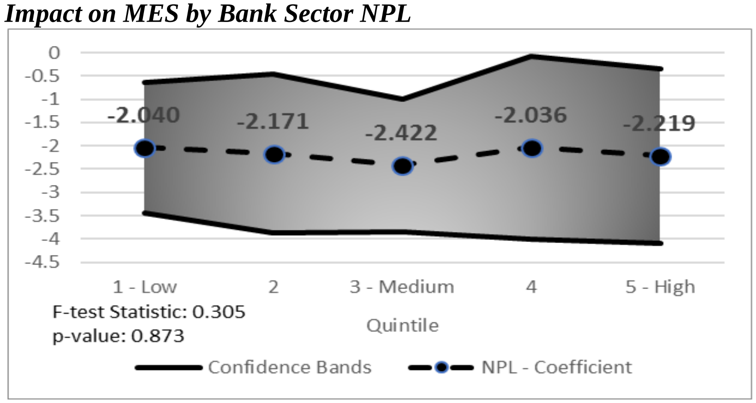
Impact on MES by Bank Sector Assets



Impact on MES by Bank Sector Assets Bank Sector Capital



Impact on MES by Bank Sector NPL



Impact on MES by Bank Sector ROA

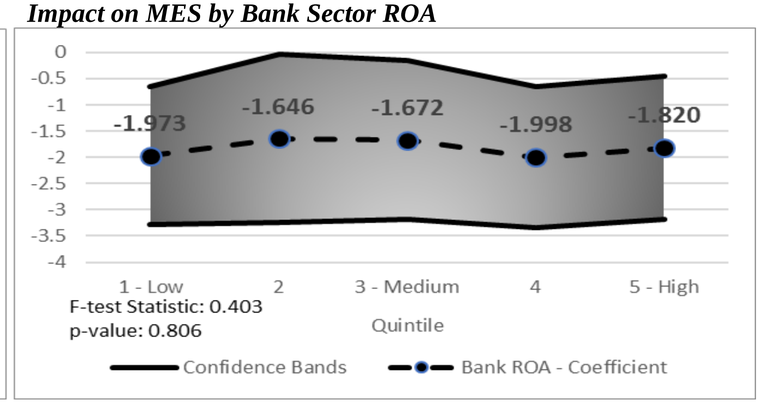
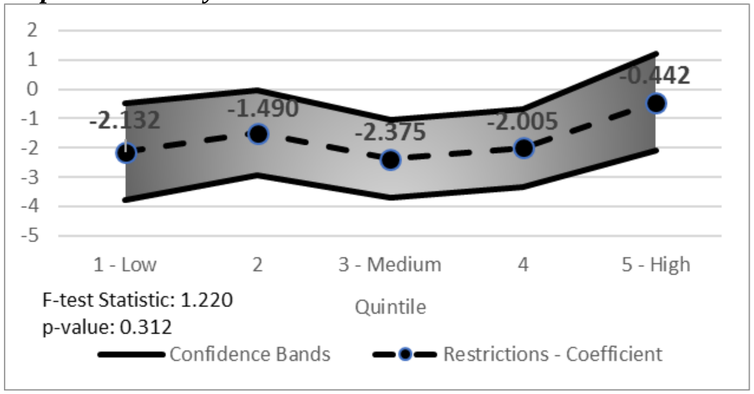


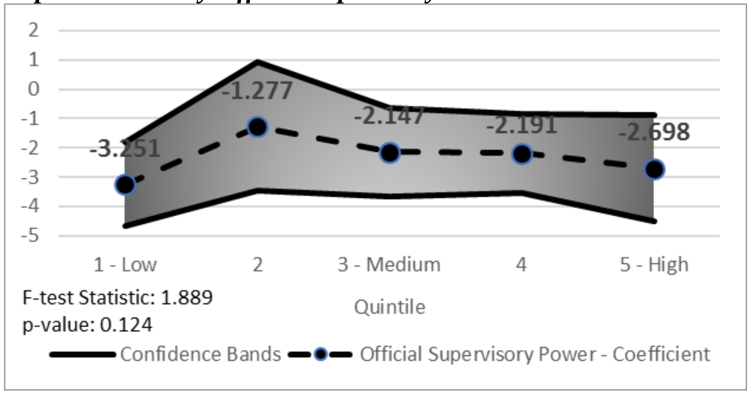
Figure 4. (continued).

Panel B. De Jure Measures

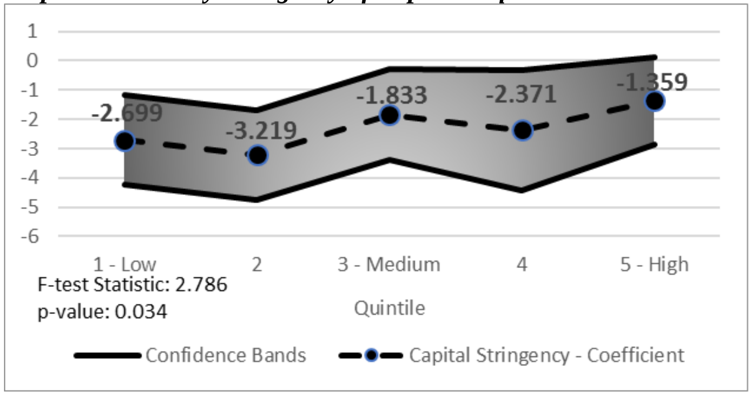
Impact on MES by Restrictions on Bank Activities



Impact on MES by Official Supervisory Power



Impact on MES by Stringency of Capital Requirements



Impact on MES by Private Monitoring

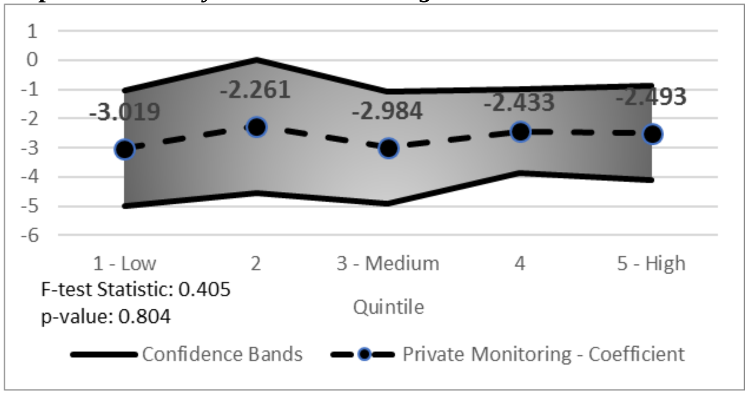


Figure 5. Long-Run Impact of Flows on Bank Systemic Risk.

This table presents coefficients from OLS regressions of bank-level marginal expected shortfall (*MES*) on instrumented bank flows (*Flows - IV*) at time *t, t-1, t-2,* and *t-3.* We include bank and year fixed effects in all regressions. The shaded regions show the 95% confidence intervals. Significance of coefficients is based on robust standard errors clustered at the country level. The sample period is 2000-2014. All variables are defined in Appendix A.

Long-Run Impact of Bank Flows on MES

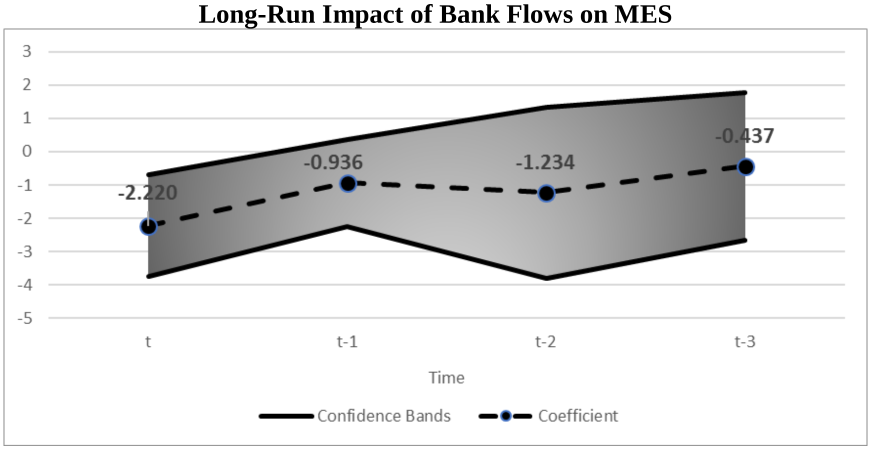
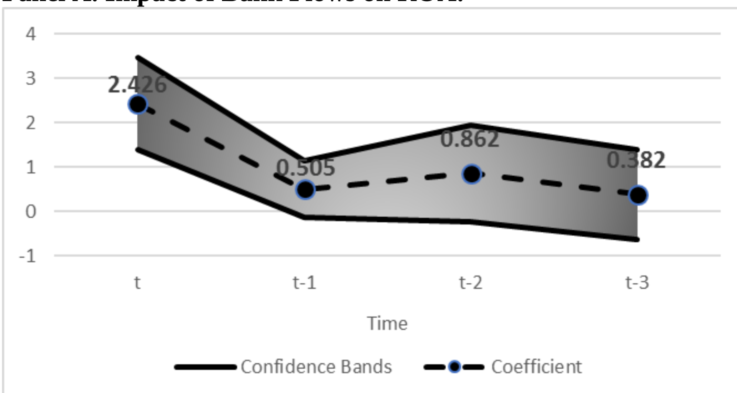


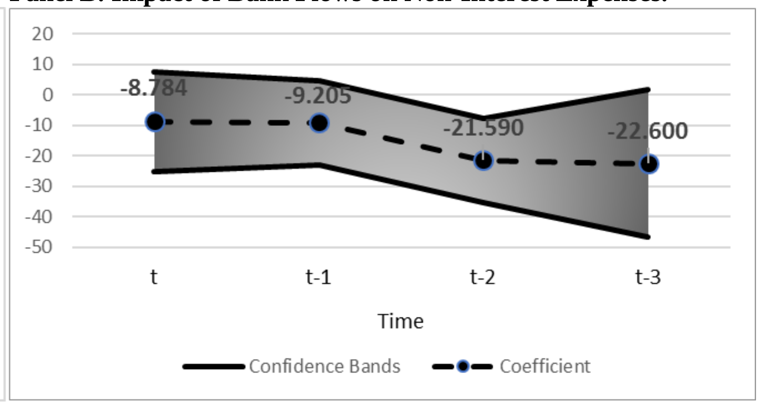
Figure 6: Long-Run Impact on Bank Performance.

This figure presents coefficients from OLS regressions of measures of bank performance on instrumented bank flows (*Flows – IV*) at time *t*, *t-1*, *t-2*, and *t-3*. The dependent variables are: 1) *ROA*; 2) *Non-interest expense*; 3) *Leverage, and* 4) *Non-Performing-to-Gross-Loans*. We obtain all bank-level variables from Fitch fundamentals financial data and DataStream. We include bank and year fixed effects in all regressions. The shaded regions show the 95% confidence intervals. Significance of coefficients is based on robust standard errors clustered at the country level. Sample period is 2000-2014. All variables are defined in Appendix A.

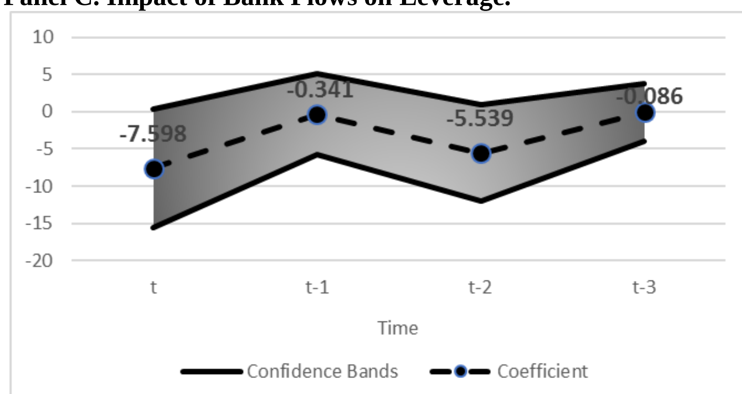
Panel A. Impact of Bank Flows on ROA.



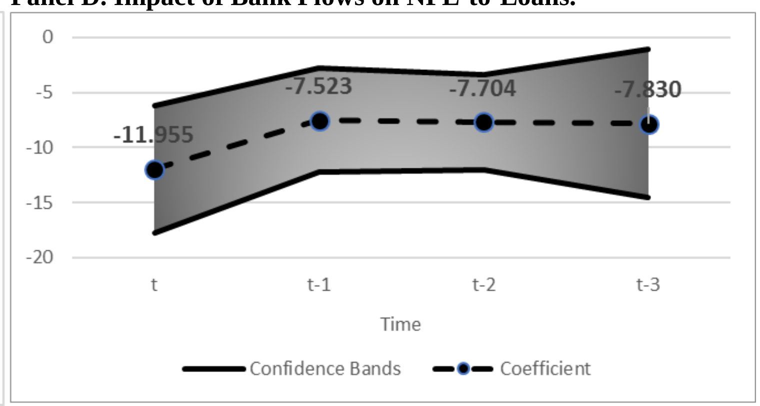
Panel B. Impact of Bank Flows on Non-Interest Expenses.



Panel C. Impact of Bank Flows on Leverage.



Panel D. Impact of Bank Flows on NPL-to-Loans.



Appendix A: Definitions and Sources

Variable	**Definition**	**Source**
Country-Level:		
MES (%)	The negative of the average stock return of the bank when the country's stock market is in the 5% left tail of returns. The country level measure is the annual value-weighted average *MES* of all banks in a country.	Stock return data - DataStream
SRISK-to-GDP (%)	Year-end value of *SRISK* for the country divided by the annual GDP of the country.	SRISK – NYU V-Lab (http://vlab.stern.nyu.edu/en/)
Key Independent Variables:		
Bank Flows$_{s,r,t}$	Aggregate value of cross-border banking flows from source country *s* to recipient country *r* from year *t-1* to year *t*. Following Houston et al. (2012) it is calculated as the log difference (difference in log from *t-1* to *t*) of total foreign claims from source country *s* to recipient country *r*.	Bank for International Settlements (BIS) Consolidated Banking Statistics
Flows	The log difference (difference in log from *t-1* to *t*) of total foreign claims from all source countries to recipient country *r*.	Bank for International Settlements (BIS) Consolidated Banking Statistics
Δ Claims-to-assets	The BIS- break- and exchange-rate adjusted change in foreign claims to recipient country *r* from *t-1* to *t*, scaled by total banking sector assets.	Bank for International Settlements (BIS) Locational Banking Statistics; Fitch Fundamentals Financial data
Predicted Flows	Predicted values from the estimation of rolling window regressions of bilateral flows estimated following Houston et al. (2012). Predicted bilateral flows are aggregated at the recipient-country-year using lagged foreign claims as weights, following equation 4.	Bank for International Settlements (BIS) Consolidated Banking Statistics. Authors' calculations.
Inflows (Outflows)	The log difference (difference in log from *t-1* to *t*) of total foreign claims from all source countries to recipient country *r*. when there is a net inflow (outflow) of funds into country *r*, and zero otherwise.	Bank for International Settlements (BIS) Consolidated Banking Statistics
Country-Level Variables:		
GDP growth	Year-over-year change of the country's real GDP.	World Development Indicators
Volatility	Annual stock market volatility for the country.	Global Financial Development Database
Market return	Annual stock market return for the country.	Global Financial Development Database
Non-interest income	Annual value for aggregate non-interest income relative to total income for the country's banking system.	Global Financial Development Database
Bank sector assets	The log of total banking sector assets in a country.	Fitch Fundamentals Financial data
Concentration	The assets of three largest commercial banks as a share of total commercial banking assets.	Global Financial Development Database

Appendix A: Definitions and Sources. Continued.

Variable	*Definition*	*Source*
Property rights	Index that measures countries' ability to secure property rights, including the existence of legal institutions that are more supportive of the rule of law.	Fraser Institute website
Creditor rights	The index of creditor rights from Djankov et al. (2007).	Djankov et al. (2007)
Credit depth	An index of the depth of credit information in the country.	World Bank's Doing Business Database
Same language	Indicator variable equal to one if the two countries share the same language and zero otherwise.	Mayer and Zignago (2011)
Distance	Log of the circle distance (in km) between the countries' capitals.	Mayer and Zignago (2011)
Colony	Indicator variable equal to one if the two countries have ever had a colonial link and zero otherwise.	Mayer and Zignago (2011)
Contiguous	Indicator variable equal to one if the two countries share a border and zero otherwise.	Mayer and Zignago (2011)
Real exchange rate return	Annual (prior 12-month) real bilateral U.S. dollar exchange rate return.	IMF International Financial Statistics
Bilateral trade	Maximum of bilateral imports and exports between two countries. Bilateral imports (exports) are calculated as the total value of imports (exports) by a recipient country from a source country.	IMF Direction of Trade Statistics
NPL	Banking sector non-performing loans to gross loans (%). The ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans.	Global Financial Development Database
Bank Capital	Banking sector capital and reserves to total assets (%).	Global Financial Development Database
Bank ROA	Commercial banks' net income to average total assets.	Global Financial Development Database
Foreign ownership	The total foreign banking assets owned by residents of source country *s*, scaled by total banking sector assets. For a given country-pair, we aggregate the total bank assets owned by a source country across all regions of the world, excluding the region in which the recipient country *r* is located. We then aggregate the bilateral Foreign ownership at the recipient country-year level using the total distance (distance in kilometers between country capitals) between a source country *s* and recipient country *r* as the weight.	Claessens and Van Horen (2014) and Fitch Fundamentals Financial data

Appendix A: Definitions and Sources. Continued.

Variable	**Definition**	**Source**
Developed	Indicator variable that equals one for countries in the MSCI Developed Markets Index and zero otherwise.	
Restrictions on bank activities	Index measuring regulatory impediments to banks engaging in securities market activities, insurance activities, and real estate activities.	Barth, Caprio, and Levine. (2013)
Stringency of capital regulation	Index measuring the stringency of regulations regarding how much capital banks must hold, as well as the sources of funds that count as regulatory capital. The index ranges from 0-10, with higher values indicating greater stringency.	Barth, Caprio, and Levine. (2013)
Stringency of capital regulation	Index measuring the stringency of regulations regarding how much capital banks must hold, as well as the sources of funds that count as regulatory capital. The index ranges from 0-10, with higher values indicating greater stringency.	Barth, Caprio, and Levine. (2013)
Official supervisory power	Index measuring whether supervisory entities have authority to take action to prevent and correct problems. The index ranges from 0-14, with higher values indicating greater power.	Barth, Caprio, and Levine (2013)
Bank-Level Variables:		
Size	Log of total assets	Fitch Fundamentals Financial data
NPL-to-loans	Total non-performing loans (past-due 90 days or more) divided by total loans.	Fitch Fundamentals Financial data
Non-interest expense	Total non-interest expense divided by gross revenues	Fitch Fundamentals Financial data
ST funding	Non-deposit short-term funding (repurchase agreements and other short-term borrowings) divided by total liabilities.	Fitch Fundamentals Financial data
Leverage	Total assets divided by the book value of equity.	Fitch Fundamentals Financial data
ROA	Net income divided by average total assets	Fitch Fundamentals Financial data
Non-interest income-to-income	Non-interest income divided by the sum of-interest and non-interest income.	Fitch Fundamentals Financial data

Appendix B. Descriptive Statistics by Country.

This table provides summary statistics at the country level for the 75 countries in our analysis with available data on either of our two measures of systemic risk: 1) *MES* – the negative value of the value-weighted *MES* for all banks in a country and 2) *SRISK-to-GDP*. We include two measures of international bank flows. 1) *Flows* – The log difference (difference in log from t-1 to t) of total foreign claims (BIS Consolidated Banking Statistics) from all source countries to recipient country *r*, and 2) *Δ Claims-to-assets* – the BIS- break- and exchange rate-adjusted change in foreign claims (from the BIS Locational Banking Statistics) on recipient country r from *t-1* to *t*, scaled by total baking sector assets. All variable definitions are in Appendix A. We average each measure across the full sample period 2000-2014.

Country	*MES (%)*	*SRISK-to-GDP*	*Flows*	*Δ Claims-to-assets*
Argentina	3.291	0.160	-0.060	-2.863
Australia	2.094	.	0.066	1.682
Austria	3.203	2.396	0.072	1.876
Bahrain	1.431	0.063	-0.046	0.632
Bangladesh	0.407	.	0.289	1.753
Belgium	2.900	7.172	0.071	0.822
Bermuda	.	0.012	0.064	4.333
Bosnia and Herzegovina	0.042	.	-0.065	-2.070
Brazil	2.676	0.811	0.087	0.698
Bulgaria	1.559	.	0.049	3.453
Canada	1.751	3.898	0.078	1.009
Chile	1.293	0.105	0.050	1.369
China	2.460	1.599	0.200	0.740
Colombia	1.748	0.000	0.071	-0.102
Croatia	1.350	0.006	0.101	3.293
Cyprus	5.426	13.681	0.086	3.711
Czech Republic	.	0.000	0.118	2.003
Denmark	2.229	4.668	0.111	1.528
Egypt	2.829	0.000	0.070	0.548
Finland	1.957	0.245	0.126	4.636
France	3.615	9.773	0.075	1.533
Germany	2.828	5.342	0.063	0.788
Greece	5.419	3.669	-0.037	0.029
Hong Kong	2.160	0.414	0.066	0.851
Hungary	.	0.060	0.115	4.360
Iceland	5.218	.	-0.626	-15.935
India	3.474	1.895	0.137	2.879
Indonesia	3.612	0.072	0.060	0.049
Ireland	3.033	5.205	0.117	5.326
Israel	2.436	5.034	0.066	0.166
Italy	3.533	3.215	0.040	0.903
Japan	3.119	6.762	0.038	0.209
Jordan	1.934	0.000	0.051	0.292
Kazakhstan	0.615	0.340	-0.179	-2.573
Kenya	1.011	.	0.132	2.195
Kuwait	2.130	0.015	0.064	0.994
Lebanon	.	0.255	-0.028	0.379
Lithuania	2.034	.	0.118	7.693
Luxembourg	0.661	3.848	0.071	6.648
Malaysia	1.817	0.954	0.069	0.732
Malta	.	0.157	0.106	12.600
Mauritius	.	0.127	0.133	10.487
Mexico	2.124	0.034	0.097	1.282
Morocco	1.638	0.083	0.097	0.048
Netherlands	3.640	8.486	0.065	3.212
New Zealand	.	0.009	0.087	0.980

Appendix B: Descriptive Statistics by Country. Continued.

Country	*MES (%)*	*SRISK-to-GDP*	*Flows*
Nigeria	2.279	0.006	0.110
Norway	2.607	1.458	0.121
Oman	2.548	0.000	0.122
Pakistan	3.264	0.012	-0.035
Peru	1.231	0.101	0.082
Philippines	2.184	0.044	0.049
Poland	2.764	0.052	0.166
Portugal	2.578	1.754	0.074
Qatar	2.661	0.000	0.114
Russian Federation	4.127	0.199	0.099
Saudi Arabia	1.575	0.010	0.156
Singapore	2.395	0.811	0.081
Slovak Republic	.	0.000	0.081
Slovenia	.	0.117	-0.090
South Africa	2.453	1.977	0.114
South Korea	3.039	3.118	0.115
Spain	3.479	2.784	0.078
Sri Lanka	2.366	.	0.048
Sweden	3.163	6.042	0.064
Switzerland	3.300	15.005	0.075
Thailand	3.361	1.153	0.067
Tunisia	0.804	.	0.053
Turkey	4.881	0.175	0.131
Ukraine	2.462	0.053	-0.289
United Arab Emirates	.	0.367	0.173
United Kingdom	2.607	8.787	0.057
United States	3.422	2.704	0.057
Venezuela	1.523	.	0.052
Vietnam	.	0.064	0.158

Appendix C. Correlations Matrix.

This table presents the correlations of the key variables used in the analysis below. The sample period is 2000-2014. All variables are defined in Appendix A. * indicates significance at the 10% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MES (%)	(1)	1											
SRISK-to-GDP (%)	(2)	0.381*	1										
Flows	(3)	-0.136*	-0.151*	1									
Δ Claims-to-assets (%)	(4)	-0.157*	-0.140*	0.478*	1								
Flows - IV	(5)	0.060*	0.227*	0.322*	0.255*	1							
Predicted Flows	(6)	-0.022	-0.018	0.021	0.065*	0.156*	1						
GDP growth (%)	(7)	-0.040	-0.157*	0.307*	0.284*	0.210*	-0.103*	1					
Market return (%)	(8)	-0.191*	-0.225*	0.219*	0.188*	0.129*	-0.034	0.273*	1				
Volatility (%)	(9)	0.511*	0.134*	-0.062*	-0.190*	-0.031	0.046	-0.154*	-0.170*	1			
Non-interest income (%)	(10)	0.022	0.178*	0.028	0.038	0.146*	0.081*	-0.020	0.046	0.025	1		
Bank sector assets	(11)	0.228*	0.532*	0.014	-0.055*	0.782*	0.156*	-0.115*	-0.125*	0.085*	0.133*	1	
Concentration (%)	(12)	-0.005	0.122*	0.022	0.066*	0.009	-0.072*	-0.040	-0.087*	-0.104*	-0.018	-0.026	1
Foreign ownership	(13)	-0.138*	-0.261*	0.018	-0.067*	-0.093*	-0.135*	0.152*	0.112*	-0.137*	-0.228*	-0.200*	-0.152*

Appendix D. Example Calculations for Instrumental Variable on Foreign Ownership.

The table shows an example of the construction of the instrumental variable, *Foreign ownership*$_{t-1}$. *Foreign ownership* is the total foreign banking assets owned by residents of source country *s*, scaled by total banking sector assets. Total foreign banking assets for a source country are computed as the sum of total assets for all banks that are owned (50 percent or more) by foreigners from source country *s*. We use data from Claessens and Van Horen (2014), who classify a bank as foreign if 50 percent or more of a bank's shares are owned by foreigners. For a given country-pair, we aggregate the total bank assets owned by a source country across all regions of the world, excluding the region (Asia in this example) in which the recipient country *r* is located. We then aggregate the bilateral *Foreign ownership* at the recipient country-year level using the total distance (distance in kilometers between countries' capitals) between a source country s and recipient country *r* as the weight. In robustness tests, we also use an equally weighted average of *Foreign ownership*.

Recipient country (*r*)	Source country (*s*)	Year	Foreign ownership % (by source) t-1	Total distance	Weight	Weighted Foreign ownership
India	Australia	2012	8.96	10,363.85	0.058	0.519
India	Austria	2012	11.79	5,571.10	0.031	0.367
India	Belgium	2012	33.08	6,419.60	0.036	1.186
India	Brazil	2012	1.24	14,251.55	0.080	0.099
India	Chile	2012	0.51	16,936.54	0.095	0.049
India	Denmark	2012	2.50	5,852.46	0.033	0.082
India	France	2012	4.87	6,594.23	0.037	0.180
India	Germany	2012	4.92	5,785.57	0.032	0.159
India	Greece	2012	24.91	5,013.93	0.028	0.698
India	Italy	2012	10.82	5,922.22	0.033	0.358
India	Japan	2012	1.17	5,847.71	0.033	0.038
India	Mexico	2012	0.03	14,673.66	0.082	0.003
India	Netherlands	2012	11.94	6,363.42	0.036	0.424
India	Panama	2012	0.61	15,161.38	0.085	0.052
India	Portugal	2012	23.98	7,782.46	0.043	1.042
India	Spain	2012	18.76	7,282.05	0.041	0.763
India	Sweden	2012	39.27	5,574.22	0.031	1.223
India	Switzerland	2012	6.21	6,249.01	0.035	0.217
India	Taiwan	2012	0.01	4,393.58	0.025	0.000
India	Turkey	2012	3.12	4,222.86	0.024	0.074
India	United Kingdom	2012	6.54	6,720.64	0.038	0.245
India	United States	2012	5.03	12,059.81	0.067	0.339
TOTAL				179,041.85		8.114

Appendix E. Computing Bilateral Bank Flows from BIS Consolidated Banking Statistics.

We obtain data used to build our proxy for international bilateral bank flows from the consolidated banking statistics published by the Bank for International Settlements (BIS). The data can be downloaded from: http://www.bis.org/statistics/full_data_sets.htm. We use the consolidated banking statistics (CBS) data following prior studies (e.g. Houston, Lin, and Ma, 2012; Cetorelli and Goldberg, 2011). The data provide details of the credit risk exposures of banks headquartered in up to 31 BIS reporting countries to all sectors of the economy in over 200 recipient countries. The number of reporting countries has changed over time. We are able to collect historical data for 26 reporting countries. BIS no longer provides data on foreign claims for banks in Norway.

Table E1 shows our sample of source countries and the first year in which data are available. Data are available on a quarterly or semiannual basis since December 1983. The consolidated foreign claims (loans, debt securities, and equities) include: 1) cross-border claims − claims granted to non-residents; 2) international claims − local claims of foreign affiliates in foreign currency; and 3) local claims of foreign affiliates in local currency (BIS, 2009). The data exclude intragroup positions (e.g., extensions of credit from a parent bank to its subsidiary in a foreign country). We obtain data on foreign claims on an immediate counterparty basis from 1983 (or first available year) through 2014. The immediate counterparty claims refer to claims to borrowers located in a given recipient country. While the CBS data are also compiled on an ultimate risk basis (which takes into account credit risk transfers to other counterparties), historical data on an ultimate risk basis is limited. In most cases, data on an ultimate counterpart risk basis is only available since the mid-2000s.

The initial sample consists of total claims from 26 source countries to 198 recipient countries. We exclude countries with missing data on our main country-level variables. Because data on foreign claims is scarce prior to 1995, in our bilateral estimations we restrict our sample to the period 1995-2014. Our final sample consists of bank flows from 26 source countries to 114 recipient countries, totaling 21,277 country-pair-year observations. The BIS data do not provide a measure of bank flows. We thus follow Houston et al. (2012) and construct our measure of bilateral bank flows as the log difference in total foreign claims between source country s and recipient country r. We also compute an aggregate measure of bank flows into a recipient country r as the log difference (from $t-1$ to t) in total foreign claims from all source countries to recipient country r.

There are two potential issues with the CBS data: 1) Breaks in series (e.g. cross-border bank acquisitions that lead to changes in the nationality of the reporting banks), and 2) the impact of exchange rate movements. The CBS data are not adjusted for these and the data required to adjust for breaks-in-series is confidential, and as a result, we are unable to make any adjustments to the data. To ensure that issues associated with breaks-in-series or exchange rate movements are not driving our results, we first winsorize bank flows at the top/bottom 1% of the distribution to mitigate the impact of outliers. In robustness tests, we also follow the approach taken by Houston et al. (2012) and drop bank flows that exceed 100% in absolute value in a given year. Finally, we also compute bank flows to a recipient country using the BIS-break- and exchange rate adjusted change in claims using the locational banking statistics (LBS). For reasons explained below, we do not use LBS data in our bilateral regressions, because the LBS data do not provide the nationality of the lending banks (see e.g. Avdjiev, Kuti, and Takáts, 2012).

The BIS also compiles data on Locational Banking Statistics (LBS). The LBS data capture both the currency composition and the geographical breakdown of the counterparties. In addition, LBS data provide outstanding claims and outstanding liabilities of internationally active banks from reporting countries to counterparties in over 200 countries (BIS 2009). The BIS provides break- and exchange rate-adjusted changes in amounts outstanding. LBS data are available on a quarterly basis since 1977 for reporting banks in up to 46 countries; however, prior to 2000, only 14 source countries report LBS data. In addition, the nature of the LBS data does not allows us to identify the source country of the claims, which prevents us from using the LBS data in bilateral regressions that control for source and recipient country characteristics. As an example, if a US bank's Italian subsidiary makes a loan to a German firm, the LBS data would record this as an Italian claim on Germany. The CBS data would correctly record this as a US claim on Germany. Both databases would correctly identify the recipient country. Given this, we do not use LBS data in our bilateral regressions, but we do use the aggregated changes in BIS break- and exchange-rate adjusted foreign claims to recipient country r to test the robustness of our findings using the CBS data. Specifically, we use the change in foreign claims to recipient country *r* from *t-1* to *t* as a proportion of total banking system assets in recipient country *r* in year *t-1*.