# Cross-Border Bank Flows and Systemic Risk[1]


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**Abstract**

Using data on cross-border bank flows from 26 source countries to 128 target countries, we find that bank inflows are associated with improved financial stability and lower systemic risk in the bank systems in the target country. The flows are greater between source (target) countries with more (less) stringent *de jure* regulations that govern the bank systems. And the link between increased flows and reductions in marginal expected shortfall (MES) are concentrated among larger banks, those with poorer asset quality, and those that rely more on non-traditional banking activities and on more volatile sources of funds. Additional evidence suggests that bank flows help to reduce MES by improving target-country bank asset quality, efficiency, and reliance on non-traditional revenue sources. Overall, we interpret our findings as in support of a benign view of regulatory arbitrage in international bank flows.



**Keywords:** Cross-border bank flows, financial institutions, bank regulation, systemic risk, financial crises

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## 1. Introduction

In the aftermath of the global financial crisis which, in turn, followed a period of rapid global expansion of bank activities, policymakers are asking anew 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). On the other hand, internationalization of banks has also been linked to increased risk (Berger et al., 2016). There is considerable evidence that the proliferation of cross-border lending activities transmit foreign shocks to target markets (Bruno and Shin, 2015; Schnabl, 2012). 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 target 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). Regulatory arbitrage has been shown to be an important determinant of both cross-border bank flows and cross-border bank acquisition activity (Houston, Lin, and Ma, 2012; Karolyi and Taboada, 2015). Yet, too little is known about the potential economic consequences of those flows linked to "regulatory arbitrage" for the target markets. In this paper, we take a first step at filling this gap in the literature.

There has been a large increase in the flow of bank capital across countries 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 (see Figure 1, Bank for International Settlements Quarterly Review, 2015). Bank flows to developed countries have seen a decline since the financial crisis driven primarily by retrenchment of European banks (IMF, 2015). In contrast, as Figure 1 shows, flows to developing countries have continued to increase since 2008 reaching a peak of $5.9 trillion as of 2014.

Cross-border bank flows continue to be an important channel for the transfer of capital across countries even after the global financial crisis. Such activity could have positive or negative consequences for the target country. On one hand, banks engaging in such forms of regulatory arbitrage could be doing so to escape from costly regulations in their home country that prevent them from investing in certain risky, but profitable projects. If this motive is the driver of regulatory arbitrage, we should observe positive economic consequences for the target country, as banks engaging in such activities can maximize value for shareholders and improve capital allocation. On the other hand, banks could engage in regulatory arbitrage to pursue value-destroying activities in the form of excessive risk-taking, for example. This form of regulatory arbitrage could have adverse consequences on bank performance and shareholder value and could destabilize the target country's financial system.

Identifying the impact of cross-border bank flows on the aggregate systemic risk of target countries is difficult because changes following inflows or outflows could be attributed to other changes in the economy around the same time. To address this identification challenge, we employ a two-pronged attack: (1) we estimate *unexpected* bank flows using a gravity model across source-target country-pair-years; (2) we exploit heterogeneity of the potential impact of unexpected flows across banks in a given target country for their respective contributions to systemic risk and for their operational changes in the years following the unexpected flows.

Regarding the first point, we estimate *unexpected* bank flows using two similar, but different approaches. 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 128 target countries over the period from 1995 through 2014 using a gravity model adapted from the international trade literature. The residuals from the model are extracted and aggregated on a weighted average basis for a given target country across all source countries in which the weights capture different measures of economic links to the target country. The goal is that we can isolate the flows from other confounding macroeconomic and capital market forces as well as institutional forces that are at work. The second approach constructs an instrumental variable for a given target country that captures restrictions on capital outflows from the *source* countries with which that target country is linked. The instrument we employ is a foreign direct and portfolio investment (FDI) outflow restrictions index built by Fernandez et al. (2015). It measures a country's *de jure* stance towards capital controls on both equity outflows that cover transactions involving shares and other securities of a participating nature and on direct investments for the purpose of acquiring a lasting economic interest. The indexes are aggregated on a weighted average basis for a given target country across all source countries in a way similar to that above. Both approaches seek to satisfy the exclusion restriction for validity by leaning on an assumption that capital controls in the *source* country will affect flows leaving a source country, but will not directly affect systemic risk in a target country except through those flows.

The second part of the paper takes on the identification challenge by drilling down to analyze these unexpected flows across individual banks that constitute the bank systems in the target countries. The basic idea of heterogeneous effects across banks originates from the very nature of systemic risk and the idea behind identifying global systemically important banks (G-SIBs) as 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 test whether the link between unexpected bank flows and the contributions to systemic risk by individual banks vary by size, by their asset quality, cost efficiency, and leverage, and by their reliance on non-traditional revenue or more volatile funding sources. Target country banks that are more exposed by their size, leverage or unstable funding sources to cross-border bank flows may be more likely to contribute to changes – whether positive or negative – in the systemic risk in the bank system. Analysis at the individual-bank level also allows us to examine the channels through which unexpected 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.

While several measures of systemic risk have been developed and used in research over the recent past (see e.g. Bisias, Flood, Lo, and Valavanis, 2012 for a survey of measures), we focus on two measures 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

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).

3 Given our large cross-section of countries, data availability prevents us from using another commonly used measure of systemic risk, *CoVaR* (Adrian and Brunnermeier, 2016).

average bank return on days when the market is in the 5% left tail of its distribution; in our analyses we use the negative value of *MES* so that both of our measures are increasing in systemic risk. *SRISK* estimates the amount of capital needed during a crisis for a bank to maintain an 8% capital-to-assets ratio. These measures have been widely used in the literature and have been shown to be suitable measures of systemic risk (see e.g. Acharya et al., 2017; Brunnermeier, Dong, and Palia, 2015; Engle, et al. 2014). The two measures are highly correlated. The advantage of *MES* is that we compute the measure directly and can do so for individual banks in a given target country, which allows us to explore the heterogeneous impact of cross-border flows across different banks. We only have *SRISK* data at the target country level, but it allows us to calibrate across the two different measures. Reassuringly, they deliver very similar inferences.

We uncover three main findings. First, unexpected flows are reliably associated with significant reductions in aggregate systemic risk. They are economically large effects. A one standard-deviation increase in flows is associated with a 1.2% reduction in *MES*, which represents 21% of the unconditional mean and 14.8% of its unconditional standard deviation across all target countries and years. The findings arise primarily for unexpected *inflows* (increases in MES following outflows are weak) and there is considerable variation across target countries and over time. The negative relationship between unexpected flows and *MES* or *SRISK* arises for over two-thirds of the target countries and for most years we study. Those countries with the largest standardized decreases in systemic risk following unexpected flows are Thailand, Argentina, Ireland, Portugal, Greece, and Spain.

The second key finding is that the impact of bank flows are also in line with regulatory arbitrage: unexpected inflows from source countries with higher quality regulatory systems are more reliably linked to reductions in systemic risk measures for among target countries. We interpret this finding as consistent with the benign form of regulatory arbitrage as the cross-border bank flows foster greater stability, not instability, in the target market bank system. To do this experiment, we divide the sample by the regulatory quality of the target countries using *de jure* measures of the stringency of capital requirements, restrictions on bank activities, private monitoring, and strength of supervisory powers from Barth, Caprio and Levine (2013). We also perform the same experiment using *de facto* measures of target country quality, such as by level of economic development, size of the bank sector, the overall sector's leverage ratios, profitability, and the ratio of their non-performing loans to gross loans.

Finally, we examine how an *individual* bank's contribution to systemic risk (*MES*) is affected by bank flows. By exploring the impact on individual banks, we can provide further (and plausibly more direct) tests of the destructive versus benign forms of regulatory arbitrage. We find the reductions in *MES* following unexpected cross-border flows are concentrated among banks that are larger, with more non-performing loans, with greater reliance on trading (non-traditional) income, and on short-term funding. We then study the channels through which the cross-border flows could reduce systemic risk in target countries. We posit that *MES* decreases could stem from a competitive response to the cross-border inflows that could arise from reduced reliance on non-traditional income, 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, which we have shown to be from stronger regulatory quality regimes. We track performance and risk-taking up to three years following inflows and find evidence of improved asset quality (lower levels of nonperforming loans), improved efficiency (lower overhead costs), reduced reliance on non-traditional income sources (lower trading income), and lower leverage. In all of our analyses, cross-border bank flows are negatively related to these outcome variables, casting doubt on the destructive view of regulatory arbitrage in cross-border bank flows.

Our paper contributes to the literature on the economic consequences of international 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, Popov, and Udell, 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. More recently, Houston, et al. (2012) examine cross-border bank flows to find evidence of regulatory arbitrage, as banks tend to predominantly transfer funds to countries with fewer regulations. They interpret these flows as a signal of a harmful "race to the bottom." Ongena, et al. (2013) find that banks from countries with tighter restrictions on bank activities and more capital requirements tend to make riskier loans abroad, which is in line with the race to the bottom view of regulatory arbitrage. However, they also find that stronger supervision at home reduces risk-taking abroad. Karolyi and Taboada (2015) confirm that regulatory arbitrage is a motive behind cross-border bank acquisition flows, but their evidence on market reactions to deal announcements is more in line with a benign form of regulatory arbitrage than a potentially destructive one.[4] We argue that regulatory arbitrage via cross-border bank flows is not necessarily a cause for concern, at least from the perspective of financial system stability in target countries.

Our study also sheds light on the debate about the benefits and costs of cross-border lending activities and bank internationalization, in general. On one hand, cross-border lending may facilitate risk-sharing and diversification and reduce banks' exposure to domestic shocks (Allen, et al., 2011; Schoenmaker and Wagner, 2011). On the other hand, through cross-border lending, banks may transmit foreign shocks to back to host markets (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). The literature, to date, does not examine the link between bank internationalization and bank risk, or how this link manifests during crises. Gulamhussen, et al. (2014), Berger, et al. (2016), and Jeon, et al. (2016) are exceptions. Berger, et al. (2016) find a positive relation between internationalization and bank risk taking; that is, 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.[5]

[4] Frame, Mihov, and Sanz (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. Temesvary (2015) also shows U.S. banks that engage in capital regulatory arbitrage are more profitable.

[5] Even more research focuses on nonfinancial firms and internationalization. Hughes, Logue, and Sweeney (1975), Rugman (1976), Agmon and Lessard (1977), Amihud and Lev (1981), and Michel and Shaked (1986) document lower risk for international corporations. Bartov, Bodnar, and Kaul (1996) and Reeb, Kowk, and Baek (1998) find international corporations are more risky. Several studies examine the channels through which these risks appear, such as Black (1990); Kwok and Reeb (2000); and Cuervo-Cazurra, Maloney, and Manrakahan (2007).

Finally, we contribute to the growing literature on the potential determinants of systemic risk. Many studies focus on how non-traditional banking activities affect banks' systemic risk. Since non-traditional banking activities may allow banks to circumvent capital regulations (Acharya, Schnabl, and Suarez, 2013), engaging in such activities may lead to increases in 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, 2010; Demirgüç-Kunt and Huizinga, 2010; Stiroh, 2004)). More recently, Engle, et al. (2014) show evidence of heterogeneity in the relation between non-traditional banking activities and systemic risk based on a country's market structure. Specifically, they document that the positive relation between non-interest income and systemic risk is driven by banks in less concentrated banking sectors. Through the provision of non-traditional banking services, banks can obtain more information that helps reduce information asymmetry inherent in a bank's lending relationships (Boot, 2000; Degryse and Van Cayseele, 2000; Bhattacharya and Thakor, 1993). What our study adds to this literature is global evidence on another important determinant of systemic risk; namely, cross-border international bank flows.

## 2. Data and Methodology

Our data for this paper come from six different sources. We obtain data on international bilateral bank flows from the Consolidated Banking Statistics (CBS) published by the Bank for International Settlements (BIS). The data provide details of the credit risk exposures of banks headquartered in 26 BIS reporting countries.[6] 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). We obtain data on foreign claims

[6] The 26 source countries are: Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Mexico, Netherlands, Panama, Portugal, South Korea, Spain, Sweden, Switzerland, Taiwan, Turkey, United Kingdom, and United States. BIS no longer provides data on foreign claims for banks in Norway.

from 1983 through 2014. The initial sample consists of total claims from 26 source countries to 198 target countries. We exclude countries with missing data on our main country-level control variables (more below). Our final sample consists of bank flows from 26 source countries to 128 target countries, totaling 47,259 country-pair-year observations. Using these data, we follow Houston, Li, and Ma (2012) and construct our measure of bank flows, *Bank Flows*$_{s,r,t}$, as the annual difference of log total foreign claims for each source-target combination. Specifically, *Bank Flows*$_{s,r,t}$ is computed as the log difference from *t-1* to *t* of total foreign claims from source country *s* to target country *r*. In our main analysis, we aggregate the annual bilateral data at the target country-year level. Details on construction are given in Appendix E.

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.

We obtain data on our second measure of systemic risk, *SRISK*, from the Volatility Institute at New York University's Stern School of Business (the V-LAB). Data on *SRISK* is available for 62 target countries in our final sample starting in 2000.[7] Coverage varies by country with 32 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

[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 (four countries), 2002 (two added), 2003 (three more added), 2004 (two), 2005 (two), 2006 (one), 2007 (one), 2008 (five), and 2009 (two). Data for Slovenia (Jordan) is only available since 2011 (2012). We include these last two countries in our main analyses for completeness, but our results are unaffected if we exclude them.

marginal expected shortfall (*LRMES*). *LRMES* is the expectation of the bank equity multi-period return conditional on a systemic event. Formally, *SRISK* is given by:

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

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). The country-level data are available on a daily basis, and we use the 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. We use the total Foreign Direct Investment (FDI) Outflow Restrictions index from Fernandez et al. (2015), which captures a country's stance towards capital controls on outflows. They build on Chinn and Ito (2006) and Schindler (2009) using the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions*. An important feature of their data for our purposes is the fact that these indices capture capital control restrictions on both inflows and outflows. The dataset covers ten categories of assets for 100 countries over the period 1995 to 2013. We use an average of outflow control restrictions on equity investments and direct investment accounts only. Since our focus is on *MES* and *SRISK* in a target country, we calculate our instrument using the respective index values of source countries that have a trade link to the given target country. The source country weight for *s* is computed as the fraction of all bilateral trade with target country *r* that is represented by the maximum of exports and imports between source country *s* and target country *r*. Data for imports and exports is from the IMF *Direction of Trade Statistics*. The key identifying assumption is that the equity and FDI outflow control restrictions of the source countries weighted by trade flows are relevant for cross-border bank outflows and that together they link to systemic risk exclusively through the bank flows.

Measures of regulatory quality to assign cross-border bank flows as consistent with regulatory arbitrage are from Barth, et al. (2013). We use four measures: (1) *Restrictions on bank activities*, 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); (2) *Stringency of capital regulation*, an index measuring how much capital banks must hold, as well as the sources of funds that count as regulatory capital; (3) *Official supervisory power*, an index that measures whether supervisory authorities have the power to take actions to prevent or correct problems, and (4) *Private monitoring*, an index that measures whether there are incentives for the private monitoring of banks. 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. These and other variables used in our analyses are described in detail in Appendix A.

Finally, we obtain a number of country-level measures from World Bank databases that have been shown to influence systemic risk (among others, Engle, Jondeau, and Rockinger, 2015; Brunnermeier, Dong, and Palia, 2015). To control for financial development and growth we use the log of GDP per capita (*Log GDP per capita*) and the growth in real GDP (*GDP growth*) obtained from the World Bank's *World Development Indicators* database. From the World Bank's *Global Financial Development* database (Beck, Demirgüç-Kunt, and Levine, 2009; Čihák et al., 2012), we obtain the total credit provided by deposit money banks to the private nonfinancial sector, scaled by GDP (*Bank credit*), as a proxy for banking sector size; the non-interest income to total income (*Non-interest income*) to proxy for the extent of noncore banking activities; stock market index returns (*Market return*), and stock market volatility (*Volatility*)– the annualized standard deviation of weekly stock market index returns. All variables used in our analyses are defined in Appendix A. Appendix B shows descriptive statistics of the international bank flows and our systemic risk measures for our final sample of 74 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 *MES* sample and for the subsample of those countries with available data on *SRISK*, respectively. The average *MES* is 2.7% for the *MES* sample and a slightly higher 3.0% for the *SRISK* subsample. On average, *SRISK* represents approximately 5.2% of GDP. In general, most of the variables are comparable across the two samples, although countries in the *SRISK* subsample tend to have larger banking sectors. The average bank credit-to-GDP ratio is 74.3% for the *MES* sample, but 84.7% for the *SRISK* subsample. Figure 2 exhibits the average *SRISK-to-GDP* and *MES* across countries from Panel B's subsample by year. Both series sensibly peak during the global financial crisis period in 2008 and remain at elevated levels through 2011. 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 non-interest income and volatility. Finally, we observe that bank flows are, on average, negatively correlated with several regulatory quality measures, consistent with Houston et al. (2012).

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

To assess the impact of actual and unexpected bank flows on the target country's systemic risk, we run various specifications of the following regressions:

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

where *Systemic Risk* refers to our measures of systemic risk, *MES* and *SRISK*. $Flows_{r,t-1}$ refers to *actual* or *residual* (as explained later) bank flows into target country *r* in year *t-1*. $X_{r,t-1}$ is a vector of target country controls that have been shown to impact systemic risk of the financial system: *Log GDP per capita, GDP growth, Volatility, Market return, Non-interest income,* and *Bank credit*. *Volatility*, *Market return*, and *Bank credit* 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). Finally, $\delta_t$ and $\theta_r$ are year and target country fixed effects, respectively. In all regressions, we cluster standard errors at the target country level.

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 *target* country's financial system. In Models (1) to (3), we use *MES* to measure systemic risk and, in Models (4) to (6), we use *SRISK-to-GDP*. Models (1) and (4) use only those variables that have been used in previous work to forecast systemic risk (Engle et al., 2015;

Brunnermeier et al., 2015). Models (2) and (5) add the actual cross-border bank flows, *Flows* (difference in log of total foreign claims to target country from *t*-1 to *t*) as the key dependent variable. This variable represents the sum of all flows entering a target country regardless of the source. In Models (3) and (6) 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.

For each model, we find reliable evidence that cross-border bank flows are correlated with a reduction in *MES* (*SRISK-to-GDP)* in the target country. Across all model specifications in which flows are included, the coefficient on *Flows* is negative and statistically significant at the 1% level. Economically, this effect is large. Taking the coefficients in Model (2) as an example, a one-standard-deviation increase in *Flows* (0.209) is associated with a reduction in *MES* of 0.105, which represents 3.9% of its unconditional mean (2.66%) and 6.3% of its standard deviation (1.681) across all target countries and years.

Our results are similar when using our alternate measure of systemic risk, *SRISK* in Models (4) to (6). Taking the coefficients in Model (5), a one-standard-deviation increase in *Flows* (0.199 for this sample) is associated with a reduction in *SRISK* of 0.614, which represents 11.9% of the unconditional mean and 7.8% of its standard deviation (7.869) across all target countries and years. Overall, our results using *SRISK* are of larger magnitudes, but consistent with those using *MES* as our measure of systemic risk.

The control variables in the specification are consistent with prior studies. Both *MES* and *SRISK* are reliably correlated with the size of the banking sector (*Bank credit*), which is consistent with Engle et al. (2015, Table 8). There is a reliably positive coefficient with the lagged market index return and market return volatility for *MES*, 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 no significant relationship at the country level for non-interest-income, although it is negative for *SRISK*. At the country level, we see that both *MES* and *SRISK* are inversely related the level of economic development (as measured by GDP per capita). 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 target country fixed effects comprise much of that explanatory power and year fixed effects do so to a much less extent.

To understand the cross-country variation in the relationship between actual bank flows and systemic risk, we perform these regressions by country across years for the subset for which there are at least three years of observations. We do not focus here on statistical precision, but the dispersion in the relationship as a diagnostic exercise. Figure 3 presents the results in Panel A for *MES* and in Panel B for *SRISK*. To facilitate comparison, we standardize the coefficients on *Flows* for the systemic risk proxy for each country by multiplying by the one-standard-deviation increase in *Flows* for that country and dividing by its own mean for systemic risk. For example, the coefficient for *MES* for Greece is -5.19. A one-standard-deviation increase in *Flows* (0.338) is associated with a 1.75% reduction in *MES* which is a 31.3% reduction relative to its unconditional mean of 5.606%. In Panel A of Figure 3, Greece has the 8th lowest standardized coefficient with Croatia, Lithuania, Ireland, Bosnia, Portugal, Denmark and Italy having lower values. It is important to note that two-thirds of the countries have negative values. A number of countries with large banking sectors experience reductions in systemic risk associated with sizeable increases in cross-border bank flows, including the U.K., U.S., and China. Just as interesting to study are the names of countries that experience a relatively rarer increase in systemic risk with more bank flows, such as Canada, Taiwan, and Belgium. Panel B presents the equivalent rank ordering for *SRISK*. There are important differences among the 48 countries in both samples. Overall, the rank correlations in these standardized coefficients is 0.33.

Panels C and D repeat the equivalent diagnostic exercises for *MES* and *SRISK* regressions by year. In other words, these are cross-country regressions by year. What we observe is that the standardized coefficients are negative for just under half of the 15 years for *MES* and *SRISK*, but it is the magnitudes of the year-by-year coefficients that are much larger when negative than when positive. The largest negative spikes for *MES* arise in 2010-2012 and for *SRISK* in 2010 during the peak of the European debt crisis period. Acharya, Eisert, Eufinger, and Hirsch (2016) focus on the real effects of the crisis period for firms and how individual banks' exposures to sovereign debt contributed to the severity of the crisis. That the PIIGS

(Portugal, Italy, Ireland, Greece and Spain) have among the largest negative standardized coefficients suggest that cross-border bank inflows during that period may have helped alleviate the credit contraction.

In Figure 4, we further diagnose how long the potential impact of cross-border bank flows for country-level systemic risk measures persist. We estimate the same specification as in Eq. (2), but add up to three lags of *Flows*. The coefficients are standardized in the same way as in Figure 3. What is different here is that we report not only the values for the contemporaneous and up to three years lagged coefficients, but also the respective 95% confidence ranges (indicated by the range lines). The figures indicate that the contemporaneous correlation between *Flows* and *MES* or *SRISK* is the largest negative value, but it remains negative for up to three years later. The precision with which we can make that statement is weaker.

### 3.1. Systemic Risk and *Unexpected* Cross-Border Bank Flows

As mentioned in the introduction, identifying the impact of cross-border bank flows on the aggregate systemic risk of target countries is difficult because changes following inflows or outflows could be attributed to other changes in the economy around the same time. In this section, we pursue the first of two ways in which we seek to address this identification challenge. That is, we estimate *unexpected* bank flows using a gravity model across source-target 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 128 target countries over the period from 1995 through 2014 using a gravity model adapted from the international trade literature. The residuals from the model are extracted and aggregated on a weighted average basis for a given target country across all source countries in which the weights capture different measures of economic links to the target country. The goal 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 estimate bank-flows by country-pair-year using various specifications of the following model using all available data from 1995 to 2014:

$$Bank\ Flow_{s,r,t} = \alpha + \beta_1 \Delta X + \beta_2 Distance + \beta_3 Same\ Language + \gamma_t + \delta_s + \theta_r + \varepsilon_{s,r,t} \quad (3)$$

where *Bank Flow*$_{s,r,t}$ is the log difference from *t-1* to *t* of total foreign claims from source country *s* to target country *r*. $\Delta X$ is a vector of controls that have been shown to influence bank flows, measured as differences between source county *s* and target country *r*, which includes: (1) the creditor rights index (*Creditor rights*) from Djankov et al. (2007) to control for the power of secured creditors; (2) the depth of credit information (*Credit depth*) from the World Bank's Doing Business database to control for the information content of credit information; (3) the property rights index (*Property rights*) from the Fraser Institute as a proxy for the quality of legal institutions; (4) the *log of GDP per capita*; 5) real *GDP growth*, and 6) the natural log of population (*Population*). We also use two variables that are 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*) and an indicator variable for countries that share the same language (*Same Language*). Finally, $\gamma_t$, $\delta_s$, and $\theta_r$ refer to year, source, and target country fixed effects, respectively.

We provide the results of these regressions in Table 3. Models presented here replicate the prior work of Houston, et al. (2012), and we find our results to be mostly consistent.[9] The coefficients on *log of GDP per capita*, *GDP growth*, and *Population* are reliably significant and negative. Cross-border bank flows are stronger in the direction of relatively less-developed markets with larger populations and faster-growing economies. The negative coefficient on *Credit depth* suggests that cross-border bank flows are not deterred by the lower quality of the credit information in the target country relative to the source country. The positive and reliably significant coefficient on *Same Language* 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.

[9] 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 Promolla (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.

In Models (2) and (3), we introduce additional variables commonly used in gravity models: *Contiguous*, which is an indicator variable equal to one if two countries share a border and zero otherwise; *Colony*, an indicator variable that is equal to one if two countries have ever had a colonial link and zero otherwise; and, *Financial Liberalization*, an index of financial liberalization from Abiad, Detragiache and Tressel (2010). We find reliable evidence that the fact that source and target markets represent contiguous land masses is associated with larger cross-border flows (over and above the reliably negative coefficient on *Distance*), but the historical colonial link between two countries is never statistically significant. The inclusion of *Financial Liberalization* significantly reduces the sample from 47,259 country-pair-year observations to only 32,613 in Model (3). But the negative coefficient is as shown in Houston et al. (2012) that cross-border flows are stronger in the direction of markets with less open markets in terms of their capital accounts.

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 coefficients on *Restrictions* and *Supervisory independence* are positive and statistically significant, confirming the findings in Houston et al. (2012) that banks transfer funds from (to) countries with more (fewer) regulations. Just as interesting is the fact that some of these measures of regulatory quality have no explanatory power, such as the degree of independence of supervisory authorities, the extent of private monitoring and the strength of external auditing for banks. In Models (5) and (6), we saturate our panel regression model with a full set of target-country-year, and source-country-year fixed effects to better control for additional unobservable time-varying factors at the country level that may explain flows. Model (5) uses all of the control variables, all of which now become insignificant, while Model (6) excludes controls other than the fixed effects. There is a significant increase in the explanatory power from Model (4) to Model (5) with the $R^2$ reaching as high as 22.5%. The adjusted $R^2$ reaches 33% in Model (6) which includes just the year, target-country-year, and source-country-year fixed effects excluding the control variables and it does so for the largest sample of country-pair-year observations (47,259), which we will exploit in our main experiments to follow.

The next step is to construct various measures of *unexpected* bank flows by aggregating the residuals from each of the various specifications in Table 3 of Eq. (3). The goal is to introduce new measures of *unexpected* bank flows into the tests of Eq. (2) in Table 2. To aggregate to the target country-year level, we compute:

$$Residual\ Flows_{rt} = \sum_{s=1}^{26} \varepsilon_{s,r,t} \times \frac{GDP_{s,t}}{TOTGDP_t}, \tag{4}$$

where *r* refers to target country, *s* refers to source country, $\varepsilon_{srt}$ are the residuals from Eq. (3), $GDP_{s,t}$ is the GDP of source country *s* in year *t*, and $TOTGDP_t$ is the total GDP of all source countries in year *t*. Note that we aggregate across all 26 BIS-reporting source countries in Eq. (4).[10] Table 1 reports summary statistics associated with the residual flows computing this approach. We find that, for our *MES* sample (Panel A), the mean residual flow is 0.007 with a standard deviation of 0.182, and for the *SRISK* subsample (Panel B), the mean residual flow is 0.003 with a standard deviation of 0.185. There is a reduction in the unconditional variation in the residual flows relative to the actual flows, which will make it more challenging when we take those to tests of Eq. (2) for systemic risk.

Table 4 presents the results of the second-pass regressions using the residual flows and our systemic risk proxies. The relevant specifications are Model (1) for *MES* and Model (4) for *SRISK*. These are the analogous specifications of Models (2) and (5) in Table 2 using the actual cross-border bank flows. For *MES*, the coefficient of -0.601 for *Residual Flows* is statistically reliable and economically as large as implied in Table 2. A one-standard-deviation increase in *Residual Flows* (0.182) is related to a 0.109% decrease in *MES* in the target country, which is 4.1% of its unconditional mean and 6.51% of its standard deviation. Likewise, using the coefficient from Model (4), a one-standard-deviation increase in *Residual Flows* (0.185 for this subsample) is related to a 0.431% decrease in *SRISK* in the target country, which is equivalent to 8.37% of its mean or 5.48% of its standard deviation. The results for *Actual Flows* were economically similar in magnitudes to those for *Residual Flows*.

[10] In robustness tests, we aggregate residuals using alternative weighting schemes for the source countries, such as equal weights and even weights by the size of the bank assets in the respective source countries.

A focus on residual flows from specifications that control for known determinants of bank flows, while far from perfect, should alleviate some concerns that bank flows may be contaminated by contemporaneous macroeconomic or capital market forces at work that can influence changes in systemic risk in the target country.

### 3.2. An Identification Strategy

While our results show that unexpected bank flows are associated with a reduction in systemic risk in the target country, these results still do not give us confidence that we have established grounds for a causal interpretation because flows are not exogenous. It is possible, for example, that improvements in financial system stability (e.g., a decline in systemic risk) in the target country attracts bank flows, which introduces a form of reverse causality that can impact the interpretation of our findings. We attempt to address these concerns by implementing a second approach: namely, we project cross-border bank flows on an instrumental variable that is relevant for cross-border flows, but yet is uncorrelated with the target country's systemic risk proxy.

To do so, we use a variable that captures restrictions on capital outflows from all the source countries that may matter for a given target country. Specifically, we use the *Total FDI outflow restrictions* index from Fernandez et al. (2015). This index captures a country's stance towards capital controls on capital outflows. Using this variable, we construct our instrumental variable as the weighted average of the *Total FDI outflow restrictions* index across all source countries with foreign claims in year *t-1* to a particular target country, *r*. But the weights on the component index values across source countries are based on bilateral trade (the maximum of exports and imports) between source country *s* and target country *r*, as a fraction of total trade activity in target country *r.* We specifically do not use components of the bank flow variables so as to maximally avoid potential violations of the exclusion restriction. We compute our variables annually for each target country using bilateral trade as of the prior year-end as weights.

Appendix D provides an example of the construction of our instrument for India in 2012. It turns out that 23 source countries have foreign claims in India in that year. The *FDI outflow restrictions* index values in Column (4) range from a low of zero in many countries with no restrictions (Australia, Korea, Switzerland) to those with more binding restrictions (values above 0.5 for Turkey, Mexico, Chile, and Brazil). The source countries in the table are sorted by the highest to lowest bilateral trade as of *t-1* or 2011 (U.S. at over $33 billion to as low as Panama at $219 million) with the respective weights as a fraction of the $182 billion indicated in the second last column. The product of the weights and the outflow restrictions index values result in a value of 0.134 for India in 2012.

Valid instruments must satisfy two conditions: the relevancy condition and the exclusion restriction. While no instrument is perfect, our instruments seem to satisfy both conditions. For the relevancy condition, our instrument is based on factors that affect source country outflows, which in turn could affect bank outflows from source country *s* to target country *r*. More restrictions on capital outflows in source country *s* may adversely impact the amount of bank flows emanating from source country *s*. Yet, while this instrument should have an impact on outflows from source country *s*, these restrictions are not related to target country characteristics, a critical ingredient for our instrument to also satisfy the exclusion restriction. Diagnostic tests confirm the validity of our instrument.

Table 4 also presents these results. The first-stage regression results in Models (2) and (5) show that our instrument exhibits significant explanatory power for cross-border bank flows. The coefficients on our instrument is negative and statistically significant in regressions of bank flows for both the MES and SRISK subsample. More equity and FDI capital outflow restrictions among the source countries that matter for a given target country adversely affect bank flows to that target country. The partial *F*-tests (*p*-value of 0.005 and 0.003) reliably reject the null hypothesis that the instrument has no explanatory power.

Turning to the second-stage results, we find that the coefficients on the instrumented *Flows* remain negative and statistically significant in Models (3) and (6) for *MES* and *SRISK*, respectively. The magnitude of the estimated coefficients are much larger than the analogous specifications in Table 2 for actual flows, and it turns out that the implied economic magnitudes are larger notwithstanding the fact that the *Flows* variable is transformed due to its first-stage projection on the *FDI outflow restrictions* instrumental variable. Using the significant negative coefficient of -4.303 in Model (3) for *MES*, a one-standard-deviation increase in instrumented *Flows* (0.118) is related to a 0.508% decrease in *MES* in the target country, which is a

30.5% decrease relative to its standard deviation of 1.66%. Likewise, using the coefficient on instrumented *Flows* of -16.908 from Model (6) for *SRISK*, a one-standard-deviation increase in instrumented *Flows* (0.129 for this subsample) is related to a 2.17% decrease in *SRISK* in the target country, or about 31% of its standard deviation. The results for *Actual Flows* are economically similar to those for *Residual Flows*.

We perform a crude test of the external validity of the instrumental variable by regressing residuals from second-stage regressions in Models (3) and (6) on the *FDI outflow restrictions* variable. The *p*-value of the respective F-statistics are well above any reasonable threshold for statistical significance, suggesting that the instrument is valid.[11]

### 3.3. Regulatory Arbitrage, Cross-Border Bank Flows and Systemic Risk

Given our interest in determining the effect of bank flows that are in line with regulatory arbitrage, we also construct measures of unexpected flows into a target country conditioning on the quality of the target country. If regulatory arbitrage in international bank flows is potentially destructive, we should observe that flows, which tend to come from countries with tougher regulatory restrictions, should adversely affect the target country's financial system by increasing systemic risk. Alternatively, if bank flows from source countries with more stringent regulatory restrictions to target countries with less stringent ones are associated with decreases in systemic risk, then we would interpret this form of regulatory arbitrage as benign or potentially beneficial. We know that cross-border flows in general are associated with lower systemic risk, so our goal in this section is to refine our interpretations in line with the original policy-oriented questions that motivated our study.

The *de jure* regulatory quality variables include: (1) *Restrictions on bank activities*; (2) *Stringency of capital regulations*; (3) *Private monitoring*; (4) *Official supervisory powers*; and, (5) *Supervisory independence*. All *de jure* regulatory variables come from Barth, Caprio, and Levine (2013). We use our five *de jure* measures of regulatory quality to sort target countries into groups of high and low quality each

[11] 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 test of the overidentifying restrictions. In earlier tests, we explored combinations of instrumental variables based on multiple combinations of source country capital export restrictions from Fernandez et al. (2012). In these cases, we were able to employ Hansen's overidentification test and our inferences were similar.

year, based on the median values of these measures. We classify a target country as *Low regulatory quality* if its measure of regulatory quality is below the cross-country median. We then estimate the equivalent of Model (2) in Table 2 for the two subsets of target country-years separately for flows to low (below median) regulatory quality target countries (e.g., *Low restrictions*, *Low capital stringency*) and for flows to high regulatory quality target countries (e.g., *High restrictions*, *High capital stringency*).

Panel A of Table 5 presents our first set of results related to subsample splits by target country quality. We report the country-level systemic risk proxy *MES* in these tables. The two specifications of Eq. (2) are estimated jointly, which allows us to test the joint equality of the coefficients for the *Flows* variable using a $\chi^2$ test for the differences (reported below the respective coefficients). We include the same control variables as those found in Model (2) from Table 2, but do not report them in this table to conserve space. Consider, for example, the results for high versus low *Restrictions on bank activities* subsamples The coefficients on *Flows* are negative and statistically significantly related to systemic risk, regardless of target country. However, the magnitude of the coefficient for the target countries with fewer restrictions on bank activities – which we would interpret as flows consistent with regulatory arbitrage – is statistically significant and negative, whereas that for the subset of target countries with more restrictions is not significant. The magnitude of the negative coefficient for the target countries with fewer restrictions is similar in magnitude to that for the overall sample in Table 2. In this particular case, the $\chi^2$ statistics of 1.33 implies that the differences are not significant.

The results separating high versus low target countries by *Capital stringency* and *Private monitoring* also suggests that the negative association with bank flows and systemic risk is concentrated in those target countries with less stringent capital requirements and weaker disclosure rules. In the case for *Capital Stringency*, the $\chi^2$ statistic proves to be significant. Distinguishing target countries by *Supervisory powers* or by *Independence of the supervisory authority* does not appear to matter.

One possibility is that separating target countries by *de jure* measures of regulatory quality may be too blunt an approach. Another possibility is to distinguish among them by *de facto* measures of the strength or vibrancy of the bank system. In Panel B of Table 5, we present similar results related to dividing our sample by measures of the level of economic development (*Emerging* versus *Developed* using the classification scheme of Morgan Stanley Capital International), and by the size (*Bank Assets* as a fraction of GDP), profitability (*ROA*), capital ratios (*Bank Capital*), and asset quality (*NPL* or non-performing loans as a fraction of gross loans) for the bank system. These data come from the World Bank's *Global Financial Development Database*. Our inferences using these *de facto* measures are typically sharper than using the *de jure* measures. Though the coefficients associated with *Flows* for regressions on *MES* are not notably or significantly different between developed and emerging target countries, those for target countries for which the bank systems are larger, but less profitable, less well capitalized, and with worse asset quality are more reliably significant than otherwise. The respective $\chi^2$ tests for high versus low *Bank assets*, *Bank capital*, *NPL*, and *ROA* suggest that these differences are statistically significant.

Overall, our results in this section cast some doubt on the destructive view of regulatory arbitrage in international bank flows. Indeed, our results show that bank flows are associated with a reduction in target countries' systemic risk when the flows are in line with regulatory arbitrage (i.e. come from source countries with better regulatory quality than the target). We believe these tests are coarse at the country-level and feel that we have greater potential to draw out more reliable inferences when we drill down to the individual bank level in the target markets for those flows.

## 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 target countries. But all the analysis to now takes place at the country level. Of course, a large fraction of these bank flows are comprised of bank-to-bank lending activities. To more closely examine how bank flows are affecting systemic risk in the target countries, we now turn our attention to the banks within the target 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 up with a final sample of 1,686 banks in 61 countries, totaling 14,518 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 the impact of globalization of bank systems on bank-level systemic risk. This portion of our study is motivated by the emerging literature on how banks change their performance, their risk-taking and other policies, as they become more globalized. There is some recent research on this question (Gulamhussen, et al. (2014); Berger, et al. (2016); and Jeon, et al. (2016)) that suggests that the riskiness of banks increases as they expand globally. However, these papers do not directly address the systemic risk consequences of globalization for the target 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 targets of the cross-border bank flows. However, given that our bank-level market-based measure of systemic risk is obtained from *DataStream*, which covers large banks, 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.

## 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 $3.0 billion ($2.3 billion). For the average bank, income from nontraditional banking activities (non-interest income) represents about 26.4% 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 0.68%.

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 clustered at the country level. We include several country and bank-level variables that have been shown to impact systemic risk (see e.g. Laeven, Ratnovski, and Tong, 2014; Anginer, Demirgüç-Kunt, and Zhu, 2014). Firm-level controls include: *Size* (log of assets); the proportion of income generated from nontraditional commercial bank activities (*Non-interest income*); profitability (*ROA*); reliance on non-deposit short-term funding (*ST funding*), and proxies for asset quality (*NPL-to-loans*) and cost efficiency (*Non-interest expense*). We also incorporate country-level controls, including: *Log GDP per capita*, *GDP growth*, *Volatility*, *Market return*, *Non-interest income*, *Bank credit*, 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* is -0.516 and is statistically significantly 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* (0.164) is related to a 0.085 decrease in *MES*, which represents about a 5.2% decrease relative to its mean (1.61). 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) from 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 related to the systemic risk of individual banks, consistent with the benign view of regulatory arbitrage and with the diversification view of globalization, which suggests that risk is lower for globally diverse banks.

When we decompose the *Flows* into the *Residual Flows* using the gravity model in Table 3, our inferences remain intact. The reliable negative coefficient of -0.385 in Model (3) of Table 8 implies an economic link between flows and systemic risk that is similar in magnitude to what we showed at the country level in Table 4. A one-standard deviation increase in *Residual Flows* (0.160) is associated with a decrease of 0.062 in *MES*, which is 3.8% of the unconditional mean and 3.3% of the unconditional standard deviation across all individual bank-years in our sample.

In Models (4)-(5), we show results from first-and second-stage 2SLS regressions using the *FDI outflows restrictions* instrumental variable constructed at the target country level. The first-stage regression projects the actual *Flows* on the instrumental variable including the bank and country level controls. The coefficient on *FDI outflows restrictions* is reliably negative as before. The first-stage *F*-statistics allow us to reject the null hypothesis that it is insignificantly correlated with bank flows. In Model (5), the coefficient on instrumented *Flows* for individual bank *MES* is -2.751 and it is statistically significantly different from zero. A one-standard-deviation increase in instrumented *Flows* (0.19) is associated with a 0.515 decrease in *MES*, or 31.9% of its unconditional mean at the individual bank-year level.

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 14,518 observations. Beyond these fixed effects, the only bank-level variable that has reliable explanatory power in this setting is the log of bank assets, which is positive. Larger banks, as expected, contribute more to systemic risk. Brunnermeier et al. (2015, their Table V) confirm this finding for their measure of realized systemic expected shortfall for U.S. banks during the global financial crisis. Additionally, there is some weak evidence that the weaker the loan quality, the higher is a bank's contribution to systemic risk. In Models (1) to (3), the coefficient on *NPL-to-loans* is positive and significant at the 10% level. In this bank-level sample, we confirm the findings in Table 2 that market index returns are reliably positively correlated with *MES*, but, unlike for the target country-year sample in the earlier table, we now find reliable evidence that *MES* is larger for slower growing, more developed countries.

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, activities, funding mix, asset quality, profitability, and cost efficiency. To this end, we interact *Flows* with proxies for size (*Size,* or log assets), non-traditional banking activities (*Non-interest income* as a fraction of total income), funding strategy (*ST funding*, which is non-deposit funding divided by total liabilities), leverage (*Leverage*), asset quality (*NPL-*

*to-loans,* which divides by gross loans), profitability (*ROA*), and cost efficiency *(Non-interest expense,* as a fraction of gross revenues).

Table 8 presents results using our interaction terms with various bank characteristics. All regressions are OLS estimates that include bank and year fixed effects. Standard errors are clustered at the country level, as before. We find that overall flows reduce *MES* for larger banks, as the coefficient on our interaction term between *Size* banks and *Flows* in Model (1) is negative and statistically significant. The coefficient on *Flows* itself is negative and significant which means that the association with *Flows* is not exclusively for larger banks. Rather, we interpret that the effects are stronger and more reliably negative among them. In Models (2) to (7) of Table 8, we assess the impact of bank flows on banks using additional bank characteristics. Bank flows reduce systemic risk for those banks that rely more on short-term funding, those that have better asset quality, and banks that are less profitable. We observe no significant reduction in *MES* for banks that engage in more nontraditional banking activities, banks with higher leverage, and those that are less efficient (higher *Non-interest expense*).

Overall, our results in this section add further support to a benign view of regulatory arbitrage. Cross-border bank flows appear to be associated with a decrease in *MES*. And further these bank flows are associated with a decrease in *MES* through a bank channel involving those that are larger, less profitable, with better asset quality and more reliance on volatile funding sources.

### 4.3. Long-run Impact of Bank Flows for Performance and Risk-Taking

In a final experiment, we conduct a series of tests to investigate the channels by which systemic risk can be reduced as a result of cross-border bank flows. In this analysis, we focus on the longer-term impact of inflows into a target country at the individual bank level. That is, we only examine inflows and ignore those target-country-years in which the flows are zero or negative. With the additional flows into a target market, our goal is to assess how banks in the target market 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 on assessing the *average* impact for individual banks in the target country rather than just those for which the *MES* experienced a decrease as in Tables 7 and 8.

We examine the long-term impact of bank flows by exploring the impact of inflows in year *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 non-traditional banking activities (*Trading Assets*), funding (Short-term non-deposit funding divided by total liabilities, *S-T Funding*), asset quality (*NPL-to-loans*), profitability (*ROA*), and efficiency (*Non-interest expense* as a fraction of total income). We estimate OLS regressions projecting these respective variables on contemporaneous and up to three lags of *Inflows* and we include bank and year fixed effects. Further, we compute the standardized coefficients as a fraction of the unconditional mean of the performance variable of interest across all bank-year observations. The results are plotted in Figure 5. Consider, for example, the ROA results (top-left figure), for which the contemporaneous (year *t*) regression coefficient on *Inflows* is 0.539. A one-standard-deviation increase in *Inflows* (0.119) is associated with a 0.064 increase in *ROA*, which represents a 9.5% increase. This standardized coefficient is what we plot for year *t* in the figure. Note that we also compute these standardized coefficients for those values of the coefficients associated with the 95% confidence range defined by the standard errors in the respective regressions.

The results in Figure 5 reveal that bank flows are associated with improvements in annual profitability of over 9% that sustains for up to three years following the cross-border bank inflows. Table 6 shows that a typical bank's net income as a fraction of total assets average is 0.678%, so a 9% increase represents an increase in *ROA* to 0.739%. How this gain in profitability is realized may be through greater cost efficiency. The long-run impact of bank inflows is associated with a steady decrease to as much as 2% lower non-interest expenses as a fraction of gross revenues reaching by the third year (bottom-left in Figure 5). There is some evidence of long-term improvements in asset quality as well. The impact here appears statistically and economically significant (bottom right panel). We find that a one-standard deviation increase in *Inflows* (0.119 for this sample) is associated with a 0.267 decline in *NPL-to-loans*, or a 6.41% decline relative to its mean (4.16% of non-performing loans as a fraction of gross loans outstanding). The impact is even stronger in the next three years subsequent to the inflows. The impact on leverage is negligible until up to three years following the bank *Inflows* and even then it reaches 3% of the unconditional mean of 13.539% of book value of bank equity relative to total assets.

The observed improvements in asset quality, profitability, and cost efficiency associated with bank inflows appear to be inconsistent with the race to the bottom view of regulatory arbitrage and the risk-taking view of bank globalization. Rather than increasing risk-taking by banks, which would lead to poor asset quality, such flows are associated with improvements in asset quality. Perhaps the greater presence of source banks in the target market by means of these inflows serves as a greater monitoring role or one that stimulates better risk management processes. By greater monitoring or by stimulating more discipline toward risk in target bank activities, the banks that represent the source inflows are typically from more stringent regulatory regimes (Houston et al., 2012) and they seem to help target banks lower their exposure to riskier activities, improve their asset quality, cost efficiency, and profitability, which, in turn, lead to improvements in the stability of the banks and the banking sector.

4.4. Impact of the Financial Crisis

To better assess the impact of the financial crisis, we perform a clinical experiment similar in spirit to that of Brunnermeier et al. (2015) in their assessment of the impact of nontraditional banking activities on systemic risk around the Lehman bankruptcy. Specifically, our goal is to assess the differential impact on bank performance during the crisis for countries that experienced large inflows prior to the financial crisis. To this end, we run regressions similar to those in Table 7 using four measures of bank performance as our dependent variable: 1) *ROA*; 2) *Leverage*; 3) *Non-interest expense*, and 4) *NPL-to-loans*. Our key independent variable, *High Inflows 2006*, is an indicator that is equal to one for countries with *Inflows* as of 2006 in the top quartile of the distribution and zero otherwise. We run regressions using interactions between *High Inflows 2006* and *Crisis* – an indicator variable that is equal to one for the years 2008 and 2009 and zero otherwise.

We report results in Table 9. In Panel A we show results from panel regressions with bank and year fixed effects. In Panel B, we report results from cross-sectional regressions using the change in each performance measure between 2007 and 2009 as the dependent variable. We use the same set of country and bank-level controls as in Table 7, but omit them to conserve space. The results in Panel A of Table 9 show that banks in countries with large inflows in 2006 had lower leverage and lower non-interest expense during the crisis. The impact is economically significant. Banks in countries with high inflows in 2006 had leverage that was 1.59 lower than banks in other countries, which represents an 11.3% reduction relative to its mean (13.539). We observe a similar result using noninterest expense. We observe no difference in *ROA* or asset quality (*NPL-to-loans*). The results in Panel B corroborate the results in Panel A with respect to changes in leverage. The reduction in leverage between 2007-2009 is significantly larger for banks in countries with large inflows as of 2006. We do not observe a significant reduction in noninterest expense in Panel B.

Overall, the results from this clinical experiment suggest that bank inflows had a positive impact on bank leverage and efficiency during the crisis.

### 5. Robustness Tests

We perform various tests to examine the robustness of our results. First, we examine the robustness of our specifications for the gravity model in Table 3 toward computing the residual flows. To this end, we replicate our main results in Table 4 using alternate measures of *Residual Flows.* We present these results in Table IA.1 of our online appendix. Specifically, we run regressions in Model (1) of Table 4 using value-weighted residual flows from Models (1)-(5) of Table 3. In all cases, the coefficient on *Residual Flows* remains negative and statistically significant at the 10% level or better. It may be that our results are the product of our choice of estimation window. We currently use *all* available data (1995 to 2014) to estimate residual flows. This may introduce a look-ahead bias to our results. Accordingly, we test the robustness of our results to the use of alternate estimation windows. Rather than using all available data to estimate our residual flows, we use a 15-year rolling window as well as an expanding window with a fixed starting point of 1990. We do not allow our estimation window for residuals to overlap with our systemic risk measures in any of these tests. The results are robust to the alternative estimation windows proposed, as the coefficient on *Residual Flows* is statistically significant across all regression specifications.

We also examine whether our results are driven by the financial crisis by running regressions in Table 4 including an interaction term between our *Flows* (*Residual Flows*) and an indicator for the crisis period of 2008-2009. We present these results in Table IA.2 of our online appendix. We find that the coefficient on *Flows* (*Residual Flows*) remains negative and statistically significant at the 5% level, while the interaction term *Flows (Residual Flows)* × *Crisis* is insignificant. In addition, we examine whether our results are driven by bank flows directed towards struggling European countries: Portugal, Ireland, Italy, Greece, and Spain (PIIGS). To this end, we run regressions excluding these countries using *Inflows* as our key independent variable. We report our results in Table IA.3 of our online appendix. We find results consistent with our main findings after excluding PIIGS. In all regression specifications, the coefficient on *Inflows* (*Inflows-IV*) is negative and statistically significant at the 10% level or better.

We also test the robustness of our results to alternate measures of systemic risk and report these in Table IA.4 of our online appendix. Specifically, we use five 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)); *R-squared* (see, e.g., Anginer, et al. (2014)), and *Systemic PCA*– the first principal component of *SRISK-to-GDP*, *MES*, *CatFin*, and *R-squared*.[12] With the exception of *Catfin* and *Turbulence*, we find that our results are robust to these alternate measures of systemic risk.[13]

All of our measures of bilateral flows between source and target countries use the Consolidated Banking Statistics (CBS) from the BIS. The consolidated foreign claims (loans, debt securities and equity holdings) include claims granted to non-resident entities, international claims (which are local claims of foreign affiliates in foreign currency) and local claims of foreign affiliates in local currency. The BIS also

[12] *R-Squared* is a measure that is used commonly in the convergence of asset prices (see, e.g., Bekaert and Wang (2009), or Bekaert and Harvey (2000)). In the banking literature, *R-squared* is measured as the total variation of returns of a given bank explained by the returns of all other banks in a country (Anginer and Demirgüç-Kunt (2015)). *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 countries in a given country.

[13] The coefficient on *Flows* remains negative, but is statistically insignificant in regressions using *CatFin* and *Turbulence*. Our sample size is reduced to 490 (428) when using these measures, which may explain the lack of significance.

compiles data on Locational Banking Statistics (LBS), which capture the currency composition and geographical breakdown of the counterparties. Up until 2000, only 14 source countries report LBS to the BIS, so the sample is more restricted. Nevertheless, in Appendix E (in which we explain the differences between CBS and LBS), Table E2 presents regression results for *MES* using percent changes in net claims to GDP and relative to total bank assets that affirm our original findings in Table 2.

We also conduct robustness tests for our main bank-level results (Table 7). First, we use alternate measures of *Residual Flows* from above. Specifically, we estimate Model (3) of Table 7 using residual flows estimated from Models (1) to (5) of Table 3. We also estimate residuals using a 15-year rolling window and an expanding window with a fixed starting point of 1990. We report these results in Table IA.5 in our online appendix. In all regressions, the coefficient on *Residual Flows* is negative and statistically significant at the 5% level or better. We also replicate our bank-level results using LBS data, which allow us to capture net inflows of funds into a recipient country. As before, we use the percent changes in net claims to GDP (net claims-to-total assets) as our measure of flows. We further test the robustness of our results to the exclusion of the financial crisis. 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 Table IA.6 in our online appendix.

## 4. Conclusion

This paper examines the link between cross-border bank flows and the financial stability of target countries by assessing how bank flows affect the country's systemic risk, measured by *SRISK* and *MES*. The goal of the study is to shed new light on the ongoing debate on whether regulatory arbitrage in international bank flows is detrimental or potentially beneficial to the target country. Overall, these bank flows are associated with improved financial stability (i.e. lower systemic risk) in the target country. The relationship is stronger when bank flows target countries with relatively less stringent regulations governing the bank sector. Overall, our findings suggest that bank flows are beneficial to the target country, which adds support to the benign view of regulatory arbitrage.

We also find that the impact of bank flows differs across banks in the target country. Specifically, we find a reduction in systemic risk for larger, less profitable banks and those with poorer asset quality and more reliance on volatile funding sources. Furthermore, the bank flows appear to affect systemic risk in the target country by improving banks' profitability, asset quality and cost efficiency.

Overall, our findings provide support for the more benign view of regulatory arbitrage in international bank flows. The evidence should be of particular interest to regulators who may be concerned with the impact of cross-border regulatory arbitrage and macroprudential regulation surrounding aligning rules across international financial systems. 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. Country-level data are reported as of December of each year. Panel A presents summary statistics for all countries in our sample with available data on our main systemic risk measure (Marginal Expected Shortfall, *MES*). *SRISK* data is not available for all countries in our sample, and thus restricts our sample size throughout the analysis. Panel B presents summary statistics for the subset of 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 |
| Bank flows | 758 | 0.076 | -0.038 | 0.059 | 0.193 | 0.209 |
| Residual Flows | 758 | 0.007 | -0.108 | 0.003 | 0.104 | 0.182 |
| MES (%) | 758 | 2.660 | 1.410 | 2.316 | 3.521 | 1.681 |
| SRISK-to-GDP | 531 | 5.246 | 0.268 | 1.347 | 7.326 | 8.026 |
| Log GDP per capita | 758 | 9.233 | 8 | 9 | 10 | 1.312 |
| GDP Growth | 758 | 8.495 | 0 | 8 | 15 | 12.558 |
| Volatility | 758 | 22.941 | 16 | 21 | 27 | 9.818 |
| Market return | 758 | 10.385 | -10 | 9 | 25 | 30.184 |
| Non-interest income | 758 | 35.190 | 27.559 | 33.688 | 41.017 | 12.114 |
| Bank credit | 758 | 74.252 | 33.707 | 68.195 | 103.944 | 46.412 |
| Concentration | 758 | 64.872 | 47.162 | 65.120 | 81.886 | 20.512 |
| Restrictions on bank activities | 758 | 7.228 | 6.000 | 7.000 | 9.000 | 2.028 |
| Official supervisory power | 758 | 11.191 | 9.692 | 11.000 | 13.000 | 2.409 |
| Independence of supervisory | 738 | 1.744 | 1.000 | 2.000 | 2.000 | 0.877 |
| Stringency of capital regulation | 755 | 6.250 | 5.000 | 6.000 | 8.000 | 1.924 |
| Private monitoring | 758 | 8.379 | 8.000 | 8.000 | 9.000 | 1.365 |
| Total FDI outflow restrictions | 664 | 0.104 | 0.072 | 0.101 | 0.131 | 0.051 |
| Panel B. SRISK subsample (62 countries). 2000-2014. | | | | | | |
| | N | Mean | 25th Percentile | Median | 75th Percentile | Standard Deviation |
| Bank flows | 606 | 0.065 | -0.053 | 0.043 | 0.192 | 0.199 |
| Residual Flows | 606 | 0.003 | -0.122 | 0.000 | 0.100 | 0.185 |
| MES (%) | 531 | 2.966 | 1.766 | 2.649 | 3.868 | 1.729 |
| SRISK-to-GDP | 606 | 5.147 | 0.212 | 1.264 | 7.326 | 7.869 |
| Log GDP per capita | 606 | 9.581 | 9 | 10 | 11 | 1.176 |
| GDP Growth | 606 | 7.316 | 0 | 8 | 14 | 11.422 |
| Volatility | 606 | 23.737 | 17 | 22 | 28 | 10.041 |
| Market return | 606 | 7.004 | -11 | 6 | 22 | 26.748 |
| Non-interest income | 606 | 35.653 | 27.466 | 33.985 | 42.006 | 12.737 |
| Bank credit | 606 | 84.716 | 49.881 | 82.264 | 112.300 | 45.984 |
| Concentration | 606 | 65.988 | 48.211 | 67.200 | 85.071 | 21.447 |
| Restrictions on bank activities | 606 | 7.007 | 5.000 | 7.000 | 8.000 | 2.047 |
| Official supervisory power | 606 | 10.906 | 9.000 | 11.000 | 13.000 | 2.503 |
| Independence of supervisory | 589 | 1.842 | 1.000 | 2.000 | 2.000 | 0.827 |
| Stringency of capital regulation | 605 | 6.197 | 5.000 | 6.000 | 8.000 | 1.879 |
| Private monitoring | 602 | 8.492 | 8.000 | 8.000 | 9.000 | 1.298 |
| Total FDI outflow restrictions | 529 | 0.099 | 0.068 | 0.099 | 0.128 | 0.050 |

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

This table presents OLS results of estimating systemic risk using known determinants including volatility and non-traditional income (Engle, et al. (2015), Brunnermeier, et al. (2015)), as well as cross-border banking flows. Models (1)-(3) examine Marginal Expected Shortfall (*MES*) and Models (4)-(6) examine *SRISK* (normalized by the country's GDP). Models (1) and (4) use known determinants of systemic risk. Models (2) and (5) include actual cross-border bank flows (log difference in total foreign claims from *t-1* to *t*). In Models (3) and (6) we separate positive (*Inflows*) and negative (*Outflows*) bank flows for target countries. Controls include: *Log of GDP per capita*; *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank credit*, 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) |
| Actual Flows $_{t-1}$ | | -0.504** | | | -3.087*** | |
| | | (-2.05) | | | (-3.02) | |
| Inflows $_{t-1}$ | | | -0.692** | | | -3.253* |
| | | | (-2.23) | | | (-1.83) |
| Outflows $_{t-1}$ | | | 0.724 | | | -0.629 |
| | | | (1.56) | | | (-0.32) |
| Log GDP per capita $_{t-1}$ | -1.283 | -1.154 | -1.274 | -10.604* | -9.898* | -10.351* |
| | (-1.07) | (-0.98) | (-1.04) | (-1.93) | (-1.88) | (-1.93) |
| GDP growth $_{t-1}$ | -0.002 | -0.002 | -0.001 | -0.023 | -0.018 | -0.017 |
| | (-0.48) | (-0.46) | (-0.27) | (-0.85) | (-0.70) | (-0.67) |
| Market return $_{t-1}$ | 0.010*** | 0.010*** | 0.010*** | -0.014 | -0.012 | -0.013 |
| | (4.12) | (4.55) | (4.18) | (-1.62) | (-1.54) | (-1.60) |
| Volatility $_{t-1}$ | 0.025** | 0.026** | 0.025** | -0.013 | -0.014 | -0.012 |
| | (2.15) | (2.25) | (2.21) | (-0.20) | (-0.22) | (-0.19) |
| Non-interest income $_{t-1}$ | 0.009 | 0.010 | 0.010 | -0.045 | -0.045 | -0.045 |
| | (1.23) | (1.31) | (1.31) | (-1.23) | (-1.24) | (-1.23) |
| Bank credit $_{t-1}$ | 0.012*** | 0.011** | 0.011** | 0.050** | 0.045** | 0.046** |
| | (2.73) | (2.60) | (2.53) | (2.37) | (2.23) | (2.23) |
| Concentration | 0.004 | 0.005 | 0.004 | 0.043 | 0.047 | 0.045 |
| | (0.79) | (0.88) | (0.76) | (1.15) | (1.26) | (1.22) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 758 | 758 | 758 | 606 | 606 | 606 |
| Adjusted $R^2$ | 0.603 | 0.605 | 0.605 | 0.723 | 0.726 | 0.724 |
| # countries | 64 | 64 | 64 | 62 | 62 | 62 |

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

This table presents results from OLS panel regressions of cross-border bank flows on a country pair-year level, following Houston, et al. (2012). Bank flows are the log difference (difference in log from *t-1* to *t*) of total foreign claims from source country *s* to target country *r*. All models use standard variables to estimate the change in cross-border bank flows. We use the results from Model (6) to estimate unexpected bank flows. 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.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Δ Creditor rights | -0.120 | -0.119 | -0.158 | -0.200 | 8.467 | |
| | (-1.24) | (-1.23) | (-1.10) | (-1.28) | (0.80) | |
| Δ Credit depth | -0.033** | -0.033** | -0.064*** | -0.018 | 0.727 | |
| | (-2.39) | (-2.38) | (-3.89) | (-1.47) | (0.99) | |
| Δ Property rights | -0.012 | -0.012 | -0.040 | -0.019 | 0.367 | |
| | (-0.79) | (-0.79) | (-1.52) | (-1.24) | (1.05) | |
| Δ Log GDP per capita | -0.217* | -0.216* | -0.058 | -0.152 | -0.925 | |
| | (-1.90) | (-1.89) | (-0.35) | (-1.51) | (-0.28) | |
| Δ GDP growth | -0.002*** | -0.002*** | -0.002** | -0.002** | 0.013 | |
| | (-2.86) | (-2.87) | (-2.19) | (-2.41) | (0.47) | |
| Δ Population (log) | -0.910*** | -0.911*** | -1.539*** | -0.560** | -26.452 | |
| | (-3.52) | (-3.52) | (-5.06) | (-2.47) | (-1.31) | |
| Same language | 0.022** | 0.022* | 0.022 | 0.042*** | | |
| | (2.01) | (1.96) | (1.46) | (2.81) | | |
| Distance | -0.055*** | -0.045*** | -0.044*** | -0.022*** | | |
| | (-7.55) | (-6.03) | (-5.56) | (-4.13) | | |
| Contiguous | | 0.110*** | 0.122*** | 0.107*** | | |
| | | (3.79) | (3.95) | (3.47) | | |
| Colony | | -0.022 | -0.018 | -0.038 | | |
| | | (-1.07) | (-0.62) | (-1.50) | | |
| Δ Financial liberalization | | | -0.074*** | | | |
| | | | (-3.55) | | | |
| Δ Restrictions on bank activities | | | | 0.019** | -0.414 | |
| | | | | (2.58) | (-0.54) | |
| Δ Independence of supervisors | | | | 0.001 | -0.104 | |
| | | | | (0.29) | (-0.32) | |
| Δ Stringency of capital regulation | | | | 0.028* | 1.422 | |
| | | | | (1.71) | (1.18) | |
| Δ Private monitoring | | | | 0.009 | -2.482 | |
| | | | | (0.89) | (-0.58) | |
| Δ Strength of external audit | | | | 0.004 | 1.029 | |
| | | | | (0.31) | (0.61) | |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Source country fixed effects | Yes | Yes | Yes | Yes | No | No |
| Target Country fixed effects | Yes | Yes | Yes | Yes | No | No |
| Source Country-Year fixed effects | No | No | No | No | Yes | Yes |
| Target Country-Year fixed effects | No | No | No | No | Yes | Yes |
| Observations | 47,259 | 47,259 | 32,613 | 36,984 | 36,984 | 47,259 |
| Adjusted $R^2$ | 0.059 | 0.059 | 0.090 | 0.048 | 0.225 | 0.330 |
| # of target countries | 128 | 128 | 88 | 116 | 116 | 128 |

**Table 4. Instrumental Variables Regressions using Marginal Expected Shortfall and SRISK.**

This table presents 2SLS results and results related to a two-stage estimation process. In Models (1)-(3) 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. In Model (1) we use the residual flows between countries as the key independent variable. Residual, or unexpected, flows are the residuals from estimations of Eq. (3) or Model (6) of Table 3, aggregated at the target country-year. In Models (2)-(3) we report first- and second-stage results from regressions of actual flows instrumented using the *FDI outflow restrictions index,* calculated relative to the source country using MES. In Models (4) to (6), we replicate results using *SRISK-to-GDP* as the dependent variable. Controls include: *Log of GDP per capita*; *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank credit,* and *Concentration*. The sample period is 2000-2014 and robust *t*-statistics based on standard errors clustered at the country level are in parentheses. 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 (2) and (5) as our dependent variable on our instrument, the *FDI outflow restrictions index.* All variables are defined in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable: | *MES (%)* | 1st Stage Model - Flows | *MES (%)* | *SRISK/GDP (%)* | 1st Stage Model - Flows | *SRISK/GDP (%)* |
| Residual Flows $_{t-1}$ | -0.559* | | | -3.847** | | |
| | (-1.79) | | | (-2.01) | | |
| FDI Outflow Restrictions Index $_{t-1}$ | | -0.639*** | | | -0.789*** | |
| | | (-2.74) | | | (-3.45) | |
| Inflows (Instrumented) $_{t-1}$ | | | -7.036** | | | -26.529 |
| | | | (-2.08) | | | (-1.56) |
| Log GDP per capita $_{t-1}$ | -1.285 | 0.255** | -0.154 | -10.766* | 0.156 | -9.437*** |
| | (-1.08) | (2.54) | (-0.18) | (-1.97) | (1.34) | (-3.26) |
| GDP growth $_{t-1}$ | -0.003 | 0.001 | 0.000 | -0.027 | 0.002 | 0.011 |
| | (-0.60) | (0.76) | (0.07) | (-0.96) | (1.64) | (0.46) |
| Market return $_{t-1}$ | 0.009*** | 0.001** | 0.013*** | -0.014 | 0.000 | -0.007 |
| | (4.09) | (2.21) | (4.69) | (-1.58) | (0.55) | (-0.74) |
| Volatility $_{t-1}$ | 0.025** | 0.001 | 0.028*** | -0.013 | -0.001 | 0.001 |
| | (2.18) | (0.33) | (3.79) | (-0.20) | (-0.42) | (0.02) |
| Non-interest income $_{t-1}$ | 0.010 | 0.001 | 0.013** | -0.045 | 0.001 | -0.029 |
| | (1.29) | (1.53) | (2.48) | (-1.22) | (0.75) | (-1.41) |
| Bank credit $_{t-1}$ | 0.012*** | -0.001** | 0.006 | 0.049** | -0.001** | 0.029* |
| | (2.73) | (-2.50) | (1.44) | (2.39) | (-2.24) | (1.94) |
| Concentration $_{t-1}$ | 0.004 | 0.001 | 0.006 | 0.042 | 0.001* | 0.072*** |
| | (0.71) | (1.27) | (1.47) | (1.15) | (1.68) | (3.59) |
| Target country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 758 | 664 | 664 | 606 | 529 | 529 |
| Adjusted $R^2$ | 0.606 | 0.237 | 0.629 | 0.725 | 0.311 | 0.757 |
| Partial $R^2$ | | | 0.014 | | | 0.019 |
| 1st stage *F*-statistic | | 8.67 | | | 8.82 | |
| 1st stage *p*-value | | 0.005 | | | 0.003 | |
| External validity *F*-statistic | | | 0.001 | | | 0.002 |
| External validity *p*-value | | | 1.000 | | | 1.000 |

**Table 5. Tests of Cross-border Flows and Systemic Risk by Target Country De Facto and De Jure Measures.**

This table presents coefficient estimates on *Flows* from OLS regressions using *MES* (%) as the dependent variable. *Flows* are the log difference (difference in log from *t-1* to *t*) of total foreign claims to target country *r*. In Panel A we show results from separate regressions for target countries based on five de facto measures of development and banking sector stability: *Developed* countries are those in the MSCI Developed Markets index. We also run regressions separately for target countries with high (above median) and low banking sector stability based on the following measures: 1) *NPL* – Non-performing loans-to-gross loans; 2) *Bank Capital* – capital–to-assets ratio; 3) *Bank ROA* – net income-to-average assets ratio, and 4) *Bank assets* – total deposit money banks' assets-to-GDP. We obtain these four measures from the Global Financial Development database. In Panel B, we show results using five measures of regulatory quality from Barth et al. (2013) to sort target countries: 1) *Restrictions*; 2) *Capital stringency*; 3) *Private monitoring;* 4) S*upervisory power*, and 5) *Supervisory Independence*. Controls (not shown to conserve space) include: *Log of GDP per capita; GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank credit*, and *Concentration*. The sample period is 2000-2014 and *t*-statistics based on standard errors clustered at the country level are in parentheses. We report the $\chi^2$ for the test of differences in *Flows* between groups of target countries with high/low banking sector stability (regulatory quality). Detailed definitions of all variables are provided in Appendix A. $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. *De Jure* Measures.

| | Flows | *t*-statistic | Observations | Adjusted $R^2$ | # of countries | Controls, country and year fixed effects |
|---|---|---|---|---|---|---|
| *High Restrictions* | -0.182 | (-0.51) | 270 | 0.532 | 18 | Yes |
| *Low Restrictions* | -0.624* | (-1.85) | 488 | 0.656 | 33 | Yes |
| $\chi^2$ test of difference | *1.33* | | | | | |
| *High Capital Stringency* | 0.037 | (0.09) | 271 | 0.600 | 18 | Yes |
| *Low Capital Stringency* | -0.911** | (-2.65) | 484 | 0.653 | 32 | Yes |
| $\chi^2$ test of difference | *4.90*** | | | | | |
| *High Private Monitoring* | -0.206 | (-0.59) | 332 | 0.598 | 22 | Yes |
| *Low Private Monitoring* | -0.612* | (-1.91) | 426 | 0.652 | 28 | Yes |
| $\chi^2$ test of difference | *0.12* | | | | | |
| *High Supervisory Power* | -0.478 | (-1.37) | 327 | 0.598 | 22 | Yes |
| *Low Supervisory Power* | -0.497 | (-1.38) | 431 | 0.648 | 29 | Yes |
| $\chi^2$ test of difference | *0.60* | | | | | |
| *High Sup. Independence* | -0.761 | (-1.19) | 171 | 0.568 | 11 | Yes |
| *Low Sup. Independence* | -0.421 | (-1.37) | 567 | 0.624 | 38 | Yes |
| $\chi^2$ test of difference | *0.02* | | | | | |

Panel B. *De Facto* Measures.

| | Flows | t-statistic | Observations | Adjusted $R^2$ | # of countries | Controls, country and year fixed effects |
|---|---|---|---|---|---|---|
| *Developed* | -0.512 | (-1.42) | 296 | 0.674 | 22 | Yes |
| *Emerging* | -0.527* | (-1.69) | 462 | 0.625 | 42 | Yes |
| $\chi^2$ test of difference | *0.95* | | | | | |
| *High NPL* | -1.004** | (-2.32) | 344 | 0.653 | 23 | Yes |
| *Low NPL* | 0.185 | (0.50) | 366 | 0.657 | 24 | Yes |
| $\chi^2$ test of difference | *4.67*** | | | | | |
| *High Bank Capital* | -0.240 | (-0.74) | 339 | 0.614 | 23 | Yes |
| *Low Bank Capital* | -1.048** | (-2.29) | 364 | 0.652 | 24 | Yes |
| $\chi^2$ test of difference | *7.71**** | | | | | |
| *High Bank ROA* | 0.066 | (0.18) | 366 | 0.625 | 24 | Yes |
| *Low Bank ROA* | -1.299*** | (-3.38) | 374 | 0.650 | 25 | Yes |
| $\chi^2$ test of difference | *10.13**** | | | | | |
| *High Bank Assets* | -0.940** | (-2.61) | 367 | 0.673 | 24 | Yes |
| *Low Bank Assets* | -0.277 | (-0.86) | 377 | 0.567 | 25 | Yes |
| $\chi^2$ test of difference | *3.11** | | | | | |

**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 *Market-to-book* is the market value of equity divided by the book value of equity. *Flows* is the log difference of total foreign claims from *t-1* to *t* to target country *r*; *Residual flows* are residuals from model (6) of Table 3 aggregated at the target-country-year. *Flows-IV* are bank flows instrumented using the FDI outflows restrictions index; *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; *Log GDP per capita* is the natural logarithm of the country's gross domestic product (GDP) per capita; *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 credit* is the private credit by deposit money banks and other financial institutions as a share of GDP; and *Concentration* is the assets of three largest commercial banks as a share of total commercial banking assets. 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.

| Panel A - Bank Level sample- All countries | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | $25^{th}$ | Median | 75th | Std. deviation |
| *Bank level variables:* | | | | | | |
| MES | 14,518 | 1.613 | 0.197 | 1.242 | 2.490 | 1.868 |
| Size | 14,518 | 8.015 | 6.315 | 7.735 | 9.623 | 2.260 |
| Non-interest income | 14,518 | 26.369 | 15.300 | 24.000 | 34.610 | 16.598 |
| ST funding | 14,518 | 5.483 | 0.092 | 2.801 | 7.570 | 7.697 |
| Leverage | 14,518 | 13.539 | 9.416 | 11.732 | 15.416 | 7.809 |
| NPL-to-loans | 14,518 | 3.703 | 0.510 | 1.800 | 4.710 | 5.299 |
| ROA | 14,518 | 0.678 | 0.212 | 0.538 | 1.144 | 1.225 |
| Non-interest expense | 14,518 | 65.678 | 54.570 | 63.420 | 72.550 | 23.338 |
| Market-to-book | 13,667 | 2.012 | 0.786 | 1.299 | 2.010 | 3.423 |
| *Country-Level Controls* | | | | | | |
| Flows-actual | 14,518 | 0.067 | -0.029 | 0.103 | 0.163 | 0.164 |
| Residual flows | 14,518 | -0.023 | -0.102 | -0.051 | 0.077 | 0.160 |
| Flows-IV | 13,506 | 0.073 | -0.064 | 0.105 | 0.229 | 0.190 |
| Inflows | 14,518 | 0.104 | 0.000 | 0.103 | 0.163 | 0.114 |
| Outflows | 14,518 | -0.036 | -0.029 | 0.000 | 0.000 | 0.079 |
| Log GDP per capita | 14,518 | 9.974 | 10.014 | 10.620 | 10.699 | 1.233 |
| GDP Growth | 14,518 | 6.073 | 0.000 | 6.667 | 9.091 | 9.224 |
| Volatility | 14,518 | 21.270 | 15.608 | 21.040 | 24.684 | 7.727 |
| Market return | 14,518 | 5.992 | -10.192 | 7.526 | 18.401 | 21.235 |
| Banking sector non-interest-income | 14,518 | 36.595 | 31.600 | 37.327 | 40.821 | 8.718 |
| Bank credit | 14,518 | 64.333 | 48.685 | 51.537 | 72.669 | 34.628 |
| Concentration | 14,518 | 43.426 | 29.870 | 34.964 | 54.928 | 21.042 |

**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. Models (1) through (3) show results from OLS regressions. *Actual flows* are the log difference (difference in log from *t-1* to *t*) of total foreign claims to target country *r*. *Inflows* (*Outflows*) are the log difference in foreign claims between *t-1* and *t* when there is an inflow (outflow) of funds into a country, and zero otherwise. *Residual flows* are the residuals from estimations of equation 3 (Model 6 of Table 3), aggregated at the target country-year. In Models (4) and (5) we report first- and second-stage results from regressions of actual flows instrumented using the *FDI outflow restriction index*, calculated relative to the source country. Bank-level controls include: *Size* (log of assets); *Non-interest income*; *ST funding*; *Leverage*; *NPL-to-loans*; *ROA*; and *Non-interest expense*. We also incorporate country-level controls, including: *Log GDP per capita*, *GDP growth*, *Volatility*, *Market return*, *Non-interest income*, *Bank credit*, 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.

| | OLS | | | 2SLS | |
|---|---|---|---|---|---|
| | | | | First-Stage | Second-Stage |
| Dependent variable: | *MES (%)* | *MES (%)* | *MES (%)* | *Actual Flows* | *MES (%)* |
| | (1) | (2) | (3) | (4) | (5) |
| Actual Flows | -0.516** | | | | |
| | (-2.21) | | | | |
| Inflows | | -0.733** | | | |
| | | (-2.34) | | | |
| Outflows | | -0.194 | | | |
| | | (-0.59) | | | |
| Residual Flows | | | -0.385** | | |
| | | | (-2.32) | | |
| FDI outflow restrictions | | | | -0.949** | |
| | | | | (-2.12) | |
| Flows- IV | | | | | -2.751** |
| | | | | | (-2.21) |
| Size t-1 | 0.370*** | 0.372*** | 0.375*** | -0.025* | 0.339*** |
| | (7.98) | (8.06) | (7.70) | (-1.76) | (5.60) |
| Noninterest income-to-income t-1 | -0.000 | -0.000 | -0.000 | 0.000* | 0.000 |
| | (-0.08) | (-0.09) | (-0.26) | (1.96) | (0.17) |
| S-T funding t-1 | 0.005 | 0.005 | 0.006 | -0.002*** | 0.003 |
| | (1.25) | (1.25) | (1.44) | (-3.42) | (0.60) |
| Leverage t-1 | 0.002 | 0.002 | 0.002 | -0.000 | -0.001 |
| | (0.58) | (0.59) | (0.61) | (-0.75) | (-0.22) |
| NPL-to-loans t-1 | 0.010* | 0.010* | 0.011* | -0.003** | 0.000 |
| | (1.72) | (1.79) | (1.94) | (-2.12) | (0.04) |
| ROA t-1 | -0.035 | -0.036 | -0.035 | 0.000 | -0.031 |
| | (-1.04) | (-1.05) | (-1.00) | (0.14) | (-0.85) |
| Non-int. expense t-1 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 |
| | (0.81) | (0.78) | (0.79) | (0.39) | (1.43) |
| Log GDP per capita t-1 | -2.127*** | -2.149*** | -2.183*** | 0.120 | -2.228*** |
| | (-3.77) | (-3.74) | (-3.86) | (0.73) | (-3.22) |
| GDP growth t-1 | -0.010*** | -0.010*** | -0.010*** | -0.000 | -0.008*** |
| | (-3.57) | (-3.56) | (-3.88) | (-0.38) | (-3.03) |
| Volatility t-1 | 0.015 | 0.015 | 0.015 | 0.000 | 0.012 |
| | (1.65) | (1.63) | (1.62) | (0.03) | (1.18) |
| Market return t-1 | 0.008*** | 0.008*** | 0.007*** | 0.002** | 0.013*** |
| | (3.98) | (3.94) | (3.75) | (2.23) | (4.80) |
| Non-interest income (%) | 0.010 | 0.010 | 0.009 | 0.002 | 0.013* |
| | (1.52) | (1.53) | (1.49) | (1.37) | (1.85) |
| Bank credit t-1 | 0.001 | 0.001 | 0.002 | -0.001* | -0.002 |
| | (0.35) | (0.26) | (0.47) | (-1.88) | (-0.63) |
| Concentration t-1 | 0.004 | 0.004 | 0.003 | 0.001 | 0.004 |
| | (0.96) | (0.87) | (0.76) | (1.40) | (0.75) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,518 | 14,518 | 14,518 | 13,506 | 13,506 |
| Adjusted $R^2$ | 0.583 | 0.583 | 0.583 | 0.285 | 0.587 |
| Partial $R^2$ | 61 | 61 | 61 | 61 | 61 |
| 1st stage *F*-statistic | | | | 5.113 | |
| 1st stage *F*-statistic *p*-value | | | | 0.027 | |

**Table 8. Bank-Level Results by Bank Characteristics.**

This table presents ordinary least squares (OLS) regression results. The dependent variable is *MES* – the negative of the average bank returns during the worst 5% market return days in a year. The key independent variable is Flows–the log difference (difference in log from *t-1* to *t*) of total foreign claims to target country *r*. We present results using interactions between *Flows* and seven bank characteristics: 1) *Size* (log of assets); 2) *Non-interest income-to-income*–non-interest income divided by the sum of-interest and non-interest income; 3) *ST funding*– nondeposit short-term funding divided by total liabilities; 4) *Leverage*– total assets divided by the book value of equity; 5) *NPL-to-loans*– the ratio of non-performing loans-to-total loans; 6) *ROA*–net income divided by average total assets, and *7) Non-interest expense* – the ratio of non-interest expense-to-gross revenues. In all regressions, we include a set of bank- and country-level controls (not shown to conserve space). Bank-level controls include: *Size* (log of assets); *Non-interest income*; *ST funding*; *Leverage*; *NPL-to-loans*; *ROA*; and *Non-interest expense*. Country-level controls include: *Log GDP per capita, GDP growth, Volatility, Market return, Non-interest income, Bank credit,* 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 (%)* | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Flows x Size | -0.323*** | | | | | | |
| | (-3.86) | | | | | | |
| Flows x Non-interest income | | 0.003 | | | | | |
| | | (0.52) | | | | | |
| Flows x S-T funding | | | -0.032* | | | | |
| | | | (-1.68) | | | | |
| Flows x Leverage | | | | 0.002 | | | |
| | | | | (0.16) | | | |
| Flows x NPL-to-loans | | | | | 0.041** | | |
| | | | | | (2.16) | | |
| Flows x ROA | | | | | | 0.117* | |
| | | | | | | (1.72) | |
| Flows x Non-int. expense | | | | | | | 0.002 |
| | | | | | | | (0.22) |
| Flows | 2.210*** | -0.620** | -0.345 | -0.546 | -0.753*** | -0.632*** | -0.630 |
| | (3.41) | (-2.13) | (-1.58) | (-1.56) | (-3.00) | (-2.68) | (-0.98) |
| Bank-Level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,518 | 14,518 | 14,518 | 14,518 | 14,518 | 14,518 | 14,518 |
| Adjusted $R^2$ | 0.586 | 0.583 | 0.584 | 0.583 | 0.584 | 0.583 | 0.583 |
| # of countries | 61 | 61 | 61 | 61 | 61 | 61 | 61 |

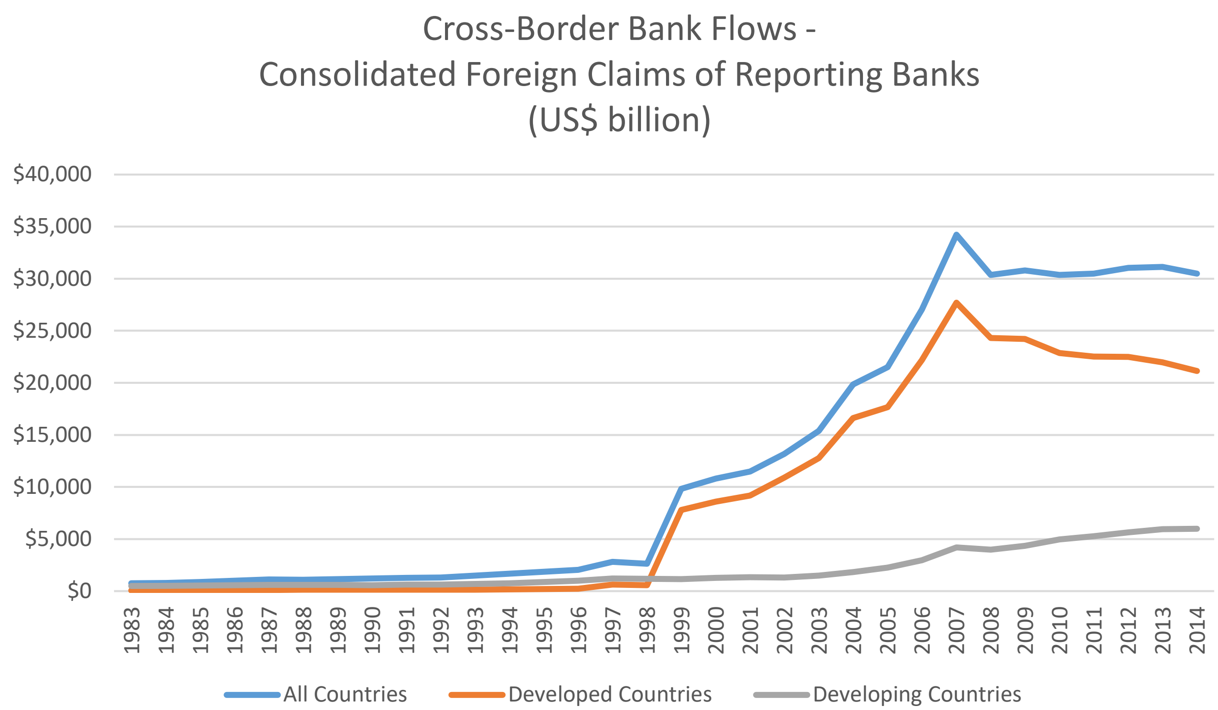
**Table 9. Impact on Bank Performance during the Crisis of 2008-2009.** This table presents results from OLS regressions of measures of bank performance. Our key independent variable, *High Inflows 2006*, is an indicator that is equal to one for countries with *Inflows* as of 2006 in the top quartile of the distribution and zero otherwise. *Crisis* is an indicator variable that is equal to one for the years 2008 and 2009 and zero otherwise. The dependent variables are: 1) *ROA*; 2) *Leverage*; 3) *Non-interest expense,* and 4) *NPL-to-loans*. In Panel A we show results from panel regressions. In Panel B, we report results from cross-sectional regressions using the change in each performance measure between 2007 and 2009 as the dependent variable. 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 *Log GDP per capita, 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 Panel A. 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 – Panel Regressions | | | | |
|---|---|---|---|---|
| Dependent variable: | *ROA* | *Leverage* | *Non-interest expense* | *NPL-to-loans* |
| | (1) | (2) | (3) | (4) |
| Crisis x High Inflows 2006 | 0.240 | -1.593*** | -5.307** | 0.100 |
| | (1.39) | (-3.70) | (-2.37) | (0.14) |
| Crisis | -0.429*** | 1.346** | 10.917*** | 1.068* |
| | (-2.69) | (2.45) | (5.07) | (1.75) |
| Controls | Yes | Yes | Yes | Yes |
| Bank fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,309 | 14,518 | 14,508 | 14,239 |
| Adjusted $R^2$ | 0.476 | 0.619 | 0.494 | 0.828 |

| Panel B – Cross-sectional Regressions | | | | |
|---|---|---|---|---|
| Dependent variable: | *ΔROA* | *ΔLeverage* | *ΔNon-interest expense* | *ΔNPL-to-loans* |
| | (1) | (2) | (3) | (4) |
| High Inflows 2006 | 0.200 | -2.089* | -3.291 | 0.048 |
| | (1.22) | (-1.92) | (-0.99) | (0.09) |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 754 | 775 | 774 | 750 |
| Adjusted $R^2$ | 0.069 | 0.098 | 0.106 | 0.378 |

**Figure 1. Consolidated Foreign Claims By Year.**

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



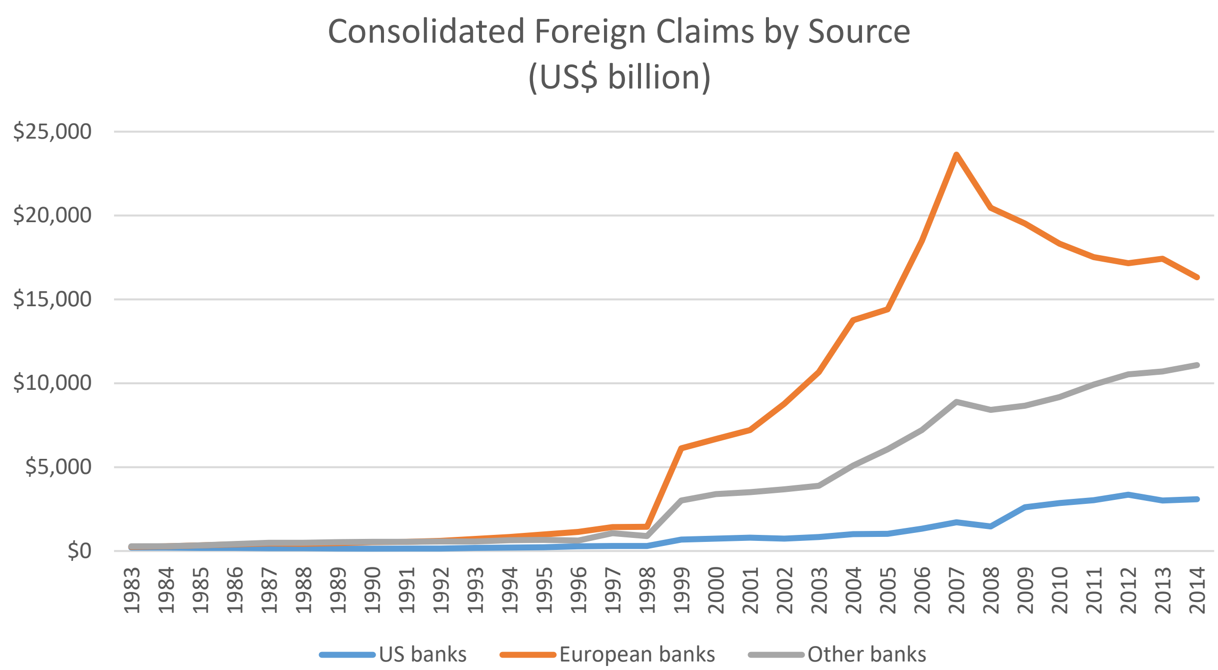



**Figure 2. Systemic Risk Measures by Year.**

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. The graph shows the cross-country average of each measure.

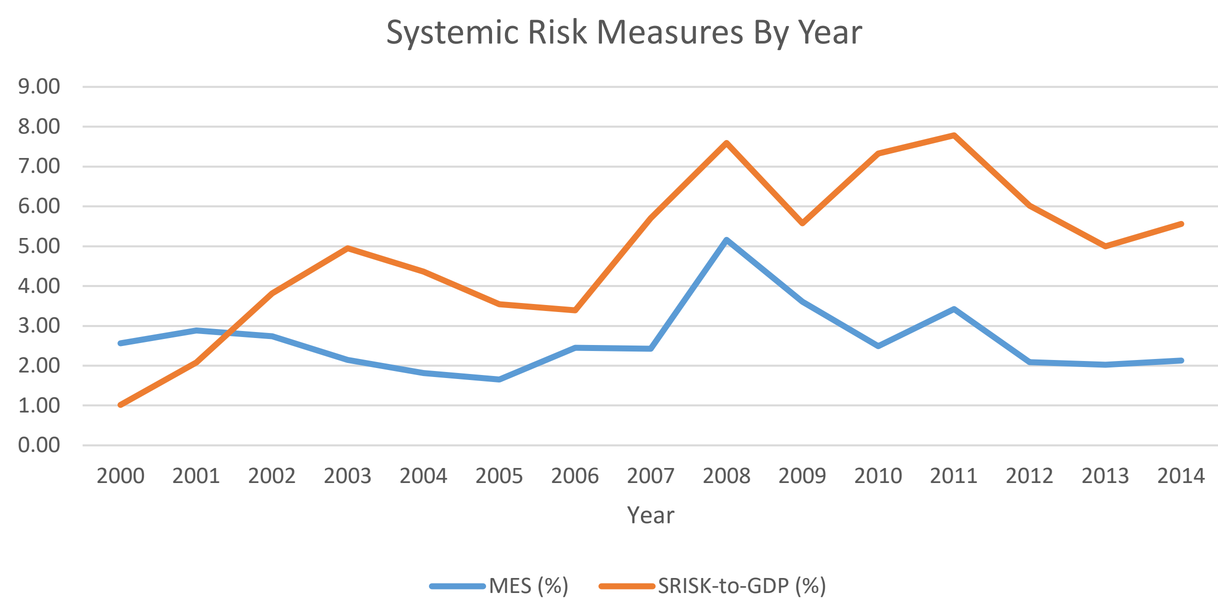
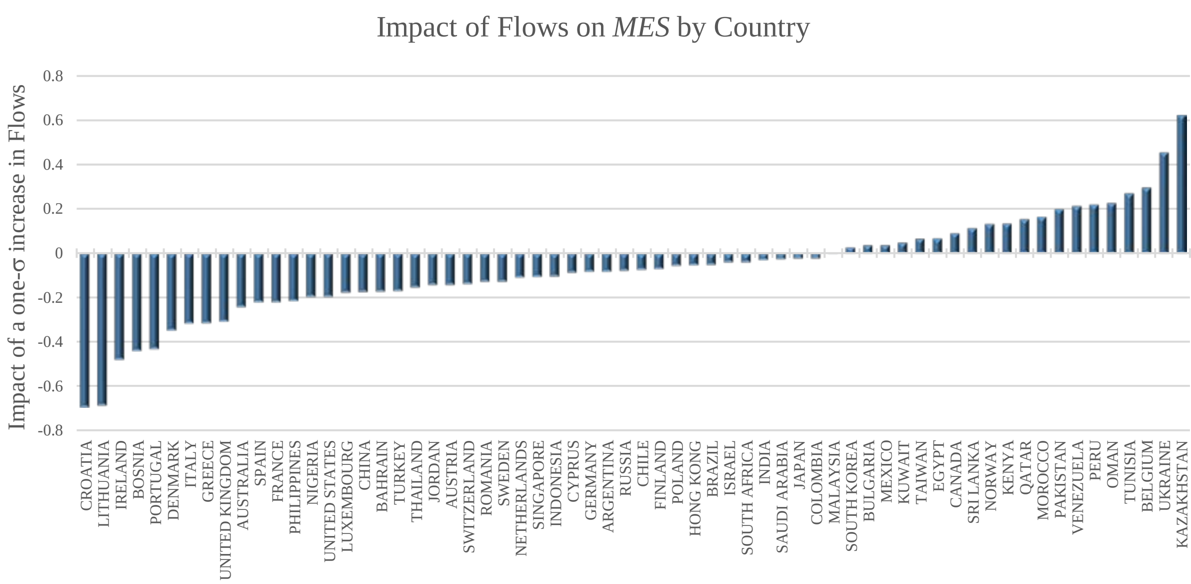


**Figure 3. Country-Level Systemic Risk Measures by Country and Year.** The figure presents coefficients from OLS regressions of country-level systemic risk measures on *Flows.* The dependent variables are: Marginal Expected Shortfall (*MES*) and *SRISK* (normalized by the country's GDP). Specifically, the graphs show the coefficient estimates of the impact of a one-standard deviation increase in *Flows* at time *t* on the average *MES* (*SRISK-to-GDP*) in a country. To obtain the coefficient, we multiply the estimated coefficient on *Flows* by its standard deviation and divide it by the average *MES* (*SRISK-to-GDP*). For example, the regression coefficient on *Flows* in the *MES* regressions for Greece is -5.189. Thus, a one-σ increase in *Flows t* (0.338) is associated with a 1.754 reduction in *MES*, which represents a 31.3% reduction (this is the coefficient reported for Greece on the first graph) relative to its mean (5.606). We estimate regressions by country only for those countries with at least three years of available data. Panel A (B) shows results by country (year). The sample period is 2000-2014. All variables are defined in Appendix A.

Panel A. *MES* By Country.




Panel B. *SRISK* By Country.

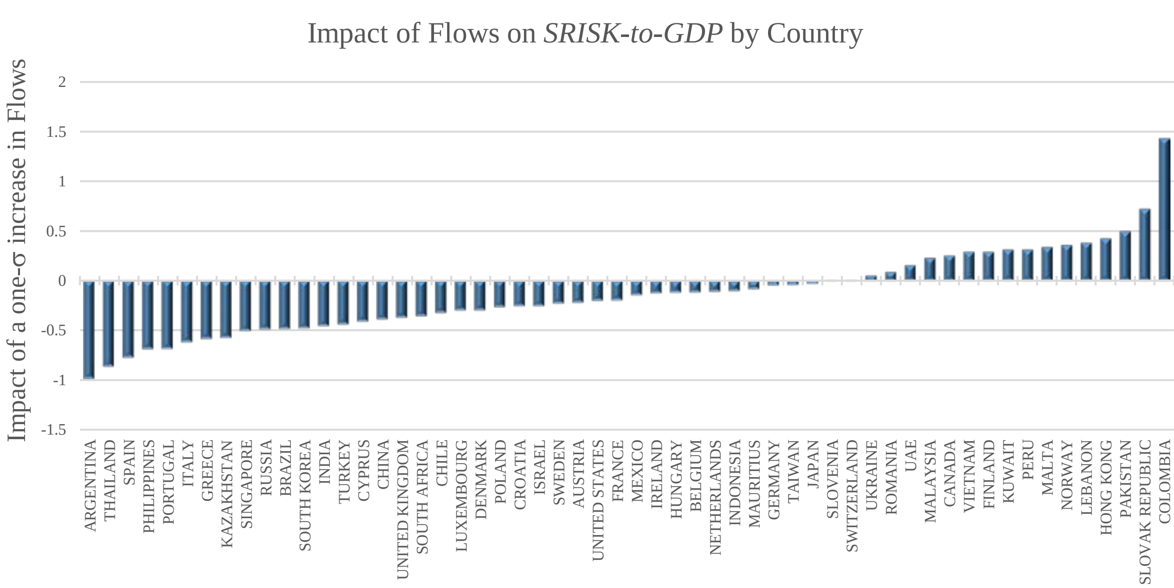
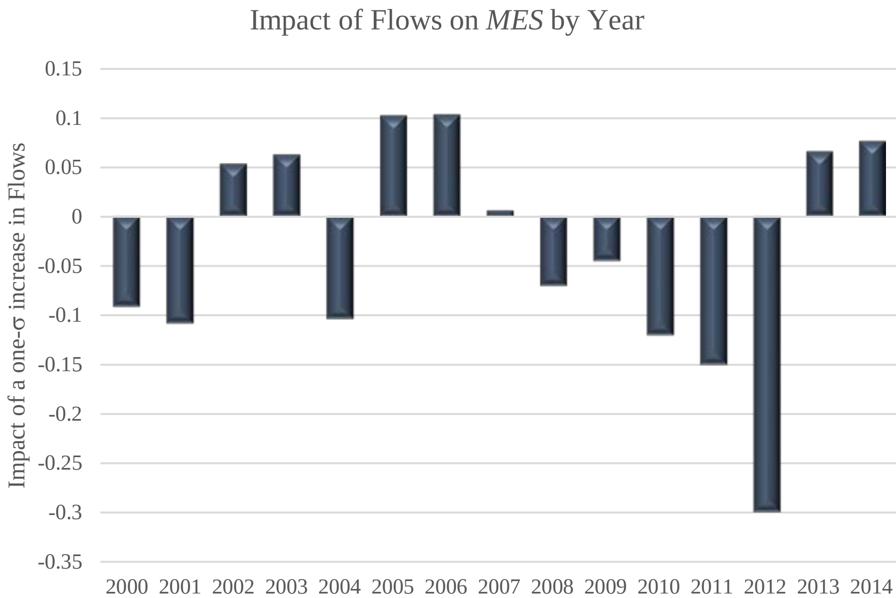


**Figure 4. Country-Level Systemic Risk Measures by Country and Year.** Continued.

Panel C. *MES* By Year.




Panel D. *SRISK* By Country.

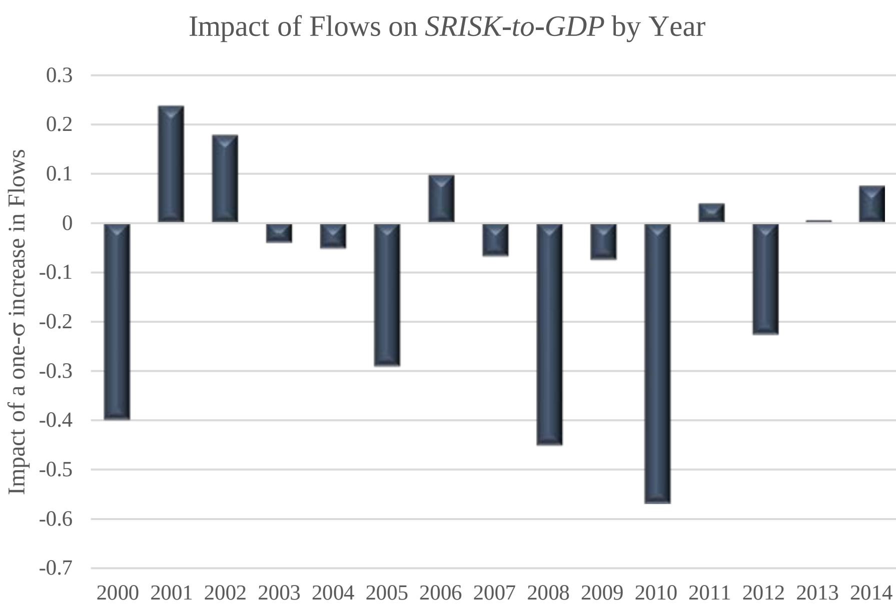
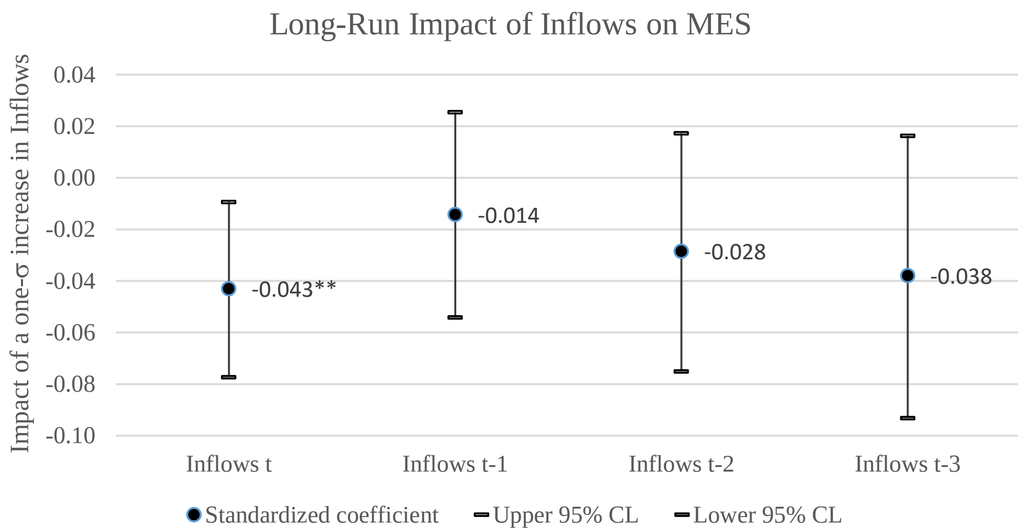


**Figure 4. Long-Run Impact of Inflows on Country-Level Systemic Risk.** This table presents coefficients from OLS regressions of country-level systemic risk measures on *Inflows* at time *t*, *t-1*, *t-2*, and *t-3*. The dependent variables are: Marginal Expected Shortfall (*MES*) and *SRISK* (normalized by the country's GDP). The graphs show the coefficient estimates of the impact of a one-standard deviation (σ) increase in *Inflows* at time *t* on the average *MES* (*SRISK-to-GDP*) in a country. For example, the regression coefficient on *Inflows t* in the *MES* regressions is -0.727. Thus, a one-σ increase in *Inflows t* (0.158) is associated with a 0.115 reduction in *MES*, which represents a 4.3% reduction (this is the coefficient on *Inflows t* on the first graph) relative to its mean (2.653). We include country and year fixed effects in all regressions. 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. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.



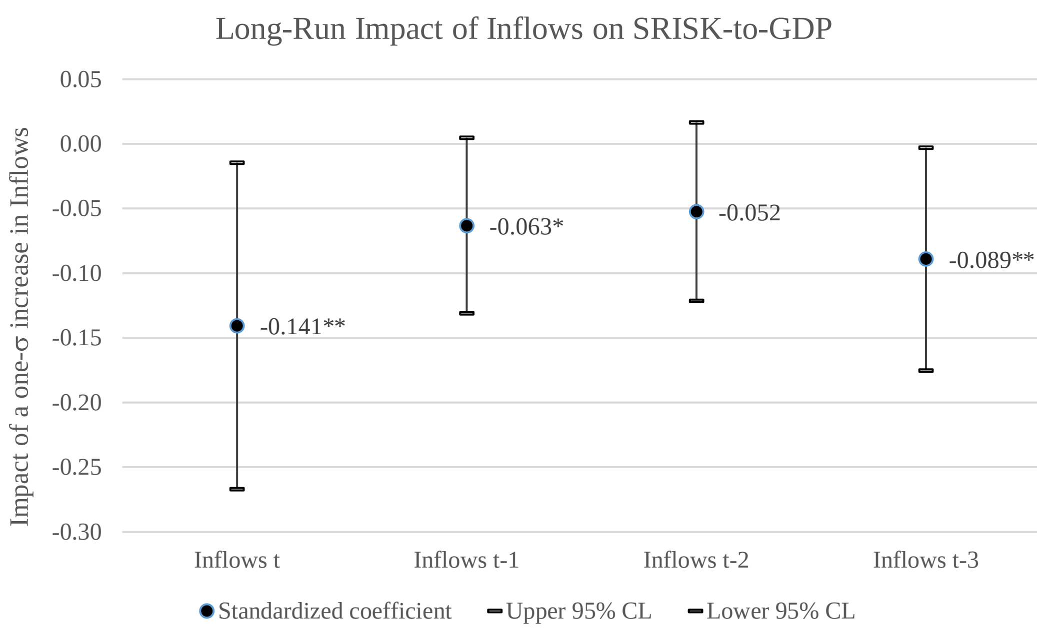
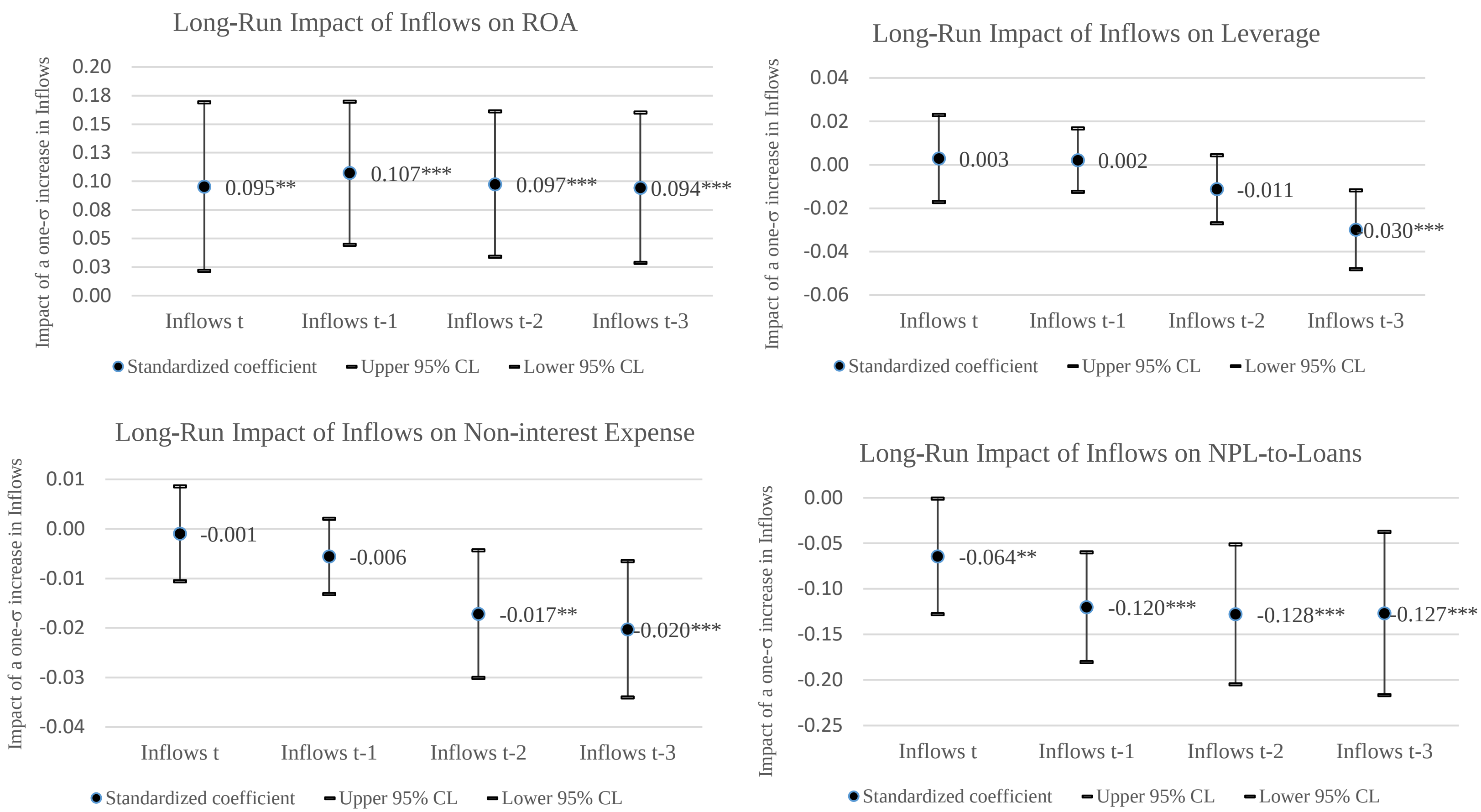



**Figure 5: Impact on Bank Performance.** This table presents coefficients from OLS regressions of measures of bank performance on *Inflows* at time *t, t-1, t-2*, and *t-3.* Specifically, the graph shows estimates of the impact of a one-standard deviation (σ) increase in *Inflows* at time *t* on the average performance measure. The dependent variables are: 1) *ROA*; 2) *Leverage*; 3) *Non-interest expense, and* 4) *NPL-to-loans*. To obtain the standardized coefficient, we multiply the estimated coefficient on *Inflows* by its standard deviation and divide it by the average performance measure. For example, for the *ROA* regressions, the regression coefficient on *Inflows t* is 0.539. Thus, a one-σ increase in *Inflows t* (0.119) is associated with a 0.064 increase in *ROA,* which represents a 9.5% increase (this is the coefficient on *Inflows t* on the first graph) relative to its mean (0.672). We obtain all bank-level variables from Fitch fundamentals financial data and DataStream. We include bank and year fixed effects in all regressions. Significance of coefficients are based on robust standard errors clustered at the country level. The sample period is 2000-2014. All variables are defined in Appendix A.



**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 target 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 target country *r*. | Bank for International Settlements (BIS) |
| *Flows* | The log difference (difference in log from *t-1* to *t*) of total foreign claims from all source countries to target country *r*. | Bank for International Settlements (BIS) |
| *Residual Flows* | Residuals from model (6) of Table 3 aggregated at the target-country-year, following equation 4. | Estimated following methodology of Houston, et al. (2012) |
| *Inflows (Outflows)* | The log difference (difference in log from *t-1* to *t*) of total foreign claims from all source countries to target country *r*. when there is a net inflow (outflow) of funds into country *r*, and zero otherwise. | Bank for International Settlements (BIS) |
| ***Country-Level Variables:*** | | |
| *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) |
| *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) |
| *Private monitoring* | Index measuring whether there exist incentives/ability for the private monitoring of banks. The index ranges from 0 to 12, with higher values indicating more private oversight. | Barth, Caprio, and Levine (2013) |
| *Independence of supervisory authority* | Index measuring the degree to which the supervisory authority is independent of the government and legally protected from the banking industry. The index ranges from 0 to 3, with higher values indicating more independence. | Barth, Caprio, and Levine (2013) |

**Appendix A: Definitions and Sources.** Continued.

| *Variable* | *Definition* | *Source* |
|---|---|---|
| *Log GDP per capita* | Annual value of the natural logarithm of the country's gross domestic product (GDP) per capita. | World Development Indicators |
| *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 credit* | The private credit by deposit money banks and other financial institutions as a share of GDP. | Global Financial Development Database |
| *Concentration* | The assets of three largest commercial banks as a share of total commercial banking assets. | Global Financial Development Database |
| *Financial liberalization* | Index of financial liberalization. Higher values indicate a higher degree of financial liberalization. | Abiad, Detragiache, and Tressel (2010) |
| *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 |
| *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 (total value of loan portfolio). | Global Financial Development Database |
| *Bank Capital* | Banking sector capital and reserves to total assets (%). Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. | Global Financial Development Database |
| *Bank ROA* | Commercial banks' net income to average total assets. | Global Financial Development Database |
| *Bank Assets* | Total assets held by deposit money banks as a share of GDP. | Global Financial Development Database |

**Appendix A: Definitions and Sources.** Continued.

| *Variable* | **Definition** | **Source** |
|---|---|---|
| *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) |
| *Strength of external audit* | An index measuring the strength of external auditors. Higher values indicate more strength. | Barth, Caprio, and Levine (2013) |
| *Independence of supervisors* | An index measuring the degree of the supervisory authority's independence from the government and protection from the banking industry. Higher values of the index indicate more independence. | Barth, Caprio, and Levine (2013) |
| *Total Foreign Direct Investment Restrictions* | An index that captures a country's stance towards capital controls on foreign direct investment outflows. It is an average of outflow control restrictions on 1) Equity investments and 2) Direct investment accounts. Equity investments include transactions involving shares and other securities of a participating nature that are not for the purpose of acquiring a lasting economic interest in the management of the enterprise concerned. Direct investment refers to investments for the purpose of establishing lasting economic relations both abroad by residents and domestically by nonresidents. The index value ranges from 0 to 2, with higher values indicating more restrictions. | Fernandez et al. (2015). |
| *Developed* | Indicator variable that equals one for countries in the MSCI Developed Markets Index and zero otherwise. | |
| ***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 |

**Appendix A: Definitions and Sources.** Continued.

| *Variable* | Definition | Source |
|---|---|---|
| *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 |
| *Market-to-book* | Market value of equity divided by the book value of equity | Fitch Fundamentals Financial data; WorldScope |

**Appendix B. Descriptive Statistics by Country.** This table provides summary statistics at the country level for the 74 countries in our analysis with available data on either of our two measures of systemic risk: 1) *SRISK-to-GDP* and 2) *MES* – the negative value of the value-weighted *MES* for all banks in a country. We include the measures of international bank flows (*Flows)*. All variable definitions are in Appendix A. We average each measure across the full sample period 2000-2014.

| Country | *MES (%)* | *SRISK-to-GDP* | *Flows* |
|---|---|---|---|
| Argentina | 3.291 | 0.140 | -0.060 |
| Australia | 2.063 | . | 0.077 |
| Austria | 3.371 | 4.831 | 0.071 |
| Bahrain | 1.457 | 0.566 | -0.095 |
| Belgium | 3.125 | 14.156 | 0.081 |
| Bosnia and Herzegovina | 0.035 | . | -0.065 |
| Brazil | 2.676 | 0.752 | 0.087 |
| Bulgaria | 1.559 | . | 0.049 |
| Canada | 1.883 | 2.198 | 0.123 |
| Chile | 1.351 | 0.224 | 0.042 |
| China | 2.460 | 1.883 | 0.200 |
| Colombia | 1.840 | 1.570 | 0.097 |
| Croatia | 1.343 | 0.272 | 0.054 |
| Cyprus | 5.042 | 22.354 | 0.057 |
| Czech Republic | . | 0.176 | 0.059 |
| Denmark | 2.229 | 8.792 | 0.111 |
| Egypt | 2.829 | . | 0.070 |
| Finland | 1.957 | 0.606 | 0.126 |
| France | 3.812 | 16.672 | 0.071 |
| Germany | 2.828 | 8.832 | 0.063 |
| Greece | 5.606 | 9.266 | -0.026 |
| Hong Kong | 2.099 | 6.791 | 0.066 |
| Hungary | . | 0.712 | -0.086 |
| India | 3.474 | 1.804 | 0.137 |
| Indonesia | 3.612 | 0.092 | 0.060 |
| Ireland | 3.046 | 8.953 | 0.097 |
| Israel | 2.436 | 4.779 | 0.066 |
| Italy | 3.533 | 5.797 | 0.040 |
| Japan | 3.119 | 6.778 | 0.038 |
| Jordan | 1.863 | 0.003 | 0.068 |
| Kazakhstan | 0.615 | 0.387 | -0.179 |
| Kenya | 1.049 | . | -0.037 |
| Kuwait | 2.134 | 0.059 | 0.073 |
| Lebanon | . | 1.074 | 0.014 |
| Lithuania | 1.984 | . | 0.192 |
| Luxembourg | 0.698 | 11.102 | 0.034 |
| Malaysia | 1.817 | 0.857 | 0.069 |
| Malta | . | 1.254 | 0.099 |
| Mauritius | . | 0.648 | 0.093 |
| Mexico | 2.124 | 0.067 | 0.097 |
| Morocco | 1.638 | 0.604 | 0.097 |
| Netherlands | 3.792 | 14.881 | 0.062 |
| New Zealand | . | 0.048 | 0.056 |
| Nigeria | 2.279 | . | 0.161 |
| Norway | 1.662 | 1.111 | 0.265 |
| Oman | 2.548 | . | 0.100 |

**Appendix B: Descriptive Statistics by Country.** Continued.

| Country | *MES (%)* | *SRISK-to-GDP* | *Flows* |
|---|---|---|---|
| Pakistan | 3.264 | 0.069 | -0.035 |
| Peru | 1.231 | 0.377 | 0.082 |
| Philippines | 2.209 | 0.162 | 0.056 |
| Poland | 2.764 | 0.230 | 0.166 |
| Portugal | 2.981 | 3.627 | 0.062 |
| Qatar | 2.131 | . | 0.075 |
| Romania | 3.519 | 0.072 | 0.184 |
| Russian Federation | 4.138 | 0.636 | 0.099 |
| Saudi Arabia | 1.572 | 0.063 | 0.157 |
| Singapore | 2.320 | 1.451 | 0.093 |
| Slovak Republic | . | 0.161 | 0.071 |
| Slovenia | . | 0.193 | -0.090 |
| South Africa | 2.412 | 1.869 | 0.092 |
| South Korea | 3.171 | 0.847 | 0.118 |
| Spain | 3.479 | 5.763 | 0.078 |
| Sri Lanka | 2.366 | . | 0.048 |
| Sweden | 3.163 | 12.393 | 0.064 |
| Switzerland | 3.300 | 27.237 | 0.075 |
| Taiwan | 2.857 | 1.622 | 0.124 |
| Thailand | 3.361 | 1.084 | 0.067 |
| Tunisia | 0.860 | . | 0.023 |
| Turkey | 4.881 | 0.705 | 0.131 |
| Ukraine | 2.440 | 0.177 | -0.294 |
| United Arab | . | 0.680 | -0.109 |
| United Kingdom | 2.607 | 16.265 | 0.057 |
| United States | 3.438 | 2.486 | 0.057 |
| Venezuela | 1.523 | . | 0.052 |
| Vietnam | . | 0.108 | 0.196 |

## 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) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1 | | | | | | | | | | | | | | | |
| (2) | 0.177* | 1 | | | | | | | | | | | | | | |
| (3) | -0.128* | -0.030 | 1 | | | | | | | | | | | | | |
| (4) | -0.140* | -0.062 | 0.321* | 1 | | | | | | | | | | | | |
| (5) | 0.039 | 0.010 | 0.090* | 0.451* | 1 | | | | | | | | | | | |
| (6) | 0.121* | -0.001 | 0.052 | -0.123* | -0.143* | 1 | | | | | | | | | | |
| (7) | -0.041 | 0.085* | 0.275* | -0.011 | -0.067* | -0.167* | 1 | | | | | | | | | |
| (8) | 0.153* | -0.058 | 0.108* | -0.169* | -0.166* | 0.298* | -0.144* | 1 | | | | | | | | |
| (9) | 0.046 | 0.018 | 0.060 | 0.219* | 0.200* | -0.011 | -0.012 | 0.058 | 1 | | | | | | | |
| (10) | -0.050 | -0.001 | 0.142* | 0.565* | 0.575* | -0.202* | -0.039 | -0.241* | -0.004 | 1 | | | | | | |
| (11) | 0.085* | -0.012 | -0.023 | 0.243* | 0.312* | 0.033 | -0.084* | -0.056 | 0.002 | 0.287* | 1 | | | | | |
| (12) | 0.024 | 0.000 | -0.039 | -0.267* | -0.381* | 0.148* | -0.035 | 0.124* | -0.219* | -0.284* | -0.191* | 1 | | | | |
| (13) | 0.068* | 0.020 | -0.014 | -0.106* | -0.284* | 0.081* | -0.041 | 0.110* | -0.155* | -0.172* | -0.106* | 0.215* | 1 | | | |
| (14) | -0.004 | -0.018 | 0.071* | 0.100* | 0.141* | -0.043 | -0.057 | -0.096* | -0.026 | 0.266* | 0.182* | -0.269* | 0.039 | 1 | | |
| (15) | -0.081* | -0.029 | 0.010 | 0.047 | -0.085* | -0.048 | -0.065* | -0.055 | -0.061* | 0.010 | -0.026 | -0.004 | 0.065* | 0.159* | 1 | |
| (16) | 0.016 | -0.007 | 0.026 | -0.002 | 0.120* | 0.002 | -0.001 | -0.025 | -0.126* | 0.139* | 0.048 | 0.030 | 0.066* | -0.048 | 0.016 | 1 |
| (17) | -0.145* | -0.073* | -0.073* | 0.057 | -0.181* | 0.065* | -0.019 | 0.110* | 0.044 | -0.182* | -0.084* | 0.039 | 0.021 | -0.074* | -0.087* | -0.063 |

| | | | |
|---|---|---|---|
| (1) | Flows | (10) | Bank credit (%) |
| (2) | Residual Flows | (11) | Concentration (%) |
| (3) | MES | (12) | Restrictions on bank activities |
| (4) | SRISK-to-GDP | (13) | Official supervisory power |
| (5) | Log GDP per capita | (14) | Independence of supervisory authority |
| (6) | GDP growth (%) | (15) | Stringency of capital regulation |
| (7) | Volatility | (16) | Private monitoring |
| (8) | Market return | (17) | Total FDI outflow restrictions |
| (9) | Non-interest income (%) | | |

**Appendix D. Example Calculations for Instrumental Variable on Total FDI Outflow Restrictions.**

The table shows an example of the construction of the instrumental variable, *Total FDI outflow restrictions*. FDI outflow restrictions is an index that captures a country's stance towards capital controls on foreign direct investment outflows. It is an average of outflow control restrictions on (1) equity investments and (2) direct investment accounts from Fernandez et al. (2015). Bilateral trade is the maximum of exports and imports between source country *s* and target country r. Data for imports and exports is from the IMF Direction of Trade Statistics (DOT). The weight is the proportion of total trade in target country *r* in year *t*-1 from source country *s*.

| Target country (r) | Source country (s) | Year | FDI outflow restrictions (source) | Bilateral trade t-1 (US$ million) | Weight | Weighted FDI outflows restrictions |
|---|---|---|---|---|---|---|
| India | United States | 2012 | 0.25 | $33,359 | 0.182 | 0.046 |
| India | Switzerland | 2012 | 0 | $31,568 | 0.173 | 0.000 |
| India | Germany | 2012 | 0.25 | $15,275 | 0.083 | 0.021 |
| India | Australia | 2012 | 0 | $13,424 | 0.073 | 0.000 |
| India | South Korea | 2012 | 0 | $12,437 | 0.068 | 0.000 |
| India | Japan | 2012 | 0 | $11,196 | 0.061 | 0.000 |
| India | Belgium | 2012 | 0.25 | $10,395 | 0.057 | 0.014 |
| India | Netherlands | 2012 | 0 | $9,734 | 0.053 | 0.000 |
| India | United Kingdom | 2012 | 0 | $8,789 | 0.048 | 0.000 |
| India | Brazil | 2012 | 1 | $5,363 | 0.029 | 0.029 |
| India | Taiwan | 2012 | 0 | $5,243 | 0.029 | 0.000 |
| India | Italy | 2012 | 0 | $5,220 | 0.029 | 0.000 |
| India | France | 2012 | 0 | $4,910 | 0.027 | 0.000 |
| India | Turkey | 2012 | 0.5 | $3,623 | 0.020 | 0.010 |
| India | Spain | 2012 | 0 | $2,986 | 0.016 | 0.000 |
| India | Mexico | 2012 | 0.5 | $2,185 | 0.012 | 0.006 |
| India | Sweden | 2012 | 0 | $2,038 | 0.011 | 0.000 |
| India | Chile | 2012 | 0.5 | $1,821 | 0.010 | 0.005 |
| India | Austria | 2012 | 0.25 | $1,027 | 0.006 | 0.001 |
| India | Greece | 2012 | 0.25 | $792 | 0.004 | 0.001 |
| India | Denmark | 2012 | 0 | $785 | 0.004 | 0.000 |
| India | Portugal | 2012 | 0.25 | $582 | 0.003 | 0.001 |
| India | Panama | 2012 | 0 | $219 | 0.001 | 0.000 |
| TOTAL | | | | $182,972 | | **0.134** |

**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 128 recipient countries, totaling 47,259 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*.

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 LBS data on bilateral claims and liabilities is limited. While we do not use LBS data in our main analysis, in robustness tests we use a proxy for bank flows using the changes in BIS-adjusted net claims (change in claims minus change in liabilities) to recipient country *r*. Specifically, we use the change in net 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*. We report results from regressions using the LBS data to compute bank flows in Table E2 below. Results confirm our findings using the CBS data.

**References**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Engle, R.F., Jondeau, E., and Rockinger, M., 2015, Systemic Risk in Europe, *Review of Finance* 19, 145-190.

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**Table E1. Source countries reporting consolidated foreign claims (immediate counterparty basis).**

| Country | First Year |
|---|---|
| Australia | 2003 |
| Austria | 1983 |
| Belgium | 1983 |
| Brazil | 2002 |
| Canada | 1983 |
| Chile | 2002 |
| Chinese Taipei (Taiwan) | 2000 |
| Denmark | 1983 |
| Finland | 1985 |
| France | 1983 |
| Germany | 1983 |
| Greece | 2003 |
| Ireland | 2006 |
| Italy | 1983 |
| Japan | 1983 |
| Mexico | 2003 |
| Netherlands | 1983 |
| Panama | 2002 |
| Portugal | 1999 |
| South Korea | 2011 |
| Spain | 1985 |
| Sweden | 1983 |
| Switzerland | 1983 |
| Turkey | 2000 |
| United Kingdom | 1983 |
| United States | 1983 |

**Table E2. Robustness Tests. Systemic Risk Regressions.** This table presents descriptive statistics and OLS results of estimating systemic risk using known determinants including volatility and non-traditional income (Engle, et al. (2015), Brunnermeier, et al. (2015)), as well as cross-border banking flows. Panel A shows descriptive statistics of the main variables, while Panel B show OLS regression results. Our systemic risk measure is the Marginal Expected Shortfall (*MES*). We measure bank flows using data on claims and liabilities from the Bank for International Settlements (BIS) locational banking statistics (LBS). Specifically, we compute bank flows as the change in net claims (change in claims minus change in liabilities) to recipient country r from *t-1* to *t*. We use the BIS- break- and exchange rate-adjusted numbers to compute net claims. In Models (1) and (2) of Panel B, we scale the change in net claims by the recipient country's GDP and we scale the change in net claims by the total banking sector assets in recipient country *r* in Models (3) and (4) of Panel B. We obtain data on total banking sector assets (the assets of all banks and bank holding companies in the country) from Fitch fundamentals financial data. Controls include: *Log of GDP per capita*; *GDP growth*; *Market return*; *Volatility*; *Non-interest income*; *Bank credit*, and *Concentration*. *ST-rate* is the short-term interest rate in the country. 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.

Panel A- Descriptive Statistics of Main Variables

| | N | Mean | 25th Percentile | Median | 75th Percentile | Standard Deviation |
|---|---|---|---|---|---|---|
| Δ Net claims-to-GDP | 758 | 0.0004 | -0.0110 | 0.0014 | 0.0115 | 0.0532 |
| Δ Net claims-to-assets | 758 | 0.0012 | -0.0062 | 0.0008 | 0.0075 | 0.0197 |
| MES (%) | 758 | 2.660 | 1.410 | 2.316 | 3.521 | 1.681 |

Panel B. OLS Regressions

| Dependent variable: | Marginal Expected Shortfall (MES) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Net claims-to-GDP | -1.242** | -1.474** | | |
| | (-1.99) | (-2.28) | | |
| Δ Net claims-to-assets | | | -4.610*** | -5.516** |
| | | | (-2.67) | (-2.55) |
| ST rate | | 0.015 | | 0.015 |
| | | (1.17) | | (1.13) |
| Log GDP per capita $_{t-1}$ | -1.251 | -1.551 | -1.240 | -1.529 |
| | (-1.05) | (-1.15) | (-1.05) | (-1.15) |
| GDP growth $_{t-1}$ | -0.002 | -0.001 | -0.002 | -0.000 |
| | (-0.48) | (-0.16) | (-0.40) | (-0.09) |
| Market return $_{t-1}$ | 0.010*** | 0.009*** | 0.010*** | 0.009*** |
| | (4.17) | (3.95) | (4.27) | (4.13) |
| Volatility $_{t-1}$ | 0.025** | 0.024* | 0.025** | 0.024* |
| | (2.18) | (1.91) | (2.16) | (1.92) |
| Non-interest income $_{t-1}$ | 0.009 | 0.012 | 0.009 | 0.012 |
| | (1.24) | (1.65) | (1.18) | (1.61) |
| Bank credit $_{t-1}$ | 0.012*** | 0.012** | 0.011** | 0.011** |
| | (2.66) | (2.54) | (2.65) | (2.52) |
| Concentration | 0.004 | 0.003 | 0.005 | 0.003 |
| | (0.80) | (0.50) | (0.90) | (0.62) |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Observations | 758 | 699 | 758 | 699 |
| Adjusted R2 | 0.603 | 0.595 | 0.605 | 0.597 |
| # countries | 64 | 58 | 64 | 58 |