ABSTRACT

Title of dissertation: FOREIGN CURRENCY DEBT
AND CAPITAL FLOWS
IN EMERGING MARKETS

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Doctor of Philosophy, 2018

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This dissertation studies the determinants and consequences of capital inflows and foreign currency (FX) debt in emerging markets. Chapter 1 summarizes the topics, questions addressed, and findings. Chapter 2 studies the effects of balance sheet shocks driven by FX debt using a unique dataset of firm FX exposures matched with firm-bank lending data from listed firms in Mexico. I find that smaller non-exporters with FX mismatch see a decrease in loan growth, resulting in stagnant employment growth and decreased growth in physical capital relative to firms with less FX mismatch. Larger non-exporters with FX mismatch also have lower loan growth in FX following the shock, but are able to increase borrowing in Peso, resulting in higher growth in employment and physical capital relative to firms with less FX mismatch. My results imply that net worth based borrowing constraints are tighter for smaller firms and for loans in FX. I present a stylized model that rationalizes these findings.

Chapter 3 examines how international capital flows into a country, that is

by which sector capital flows in and out, and what drives those flows. To do so, we construct a new dataset of capital inflows and outflows split by sector. We establish four new stylized facts highlighting the differences in responses by sector to local and global shocks. These new facts are inconsistent with the standard models in which all foreign and domestic agents invest or disinvest in the same countries as a response to domestic and global shocks.

Chapter 4 examines the link between the global financial cycle (proxied by the VIX) and the currency composition of lending by emerging market banks. I construct a country-panel dataset of lending shares in FX, and show that this moves positively with the VIX. Countries that are more open to capital inflows or have poorly capitalized banking systems, however, tend to lend more in FX when VIX is low. Using matched firm-bank data from Mexico, I find that the positive association of FX lending with global liquidity holds in the microdata, and that this relationship is driven by well-capitalized banks.

FOREIGN CURRENCY DEBT AND CAPITAL FLOWS IN EMERGING MARKETS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2018

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Dedication

This dissertation is dedicated to my wife, Morgan, whose constant support throughout this process allowed me to become the best that I could be. Thank you, I love you.

Acknowledgments

I am deeply indebted to Şebnem Kalemli-Özcan for her continued support, guidance, and advice, as well as to Felipe Saffie and Ethan Kaplan. I am thankful to John Shea, Ina Simonovska, Michael Faulkender for their support and helpful comments. I thank Carolina Villegas-Sanchez and Vadym Volosovych for their help working with the data. I benefitted from comments and discussions with Jesse Schreger, Peter Dixon, Pablo Slutzky, Riley Wilson, and numerous other individuals, as well as seminar participants at the University of Maryland, Brigham Young University, FDIC, US Treasury OCC, Federal Reserve Bank of Dallas, the Federal Reserve Board of Governors, and the Bank for International Settlements. For work on Chapter 3, we thank Luis Catão, Eugenio Cerutti, Stijn Claessens, Branimir Gruic, Gian Maria Milesi-Ferretti, and Philip Wooldridge for useful comments and suggestions and Bat-el Berger for excellent assistance with the BIS IBS data. This work was partly funded by the World Bank's Knowledge for Change Program. The views expressed here are ours only and do not necessarily reflect those of the Bank for International Settlements or the World Bank. For work on Chapter 4, I am grateful to the employees at various central banks that helped me understand their data. All errors are my own.

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Chapter 1: Introduction

Foreign currency (FX) credit is pervasive in emerging markets (EM). Often denominated in US Dollars, this credit enters the country via international capital flows. With the large increase in financial integration and capital flows over the last 30 years, emerging markets have become more exposed to swings in international credit conditions. Global shifts in credit and portfolio allocation can drastically affect the buildup of credit and the consequences when that credit dries up. Understanding how capital flows and FX credit enter a country and the implications for financial stability and risk are important questions in international finance and macro and particularly relevant given the current scale of international capital integration. This dissertation addresses these questions.

In Chapter 2, I study the impact that foreign currency (FX) borrowing has on firms following a large depreciation. More generally, I address how negative shocks to firm net worth (balance sheet shocks) affect firm activity. I construct a novel dataset of currency exposures and loan level borrowing and examine both the financial and real consequences of negative balance sheet shocks due to foreign currency mismatch.

Firms that have FX debt in excess of their FX assets have a currency mismatch on their balance sheets. In the event of a large local currency depreciation, if these positions are unhedged, the firm experiences a drop in their net worth (due to the inflated burden of their FX debt in local currency terms). This decline in net worth matters if firms face binding borrowing constraints that depend on their net worth. Thus, firms borrowing in foreign currency may find themselves unable to obtain credit following a large depreciation, leading to a decline in real economic activity. This mechanism is central to many macroeconomic models and can serve to amplify shocks and help explain larger macroeconomic outcomes.

The existing literature has been challenged to identify these effects. This is for a few reasons. First, you need data to measure a shock to a firm's balance sheet. In this case, that means getting data on the firm's FX exposure. FX liability information is scarce, but FX asset and derivative information is scarcer still. Second, you need to isolate firm balance sheet shocks from shocks to a firm's credit supply, which may be affected from the same shock. This is rarely addressed. Third, you need data on both the financial and real side of the firm in order to test the mechanism (loss of credit via borrowing constraints) and connect that to real economic activity. Most studies just look at the end result on investment. Lastly, exchange rate shocks are often driven by endogenous crises within the country of study, which can affect firm outcomes through other channels.

I address these challenges by constructing a new dataset of firms in Mexico. This dataset includes data on firm FX liabilities and assets, as well as export revenues and on balance sheet derivatives positions. This gives me a more comprehensive view of firm FX exposures, enabling me to measure a shock to the firm balance sheet. An important and unique contribution of this dataset is that it includes loan level borrowing for each firm, matched up to their banks. This allows me to control for shocks to bank credit supply by comparing firms of differing FX exposures who borrow from the same bank at the same time. In addition to this detailed financial data, the dataset also includes real outcomes like employment and investment. Lastly, this dataset covers the period surround the collapse of Lehman Brothers. This shock generated an appreciation of the US Dollar vis-a-vis many other currencies in the world. Thus, this event generated a large and very sharp depreciation of the Peso that was not driven by an underlying currency or banking crisis in Mexico.

I find that firm size and the currency denomination of debt are two important characteristics that determine the impact of these constraints. Borrowing constraints are more binding following adverse balance sheet shocks for smaller firms, indicating a net worth or size based borrowing constraint, and for foreign currency loans, suggesting an additional tighter constraint on a firm's foreign currency debt. The interaction of these two constraints leads large firms with a negative shock to decrease their foreign currency borrowing, but allows them to increase their local currency borrowing and thus remain unconstrained in their real activity. Small firms who are constrained in their total borrowing contract their real activity following a negative balance sheet shock. These results are robust to numerous specifications and controls. These differences by currency of borrowing are new results in the literature and may help serve to harmonize the existing literature by explaining how large firms are sometimes found to do better following these exchange rate shocks.

I develop a stylized 3 period model of corporate borrowing and investment to rationalize these findings. The model features simultaneous borrowing in both foreign and domestic currency, a constraint on total borrowing for the firm, and a second borrowing constraint on FX debt specifically. The intuition for the model is that failure of uncovered interest rate parity, common in emerging markets (and exogenous to the model), makes foreign currency borrowing attractive despite the risk. When a depreciation hits, small firms with FX mismatch experience a negative shock to their net worth and are constrained in their borrowing, and so must decrease their debt in response to the shock. Large firms with FX mismatch are likewise constrained in their FX debt due to the shock, but not in their total borrowing, so they increase their Peso debt in order to invest at the unconstrained optimum.

Extending the model to allow for differences in firm productivity helps explain why large firms with large balance sheet shocks actually increase their employment and physical capital growth relative to less shocked firms. In the model, firms that are more productive are willing to borrow more in foreign currency because the likelihood of future constraints binding is lower. This generates a selection into foreign currency borrowing for firms with higher future productivity. When a depreciation hits, the smaller of these firms are constrained as before, but larger firms are unconstrained and so are able to increase their investment via Peso borrowing to the new optimal level, despite the shock.

This research has a number of important implications. When examining the risk posed due to FX borrowing, it is important to analyze the FX exposure of the universe of firms, and not just the listed firms (who are more likely to have the data). As the larger firms appear not to be negatively affected, the negative impacts observed in the aggregate may be driven by firms in the smaller half of the distribution (who are more likely to be constrained if hit by a negative balance sheet shock). Further, large firms may crowd out small firms from the Peso market and may thus generate negative effects through capital misallocation. Another implication is that the liquidity of the domestic currency in the banking system is relevant for risk assessment of FX borrowing as the domestic currency market serves as a substitute for firms that lose access to FX credit.

Given the consequences of FX debt buildup on corporate balance sheets, it is important to understand how internatinoal capital arrives in a country. In Chapter 3, joint work with Stefan Avdjiev, Şebnem Kalemli-Özcan, and Luis Servén, I explore the drivers of capital flows, specifically examining the sector of the economy that is involved. That is, I seek to understand by which sector international capital flows, mostly consisting of foreign currency, enter and leave a country. It is widely recognized that international capital flows have nontrivial consequences for the transmission of real and financial shocks across borders and for macroeconomic outcomes across countries. Likewise, the domestic macroeconomic environment and global shocks affect the volume and direction of capital flows. However, the sector composition of capital flows has received comparatively much less attention. Yet, it is apparent from the history of financial crises that the vulnerability to external shocks can vary greatly depending on which economic sector(s) are on the receiving side of capital inflows.

An important contribution of Chapter 3 is to introduce a new comprehensive dataset on *gross* capital inflows and outflows at the *quarterly* frequency for a balanced panel of 85 countries for inflows and 31 countries for outflows. In addition to reporting total inflows and outflows, we also report the decomposition by borrower and lender sectors. Our dataset has two distinct advantages over existing datasets. First, the large number of developing countries and emerging markets is a big advantage of our capital inflows dataset relative to standard sources. Second, our sectoral breakdown of debt inflows and outflows into 3 borrowing groups, i) sovereigns (which we sometimes separate into government and central bank sectors), ii) banks, and iii) corporates, is of utmost importance since greater international financial integration increases the risk of crises through debt linkages.

Using our dataset, we establish 4 new stylized facts for capital flows. First, the well-known positive correlation between capital inflows and outflows is driven by banking flows, mainly by global banks in advanced countries. Second, we find that, during domestic economic downturns, inflows to domestic banks and corporates decline in all countries. In terms of outflows, banks in advanced countries invest less abroad, whereas banks and corporates in emerging markets do not respond to their own business cycles in terms of outflows. Third, in response to a country-specific slowdown, private and public inflows respond in opposite directions—a fact driven by emerging markets' sovereigns. While inflows to the private sector decline in response to economic downturns in emerging markets, sovereigns behave in a countercyclical manner by borrowing more from abroad and drawing down reserves. Fourth, in response to adverse global credit supply shocks, such as an increase in the VIX, inflows to banks and corporates decline, while domestic banks and corporates invest less abroad, decreasing their outflows. Sovereigns do not respond to such supply shocks on average.

These four facts stand in contrast to standard international macroeconomic models, which treat domestic and foreign investors symmetrically. In those models, all agents respond to an expansion in the domestic economy by investing more in the domestically and vice versa during a downturn. Likewise, for global shocks, since all countries are affected, the models predict no difference in the way domestic and foreign agents respond. In contrast, our results imply that foreign and domestic investors behave differently in response to domestic and global shocks, where "investors" are sectors such as banks, corporates and the public sector.

Global conditions can be important drivers of international capital flows as they enter domestic economies, with the banking sector playing an important role in intermediating those flows. In Chapter 4, I address how global liquidity affects FX lending by banks in emerging markets. I analyze the role of the domestic banking sector as a transmission point for global liquidity and how the currency composition of bank lending is affected. With a new dataset of the foreign currency loan share of the banking sector, I explore the link between global liquidity and foreign currency lending in emerging markets.

To address this question, I construct a country-level panel dataset of the foreign currency share of lending by the domestic banking sector of 43 emerging markets. Using this dataset, I document 2 new facts: First, I document that tighter global liquidity conditions, as measured by the VIX, are associated with a higher share of a country's external debt attributable to the domestic banking sector. It is not obvious why this should be the case, as easier credit conditions in international markets (associated with periods of low VIX) should be associated with a relative increase in foreign currency lending. Second, I find that tighter global monetary conditions lead to a larger share of bank loans in FX. This result goes against the conventional wisdom that foreign currency lending should be more pervasive when funding markets for foreign currencies are more liquid. I analyze these relationship through formal regression analysis and explore the role of country characteristics in that transmission.

In order to identify this relationship, I use a matched firm-bank dataset of loan relationships from a significant emerging market, Mexico, and explore the role of bank characteristics in transmission. This dataset consists of all lending relationships of non-financial firms listed on the Mexican Stock Exchange (BMV). It includes information on the volume of the lending relationship and currency of borrowing (foreign vs domestic). I match this data up to bank balance sheet information from Bankscope. This allows me to examine which bank characteristics matter for the transmission of global liquidity conditions into FX bank lending. While the correlation of FX lending with the VIX may indeed be driven by push factors associated with global liquidity channeled through banks, it could also be driven by demand side factors. The matched nature of the dataset allows me to control for firm demand in each currency by including firm-quarter-currency fixed effects. Thus, I focus on the role of bank characteristics interacted with global liquidity in determining the lending outcomes.

In the country-level panel, I find that global liquidity (as proxied by the VIX) is highly positively correlated with the share of domestic bank loans in foreign currency. This relationship is robust across many specifications. Capital inflows to the banking sector also correlate positively with loans in FX, indicating the role domestic banks may play in transmitting global financing and financial conditions to domestic borrowers. Country characteristics such as capital account openness, fixed exchange rates, and institutional quality don't appear to change these relationships. Banking sector capital does appear to affect the VIX-FX lending relationship, but not in a robust way in the macro data.

In the matched firm-bank panel, I confirm the positive relationship of the VIX with foreign currency lending. Even after adjusting for valuation effects, an increase in the VIX is associated with faster growth in FX credit relative to Peso credit. This result holds after controlling for time-varying firm and bank characteristics. Banks that are better capitalized drive this positive relationship. Indeed, the positive relationship of FX loan growth (relative to Peso loan growth) with the VIX for better capitalized banks gets stronger after controlling for firm-specific demand in foreign and domestic currency. This implies on the other end that poorly capitalized banks lend more in FX when global funding is loose, but restrict their FX lending when times are tight (relative to their domestic currency lending). These results suggest that capitalization of the domestic banking sector may influence how strongly global financial conditions affect FX lending in a country.

Together, these three chapters of my dissertation help to fill in some of the gaps in our understanding of foreign currency debt and capital flows in emerging markets. This research is important for the current policy debate seeking to understand spillovers from global financial conditions to emerging makrets and the implications for these movements on financial risk and stability.

Chapter 2: Foreign Currency Borrowing, Balance Sheet Shocks, and Real Outcomes

2.1 Introduction

Much of the credit extended to emerging market firms is denominated in foreign currencies.[1] In this paper, I study the impact that foreign currency (FX) borrowing has on firms following a large depreciation. More generally, I address how negative shocks to firm net worth (balance sheet shocks) affect firm activity. I construct a novel dataset of currency exposures and loan-level borrowing and examine both the financial and real consequences of negative balance sheet shocks due to foreign currency mismatch.

Standard theory predicts that balance sheet shocks, with no offsetting changes to firm revenue, will lead to tighter borrowing constraints and a consequent decline in real activity. I find that firm size and the currency denomination of debt are two important characteristics that determine the impact of these constraints. Borrowing constraints are more binding following adverse balance sheet shocks for smaller firms, indicating a net worth or size-based borrowing constraint, and

[1] See Caballero, Panizza, and Powell (2014); Chui, Kuruc, and Turner (2016); Du and Schreger (2015); Maggiori, Neiman, and Schreger (2017); R. N. McCauley, McGuire, and Sushko (2015); Shin (2013).

for foreign currency loans, suggesting an additional tighter constraint on a firm's foreign currency debt. The interaction of these two constraints leads large firms with a negative shock to decrease their foreign currency borrowing, but allows them to increase their local currency borrowing and thus remain unconstrained in their real activity. Small firms who are constrained in their total borrowing contract their real activity following a negative balance sheet shock.

Balance sheet effects are difficult to identify empirically because it is hard to separate out changes in outcomes due to firm balance sheet shocks from other channels. For example, shocks to the supply of bank credit (the bank lending channel) have been shown to be quantitatively large and important for real outcomes (Chodorow-Reich, 2014). Firm specific demand shocks are also hard to separate from the effects of firm-specific balance sheet shocks. Existing empirical work both in macro and finance cannot cleanly identify balance sheet shocks.

I address these challenges in this paper. I construct a dataset which consists of firm balance sheets and loan level outcomes for all listed non-financial firms in Mexico, matched to their banks. This dataset allows me to capture developments on both the financial and real sides of firm activity, connecting balance sheet effects to real outcomes. The dataset has two unique features that are crucial to the identification of a balance sheet shock. First, it includes data on both firms' FX assets and FX liabilities. This allows me to construct a measure of true FX exposure (currency mismatch) for each firm and to compare firms with differing levels of exposure, as larger exposure results in larger shocks to a firm's balance sheet for a given sized depreciation.[2] Second, the data includes loan-level information for each of the banks that the firm borrows from, in both foreign and domestic currency. To my knowledge, this paper is the first to employ such matched firm-bank data to identify the impacts on the firm of exchange rate-related balance sheet shocks.[3] The matched nature of the data makes it possible to compare firms who borrow from the same bank in the same currency at the same time and are thus exposed to the same bank-level shocks to credit supply. Constructing this comparison using bank*quarter*currency fixed effects controls for changes to a firm's supply of credit in either foreign or domestic currency, and isolates differences in credit outcomes due to idiosyncratic shocks to firms. Failure to control for bank credit supply shocks can bias estimates of balance sheet effects if, for instance, firms who borrow more in foreign currency also borrow more from stronger banks. I show that for regressions estimating the impact of the balance sheet shock on foreign currency loan borrowing, failure to control for credit supply shocks can bias the estimated coefficient downward (toward zero) by 40%.

I analyze the effect of a shock to the exchange rate initiated by the collapse of Lehman Brothers in 2008. This depreciation was large, unanticipated, and exogenous to Mexico's fundamentals. An endogenous exchange rate shock, such as currency crises used in previous literature, is problematic because the cause of

[2]Most datasets used in these studies only have data on debt dollarization, but not assets. Exceptions include Kalemli-Özcan, Kamil, and Villegas-Sanchez (2016), Cowan, Hansen, and Óscar Herrera (2005b), and Alvarez and Hansen (2017).

[3]Niepmann and Schmidt-Eisenlohr (2017a) use loan level data to show that firms with a higher share of foreign currency loans are more likely to default on their loans, though they do not examine changes in credit or real outcomes for these firms.

the shock likely also caused changes in outcomes through other channels. If the shock is anticipated, meanwhile, then firms may endogenously adjust their FX borrowing and behavior in advance of the shock, leading to mis-measurement of the balance sheet effect. Thus an exogenous, unanticipated depreciation is ideal to identify the balance sheet effect.

My analysis focuses on the interaction of the firm's pre-shock balance sheet exposure (FX mismatch) with an indicator variable for the period following the depreciation shock: $Exposure_f \times Shock_t$. This serves as a difference-in-difference estimator, capturing the differences in outcomes post-depreciation for firms with different exposure (and thus different size of balance sheet shock). For financial outcomes, I focus on loan growth in foreign and domestic currency, and for real outcomes, I examine growth in employment and physical capital. Examining financial outcomes is important to identify the channel by which balance sheet shocks operate, via loss of credit. Examining real outcomes is important to understand the impacts on economic activity.

Disentangling the balance sheet effect of a depreciation from other correlated effects is a significant empirical challenge. This requires separating the change in credit outcomes for the firm due to the balance sheet deterioration from changes in the supply of credit and changes in firm demand for credit. Controlling for shocks to credit supply is crucial because such shocks directly affect the channel by which the balance sheet effect operates, through the credit available to the firm. I address this issue using the loan level data and controlling for bank credit supply with bank*quarter*currency fixed effects.

I take several steps to control for changes in credit demand from the firm that are not driven by balance sheet shocks. First, I focus on non-exporting firms, who don't have significant foreign currency revenues that would increase with the favorable terms-of-trade change. Second, I control for shocks to broadly defined sectors (such as changes in demand or production costs) either by including sector interactions (with the shock) or sector*year fixed effects. Third, I control for time-varying characteristics of the firm that might affect loan demand, including firm size, leverage, sales, cash, derivatives, exports, and bond credit. Fourth, I compare the interaction of the shock with FX exposure with other interacted firm characteristics which may affect firm credit demand following the shock. Fifth, I compare the responses of large vs. small firms in my sample;[4] large and small firms should both respond to changes in demand, but smaller firms are more likely to be constrained following an adverse balance sheet shock. The differential reaction of small and large firms with similar currency mismatch would indicate whether borrowing constraints are binding due to the balance sheet effect.

Real outcomes vary at the firm level rather than the loan level. In order to control for shocks to bank credit supply in regressions on real outcomes, I construct a firm-level measure of bank credit shocks from the loan level data. I show that this measure can be used as a time varying control when time fixed effects are included in the regression, enabling me to dynamically control for shocks

[4] My sample consists of listed firms, who tend to be much larger than other firms in the economy, so "small" is a relative term. Nevertheless, both large and small firms in my sample will be subject to similar demand shocks, particularly those in the same sector in the same year, so the difference in size will be a more salient characteristic.

to credit supply at the firm level. I then proceed with the same difference-in-difference estimator as before, controlling for time varying firm characteristics and firm-specific credit supply shocks, comparing different interactions with the shock, and comparing outcomes of large and small firms.

For loan outcomes, I find the expected balance sheet effect on foreign currency loans: firms (non-exporters) with higher currency mismatch decrease their loan growth more than less exposed firms following the shock. Large firms with higher mismatch, however, compensate with an even larger increase in local currency borrowing. Smaller firms do not see this increase in their peso borrowing. Uncovered interest rate parity (UIP) fails such that foreign currency loans have lower interest rates and are more attractive to borrowers. However, the switch from foreign to domestic currency loans by large firms is not driven by changes in the interest rate differential following the shock. Foreign currency loans remain consistently cheaper than local currency loans, even comparing within-firm and within-bank variation in interest rates. This suggests that the switch to Peso loans is driven by borrowing constraints, where firms are subject to a borrowing constraint on their total borrowing and an additional, tighter constraint on their FX borrowing.

At the firm level, the impact of the shock is largely insignificant when large and small firms are pooled together. Consistent with results found with loan outcomes, I find that large, exposed non-exporters (who are able to increase their total borrowing by switching to Peso) increase their employment and investment, while small, exposed non-exporters have no change in employment growth and decrease their physical capital growth relative to firms with lower mismatch. These results together suggest that balance sheet shocks can trigger financial constraints that affect a firm's ability to borrow, which can then have real effects.

My results have two implications for policy. First, Peso liquidity and the health of the domestic banking system may be a relevant factor for risk assessment, as Peso loans provide a substitute for credit lost by large firms who experience a negative balance sheet shock. This implies that negative balance sheet effects will be stronger and more likely when a banking crisis accompanies a currency crisis, the so-called "twin crises" (Kaminsky & Reinhart, 1999). Second, negative real effects from balance sheet shocks are more likely to come from small firms, so the joint distribution of size and FX mismatch is important to understand the risk to the economy. If the FX mismatch of small and medium firms is large enough, an aggregate negative effect could be driven by the small firms, opposite the conventional wisdom that large firms are important for aggregate effects.

My empirical results suggest that a negative balance sheet shock leads small firms to decrease their FX debt and decrease their investment, while it leads large firms to decrease their FX debt, increase their Peso (and thus overall) debt, and increase their employment and investment. I develop a stylized 3 period model of corporate borrowing and investment to rationalize these findings. The model features simultaneous borrowing in both foreign and domestic currency, a constraint on total borrowing for the firm, and a second borrowing constraint on FX debt specifically. A constraint on total borrowing can be thought of as an incentive compatibility constraint to prevent the firm from overborrowing and finding defaul to be optimal. However, FX borrowing presents additional risks. The risk of a depreciation both increases the probability that a firm defaults on its debt and decreases the value of collateral (denominated in local currency) that the lender would recover in the event of default, relative to the size of the loan. This added risk to the bank incentivizes the bank to restrict the amount of foreign currency debt more tightly (or demand more collateral) than it does for overall debt. With this rationale, I include borrowing constraints based on net worth, one for total debt and a more restrictive constraint on FX debt. This matches the firm-level data, where firm leverage in Peso increases with size up to a point, despite the cost advantage of FX debt, and then Peso leverage decreases and FX leverage increases moving to the high end of the firm-size distribution.

The intuition for the model is that failure of uncovered interest rate parity, common in emerging markets (and exogenous to the model), makes foreign currency borrowing attractive despite the risk. When a depreciation hits, small firms with FX mismatch experience a negative shock to their net worth and are constrained in their borrowing, and so must decrease their debt in response to the shock. Large firms with FX mismatch are likewise constrained in their FX debt due to the shock, but not in their total borrowing, so they increase their Peso debt in order to invest at the unconstrained optimum.

Extending the model to allow for differences in firm productivity helps explain one of the more puzzling empirical results: not only are large firms with large foreign currency mismatches not affected by the shock because they can borrow in Peso, they actually increase their employment and physical capital growth relative to less exposed firms. In the model, firms that are more productive are willing to borrow more in foreign currency because the likelihood of future constraints binding is lower. This generates a selection into foreign currency borrowing for firms with higher future productivity. When a depreciation hits, the smaller of these firms are constrained as before, but larger firms are unconstrained and so are able to increase their investment via Peso borrowing to the new optimal level, despite the shock.

The remainder of the paper proceeds as follows: Section 2.2 summarizes the literature and clarifies the contribution of this paper; Section 2.3 presents and describes the data; Section 2.4 provides context for the macroeconomic environment in Mexico; Section 2.5 describes the identification strategy and results for outcomes at the firm-bank level; Section 2.6 describes the identification strategy and results for outcomes at the firm level; Section 2.7 presents the model; and Section 2.8 concludes.

2.2 Literature

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Much of the empirical work studying firm balance sheet shocks has been done in the context of exchange rate shocks.[5] This literature largely uses firm-level data and examines the effect on investment of an interaction of firm FX debt

[5]See Gan (2007) and Chaney, Sraer, and Thesmar (2012) for evidence of a balance sheet channel in the context of a real estate price shock.

with exchange rate changes.[6] Most papers draw on periods involving a crisis, with some explicitly using a difference-in-difference approach around the crisis.

Evidence of negative effects from balance sheet shocks has been found in studies for Mexico (Aguiar, 2005; Pratap, Lobato, & Somuano, 2003), as well as other emerging markets (Carranza, Cayo, & Galdon-Sanchez, 2003; Cowan et al., 2005b; Echeverrya, Fergussona, Steinerb, & Aguilara, 2003; Gilchrist & Sim, 2007). Firms with more FX debt reduce investment following the depreciation, though exporters fare better. However, several studies find either zero or positive balance sheet effects (Benavente, Johnson, & Morande, 2003; Bleakley & Cowan, 2008; Bonomo, Martins, & Pinto, 2003; Luengnaruemitchai, 2003). These positive effects are sometimes attributed to firms matching their FX debt with FX revenues, FX assets, or FX derivatives. Very few of these studies have data on FX assets or derivatives. Exceptions include Kalemli-Özcan, Kamil, and Villegas-Sanchez (2016), which uses a dummy variable indicator for holdings of FX assets in a sample of Latin American firms, and Cowan et al. (2005b) and Alvarez and Hansen (2017), which find that Chilean firms with FX liabilities match with FX assets, FX revenues, and FX derivatives. Cowan et al. (2005a) shows that controlling for FX assets can cause the positive and insignificant coefficient on FX debt (interacted with depreciation) to become negative and insignificant. On the extensive margin, Kim, Tesar, and Zhang (2015) shows that negative balance sheet shocks due to FX debt can increase the probability of firm exit. However, they highlight that

[6] See Table 1 of Cowan, Hansen, and Óscar Herrera (2005a) for a useful comparison of FX exposure measures, countries, samples, outcomes, and controls for FX assets and derivatives across papers in the literature.

large firms, who are often used in this literature due to data availability, actually increase their investment and survival probability following a negative balance sheet shock, while small firms decrease investment and increase their probability of exit.

The existing literature largely relies on variation due to crisis episodes without the ability to control for shocks to credit supply. Variation in the exchange rate during non-crisis periods is also problematic, as it is less sudden and likely driven by the economy's fundamentals. Estimates using this variation are thus more prone to bias from forward looking behavior regarding future exchange rate realizations and simultaneity of past borrowing and investment affecting future realizations of the exchange rate. Kalemli-Özcan, Kamil, and Villegas-Sanchez (2016) provides an identification strategy to separate the balance sheet shock from credit supply shocks. Using a cross-country dataset on listed firms, they compare outcomes of exporting firms during currency crises with those in countries experiencing simultaneous currency and banking crises (the "twin crises"). They find that during a depreciation, all exporting firms increase investment, but when the depreciation is accompanied by a banking crisis, only foreign-owned exporters (who have better access to capital) increase investment. Desai, Foley, and Forbes (2008) similarly conclude that affiliate firms of US multinationals in emerging markets are able to bypass credit constraints following sharp depreciations, whereas domestic firms cannot, further illustrating the importance of accounting for credit access and credit supply.

This paper contributes to and harmonizes the existing empirical literature in several ways. In addition to controlling for the value of FX assets, FX revenues, and net derivatives position, I directly control for credit supply shocks using matched firm-bank data. This allows me to use a sharp depreciation episode to measure a clear shock to the balance sheet while controlling for correlated changes in credit conditions. My results confirm those in Kim et al. (2015), finding that the conflicting results in the literature can be driven by the behavior of large firms. By comparing domestic vs. foreign currency borrowing, I can further explain how large firms are able to increase their investment precisely because they are able to access domestic currency debt, despite a negative balance sheet shock. This corroborates the evidence shown in Kalemli-Özcan, Kamil, and Villegas-Sanchez (2016), as a concurrent banking crisis, which reduces domestic currency liquidity, is more likely to generate negative effects even for large firms. Thus, crisis episodes in emerging markets are likely to generate negative balance sheet effects, but these effects measured on data from large firms could be zero or positive if there is sufficient liquidity in domestic currency loans.

Most of the existing literature does not directly examine how balance sheet shocks affect access to credit, focusing rather on firm level outcomes like profitability and investment. In addition to examining real outcomes, I test the mechanism of the balance sheet channel directly by examining borrowing outcomes for these firms, cleaned of credit supply shocks, and additionally differentiate the effects by currency of borrowing. Niepmann and Schmidt-Eisenlohr (2017a) examines the effects of balance sheet shocks on credit from the bank's side. They show evidence of balance sheet effects on loan repayment using loan-level data from US banks to firms in many emerging markets, finding that a US dollar appreciation is associated with a higher likelihood of default (becoming past due on loan payments) for firms with a higher share of loans in FX. This provides direct evidence that firm risk due to FX mismatch can transfer to banks, even if the bank has no FX mismatch. My research complements theirs by matching the loan-level data to firm FX exposures, balance sheets, and real outcomes.

This paper is also related to the literature on the determinants of foreign currency borrowing.[7] I contribute to this literature by examining how exchange rate balance sheet shocks affect the currency composition of firm borrowing.[8] Methodologically, this paper is in line with much of the recent literature on the bank lending channel, which uses credit registry and other matched firm-bank data (Chodorow-Reich, 2014; Cingano, Manaresi, & Sette, 2016; Jiménez, Ongena, Peydró, & Saurina, 2014; Khwaja & Mian, 2008). These papers exploit the matched nature of their datasets for identification, often by including various sets of fixed effects to remove confounding variation, including firm-time, bank-time, or firm-bank fixed effects to control for possible time varying characteristics of firms and banks and time invariant characteristics of a particular firm-bank match. Several of these papers specifically analyze the international transmission of shocks via the banking system (Baskaya, di Giovanni, Kalemli-Özcan, & Ulu,

[7]See for example Barajas and Morales (2003); Basso, Calvo-Gonzalez, and Jurgilas (2011); Ize and Levy Yeyati (2003); Luca and Petrova (2008); Rosenberg and Tirpák (2008) for studies using macro data and Allayannis, Brown, and Klapper (2003); Brown and de Haas (2012); Brown, Kirschenmann, and Ongena (2014); Brown, Ongena, and Yeşin (2011); Martínez and Werner (2002); Salomao and Varela (2016) for studies using micro data.

[8]Bonomo et al. (2003) finds a similar result that large firms adjust the currency composition of their debt towards local currency when exchange rate risk increases.

2017; Baskaya, di Giovanni, Peydro, Kalemli-Özcan, & Ulu, 2017; Morais, Peydró, & Ruiz, 2015; Ongena, Peydró, & van Horen, 2015; Ongena, Schindele, & Vonnak, 2016; Schnabl, 2012). While my analysis relies on an international shock (namely, the dollar appreciation due to the 2008 financial crisis), I focus on the effect of firm exposure to the shock, controlling for changes in credit supply.

Further, the construction of firm level bank shocks from loan level data is related to Alfaro, Garcia-Santana, and Moral-Benito (2016); Amiti and Weinstein (in press); Greenstone, Mas, and Nguyen (2014); Niepmann and Schmidt-Eisenlohr (2017b). My work makes an important contribution here by proving that these bank shock estimates can be included dynamically in panel regressions when properly demeaned.

In the theoretical literature, balance sheet effects are central to many macroeconomic and international finance models (Bernanke, Gertler, & Gilchrist, 1999; Kiyotaki & Moore, 1997). These models rely on a borrowing constraint that depends on the firm's collateral or net worth. Krugman (1999) adapted this mechanism to study the impact of exchange rates and foreign currency debt. Recently the theoretical literature has incorporated currency mismatch and balance sheet shocks into general equilibrium environments (Bianchi, 2011; Céspedes, Chang, & Velasco, 2004; Korinek, 2011; Mendoza, 2010). These papers generally assume that firms only borrow in FX. Salomao and Varela (2016) constructs a two period model of firm investment dynamics in which firms can choose a mix of foreign and domestic currency debt. They find that more productive firms select into larger FX mismatches, but they do not explore the consequences of balance sheet shocks for these firms.

In addition to identifying exchange rate balance sheet shocks in the data, this paper contributes to the theoretical literature by highlighting the difference in borrowing constraints by currency. This necessitates considering balance sheet shocks in an environment where firms can choose the currency of their debt. I contribute a stylized, partial equilibrium model that illustrates how separate constraints on total borrowing and FX borrowing, based on net worth, interact to affect the borrowing decisions (by currency) and investment decisions of firms. The tighter constraint on FX borrowing implies that a firm with a negative balance sheet shock may need to reduce its FX debt, but can increase its Peso debt to compensate if it is large enough. By extending my model to include selection into FX debt by more productive firms, my model also helps rationalize the finding in some of the empirical literature that large firms actually increase investment following the depreciation, despite the balance sheet shock.

2.3 Data

2.3.1 Data Description

The source of my data is quarterly financial reports of firms listed on the Mexican stock exchange, the Bolsa Mexicana de Valores (BMV). Non-financial listed firms are required to submit quarterly financial reports to the BMV, which are published on the BMV website as well as distributed by the individual firms.[9]

[9] The Mexican National Banking and Securities Commission (CNBV) requires reporting of relevant corporate information (i.e. may influence its stock price) to the regulators and public for

These reports come in pdf form and contain tables for balance sheet statements, income statements, and cash flow statements. In addition, several annex tables include more detailed information on sales, sources of credit, and currency composition of the balance sheet, among other things. These reports are consolidated, and so include the positions of any subsidiaries, whether foreign or domestic. The data from these reports are scraped from the pdf files, harmonized across different pdf formats and variable names, and assembled into a single dataset.

The reports include standard balance sheet variables, notably the value of property, plant, and equipment (physical capital) and the value of derivatives positions. In addition to standard balance sheet variables, a couple of pieces of information reported are worth noting. Firms report the volume of external sales, which is exports plus sales by foreign subsidiaries, which gives a more comprehensive measure of foreign currency revenue for the firm.[10] Also, firms include a separate line item for total employment in each quarter. This allows me to connect financial outcomes from the balance sheet with real outcomes like employment and investment.

The two most important and unique features of this dataset are the data on currency composition of the balance sheet and the data on sources of credit. The annex on currency composition lists the assets and liabilities on the balance sheet

all listed issuers on the BMV. Circular 11-28 establishes these reporting requirements, the dissemination of which is managed by the BMV (Ritch, 2001). Under the new Securities Market Law established in 2006, "listed companies are required to prepare consolidated financial statements following the standards of the CNBV...The CNBV has established procedures to review financial statements of the regulated entities in order to enforce compliance with accounting and auditing requirements...The CNBV is empowered to impose sanctions for the violation of the reporting requirements." (OECD, 2008)

[10] Sales by foreign subsidiaries to buyers in Mexico are assumed to be negligible.

in foreign currency, split into US dollar and other currencies. On average, about 90% of all foreign currency liabilities for my sample are denominated in USD. As I cannot determine which foreign currency a given loan is in, I make the simplifying assumption that all bank loans are denominated in USD for the remainder of the paper. The currency composition of both sides of the balance sheet is used to give a more complete picture of a firm's on-balance sheet exposure to an exchange rate shock.

The second unique feature of this data is the detail on credit to the firms. Firms list every loan product that they have outstanding, as well as bonds and trade credit extended by other firms. For each loan, the firm indicates the name of the bank extending the loan, the interest rate on the loan, the currency of the loan (either Peso or FX), and the remaining maturity structure on the loan (how much of the loan is due within 1 year, within 2 years, etc.). Loans are listed both from banks resident in Mexico as well as cross-border banks. The combination of data on a firm's on-balance sheet foreign currency positions with loan level data, split by currency, is a unique data contribution that is crucial to identifying the impact of a balance sheet shock.

My identification strategy relies on using matched firm-bank data on credit relationships. However, the firms list only the name of the lending bank for each loan, with no common identifiers. I harmonize by hand all of the bank names reported in the data, taking account of nicknames, abbreviations, different spellings, different languages, and name changes for the bank.[11] 5% of loans by

[11]Information on each bank (location, ownership, mergers, names and nicknames, etc.) was

volume are identified only by generic names or grouped together as "Others" or "Various". These observations are dropped from the main estimation sample. Of the remaining loans, 30% (by volume) either list multiple banks as the lenders or indicate that the loan is a syndicated loan without identifying the bank. In these cases, I reference information on syndicated loans for these firms from the Thompson One database. Where it is obvious who the lead bank is, I match the loan to the lead bank. When I cannot tell who the lead bank is, I match the loan to the largest bank by assets that I can identify as part of the syndicate. For the few cases in which the participating banks are unclear, the loan is given its own unique bank identifier.[12] With the banks uniquely identified, loans are aggregated up to the firm-bank-currency-time level.[13]

All data is presented in thousands of pesos.[14] All FX loans are cleaned of valuation effects and all series are deflated to 2010 pesos using Mexico's CPI.[15] The resulting dataset covers 134 firms over 2008q1-2015q2.[16,17]

obtained from banks' individual web pages, wikipedia, and Bloomberg pages. I further match these banks up to information in Bankscope, when possible, and use that information and notes in the Foreign Bank Ownership database, provided by Claessens and Van Horen (2014), to further identify the banks and match them up appropriately for each firm.

[12] Results are robust to excluding sydicated loans.

[13] While care has been taken to accurately match firms to banks, note that any error in the matching process will add noise to the dependent variable, loans. This measurement error works against my results by attenuating the estimates.

[14] A few financial reports are presented in thousands of US dollars. These are converted into Peso using end of period exchange rates.

[15] After the 1995 Peso crisis, Mexico introduced inflation indexed lending (UDIS) that banks could use, funded by nominal bonds which shifted the inflation risk to the government. While such lending began to be used in mortgage lending, its use in corporate lending is scarce.

[16] Balance sheet data for these firms is available from 2005q1, but I am unable to examine loan-level trends before 2008.

[17] For perspective, there are about 130 firms listed on the BMV at any given time.

2.3.2 Representativeness

Listed firms in Mexico make up an important part of the economy. The market capitalization of these firms fluctuates around 30-40% of GDP (source World Bank, BMV). The vast majority of listed firms in Mexico are non-financial firms. Between 2008-2014, the total share of GDP from non-financial firms (both listed and unlisted) was around 62%.[18]

Listed non-financial firms represent about 7% of total employment in Mexico in 2008.[19] Table A.1 plots the share of overall GDP, share of GDP in the non-financial sector, and share of total credit to the private non-financial sector made up by my full sample of firms. Listed firms make up around 10% of GDP, and up to a quarter of all non-financial output in 2009. These firms also absorb a large volume of formal credit (defined as loans + bonds) in the economy, usually around 60% of all credit to the private non-financial sector.

The firms in my data account for a large portion of the foreign currency debt in Mexico. Non-banks in Mexico (which includes government, households, etc.) had US dollar debt outstanding of $117.7 Billion USD on average in 2008.[20] In that same period, the firms in my data accounted for $55.5 Billion USD in FX debt (mostly US dollar), which is about 47% of all FX debt for non-banks in Mexico.

Relative to the largest 1000 firms in Mexico, firms in my dataset are at the

[18] Source for Market capitalization of listed firms is from the World Bank and BMV. Source for GDP share of non-financial firms is INEGI.

[19] Source is the 2009 Economic Census in Mexico. For reference, the 1000 largest firms represent 17% of total employment.

[20] Source: BIS global liquidity indicators.

top end of the size distribution. Table A.2 shows the average size, employment, sales, equipment, and operating margin of firms in Mexico in 2008, with data in the first two columns drawn from the 2009 Economic Census in Mexico.[21] While my sample is not necessarily representative of all firms in Mexico, it does represent an important segment of the overall economy, so their outcomes have ramifications for the aggregate, as well as potential spillover effects to smaller firms, such as through production network shocks or credit spillovers. These firms may also be similar to large firms in other emerging markets, so their behavior could be more widely informative.

2.3.3 Sample and Summary

For my regression analysis, I drop state owned/controlled firms, utilities, and non-financial firms that provide auxiliary financial services.[22] I also drop a few firms that are controlled by a parent company in the sample and all firms with no loans or no loans from an identifiable bank.[23]

I split the sample into exporters and non-exporters, where exporters are defined as having their median share of external sales to total sales over the sample greater than 15%. I focus my analysis in this paper on the non-exporter sample, so as to isolate the balance sheet shock from changes in export revenues, but re-

[21] Note that I remove the financial firms from the "All Firms" and "1000 Largest Firms" samples. The 1000 largest firms are then the 921 largest non-financial firms.

[22] The only quasi public firm is PEMEX, while the only auxiliary financial firm is American Express Mexico.

[23] Some firms group smaller loans into "various" or "others" categories, and some loans are identified with too generic a name for the bank in order to identify which bank it is. This drops 5% of loan volume from the sample.

sults for exporters are in the appendix for comparison. I also split the sample by firm size, where "small' is defined as having average size (measured by log assets) below the sample median.[24] These splits break the firms roughly in half for each group in the regression sample, as shown in Table 2.1. While large firms are split evenly between the exporter and non-exporter samples, more of the smaller firms are non-exporters.

These firms are spread across a variety of (broadly defined) sectors, shown in Table 2.2, though half of the firms and observations are in the manufacturing sector. These sectoral differences may be relevant for how firms are affected by and respond to the exchange rate shock and global recession. I address this in Section 2.5.

As my identification strategy relies on comparing different firms borrowing from the same bank, Table 2.3 summarizes the banking relationships in the regression sample. The vast majority of firms and loan volume in the sample are covered by firms that maintain multiple banking relationships, with firms averaging close to 7 simultaneous bank relationships. On the bank side, there are many more banks in this sample than there are firms. This is due to the sample being large listed firms that borrow both domestically and internationally. In addition to borrowing from banks resident in Mexico, each firm may borrow from any one of a wide variety of cross-border banks. This makes it more likely that these banks will lend to just one firm in the sample. Despite having a large number of banks with only one relationship with a firm in the sample, between 73-90%

[24] My results are robust to adjusting these cutoffs.

of total loan volume is covered by banks with multiple borrowers in sample. The average number of lending relationships in the sample for the full set of banks is around 3, but that number doubles when single relationship banks (which are dropped with the inclusion of bank-quarter fixed effects) are excluded.

Including the extensive set of fixed effects in separate samples reduces the firm sample size to 93 firms. Table 2.4 shows how the full sample, regression sample, and fixed effects sample compare. Dropping to the main regression sample results in firms that are slightly larger, have lower cash holdings, export slightly more, and have mildly higher FX exposure. Relative to the full sample, the fixed effect sample is similar except that the cash holdings are about the same and the levels of physical capital are a little smaller. The only significant differences between the regression and fixed-effect samples are that the fixed effect sample firms are slightly larger on average with more employees. Otherwise, my regression samples are generally indicative of the set of listed non-financial firms in Mexico.

Table 2.5 summarizes the loan observations of the regression sample, aggregated to the firm-bank-currency level. Interest rates are loan weighted averages up to the firm-bank-currency level. Non-exporters tend to have slightly more and larger loan relationships in peso than they do in FX, whereas exporting firms have substantially more and larger loan relationships in FX. However, both exporter and non-exporter firms have lower interest rates on their FX borrowing than their Peso borrowing, on average.[25] Across both groups and both curren-

[25] These are simple averages of the interest rates calculated at the firm-bank-currency level. I

cies, firms tend to have about half of their outstanding loans due within 1 year. These firms thus may need to roll over both their Peso and FX bank debt frequently.

A key variable in my analysis is the firm's foreign currency exposure (mismatch). I define this exposure as

$$Exposure_{f,t} = \frac{FXLiabilities_{f,t} - FXAssets_{f,t}}{Assets_{f,t}} \tag{2.1}$$

which captures the net share of assets that is exposed to foreign currency mismatch. As a firm increases its FX exposure, it makes itself more vulnerable to a depreciation that will have larger negative effects on the balance sheet. Table 2.6 explores the characteristics of firms that have more exposure prior to the shock. In the left panel, firms in the telecom sector have the largest mismatch, while the manufacturing sector, which accounts for the largest share of firms, has the second highest exposure. Since exposure is not even across sectors, it will be important to make sure that the effects are driven by exposure and not by sectoral differences. The right panel presents correlation coefficients for $Exposure_{f,t}$ with other firm characteristics. Exposure is higher for firms that are larger in terms of assets and physical capital, and that have higher leverage, less cash holdings, and a higher share of exports.[26] Leverage is the strongest correlate. I control for all of these variables in my regression analysis, and allow for interactions of

formally test the difference between FX and Peso interest rates in loan weighted regressions in Table 2.11.

[26]Note that my non-exporter sample can still have non-zero FX revenues. While these revenues are still small and infrequent, I control for them directly in the empirical analysis.

these attributes with the shock period dummy to ensure that I am not measuring a spurious relationship of exposure to outcomes.

The comparison between exporting and non-exporting firms highlights the degree of exposure in the non-exporting firms. Figure 2.1 plots the time series for the average share of sales to external purchasers (whether through exports or direct sales by foreign subsidiaries), with scale on the left axis, and the average on-balance sheet FX exposure, with scale on the right axis. Exporters on average receive 40-45% of their revenues from external buyers, whereas the non-export sample average is closer to 5% of their sales. Despite the substantial difference in potential FX revenue, non-exporting firms still have a relatively high exposure to FX, between 5-10% as compared to the exporter average of 10-15%. Hence while exporters may have their balance sheet positions sufficiently hedged by their FX revenues, it is less likely that the balance sheet positions of non-exporting firms are adequately hedged.

To further illustrate the importance of my measure of mismatch, Figure 2.2 plots $Exposure_{f,t}$ for my firms against the share of their loans denominated in FX. As is evident in the figure, the amount of FX loan borrowing does not always give an accurate picture of the currency exposure of the firm. Some firms with 100% of their loans in FX have a negative exposure due to their holdings of FX assets, while some firms with 0% of their loans in FX have positive exposure, due to FX borrowing in other forms (bonds, etc.).

The large, listed firms in my sample have many sources of financing and borrow both in peso and in FX. Figure 2.3 shows the liability structure of the exporters and non-exporters in my regression sample.[27] Loans are an important part of these firms' liabilities, especially so for exporters at the beginning of the sample. Exporters show a heavy reliance on FX loans early in the sample, but reduce that segment over time, replacing it with other sources, particularly FX bonds. Non-exporters, despite having little revenue denominated in FX, begin the sample with half of their loans denominated in FX. Use of Peso loans becomes increasingly important for these firms following the exchange rate shock in late 2008 and continuing through 2013.[28]

2.4 Context For Mexico

The source of the balance sheet shock comes from a sharp depreciation of the exchange rate in late 2008. The collapse of Lehman brothers in the US precipitated the global financial crisis. One important effect that accompanied this crisis was an appreciation of the US dollar vis-a-vis almost every other currency. The US Dollar Mexican Peso exchange rate is plotted in Figure 2.4. The depreciation of the peso was both sudden and unexpected. This is important for my identification because firms were not adjusting their currency positions in anticipation of a depreciation, and the exchange rate shock was not driven by Mexico's fundamentals. The currency movement was also large, as the dollar appreciated by 55% against the Peso.[29]

[27] Exporters are defined as having their median external sales (exports+sales by foreign subsidiaries) to total sales ratio above 15%.

[28] The behavior of other sources of credit is considered in Section 2.6.2.

[29] See Sidaoui, Ramos-Francia, and Cuadra (2010) for a more detailed description of Mexico's experience with and response to the global financial crisis.

The shaded area of the graph is the shock period, which captures the aftermath of the shock for 8 quarters.[30] There is also a large depreciation at the end of the sample, beginning with the Taper Tantrum in 2013.[31] However, this depreciation is a long and protracted event that was likely to be anticipated and possibly connected to Mexico's fundamentals, making it unsuitable as an experiment. I end my regression sample in 2013q1 to avoid this period.[32]

While the Lehman-induced exchange rate shock is plausibly exogenous, there are other consequences of the global financial crisis that could potentially also affect the firms in my sample, particularly because of Mexico's close proximity and ties to the United States. Figure 2.5 shows some of the macroeconomic trends in Mexico around this same period. Around the crisis, there was a clear slow down in growth in Mexico, as well as a mild decrease in exports relative to GDP. The drop in exports occurred despite the terms-of-trade improvement, which reflects decreased demand from its primary trading partner, the US.[33] This movement in exports directly affects the foreign currency revenues in the economy, so export status and revenue are important factors to account for in my analysis.

Panel (b) of Figure 2.5 examines trends in financial variables. Debt inflows

[30] Results are robust to adjusting this period to end earlier or start earlier.

[31] The Taper Tantrum was a panic in emerging markets that was initiated On May 22, 2013 the Federal Reserve announced that it would begin tapering its bond purchases. This sparked a panic in emerging markets, as an anticipated US dollar appreciation and tighter US monetary policy meant that the FX debt accumulated during quantitative easing would inflate and become difficult to service.

[32] Results are robust to extending the sample to 2015q2, the last period in my data.

[33] 80% of Mexico's exports are to the US, and 50% of its imports are from the US over the sample period (UN COMTRADE database). For the remaining trade, recent evidence from Gopinath (2015) shows that most trade is invoiced in USD, even if the US is not involved in the trade.

to the banking and corporate sectors both dropped significantly in the aftermath of the crisis, followed by a strong recovery. Also plotted is the growth of total US dollar credit to non-banks throughout Latin America, which highlights the general trends of dollar liquidity over the period, matching the capital inflows. Changes in these flows could affect the price and availability of foreign currency credit. Key to my identification is the ability to control for shocks to credit supply in each currency.

Despite the growth slowdown, drop in exports, and drying up of external and USD financing, Mexico was able to recover fairly quickly from the crisis. Mexico's banking system was well capitalized ahead of the shock (Sidaoui et al., 2010). The Basel III regulatory framework released in 2010 suggests a capital adequacy ratio (CAR) of about 8-10%, whereas Mexico's aggregate CAR has been around 16% over the whole sample period (Banco de Mexico). Mexico's banking system is dominated by several large foreign banks, but the Credit Institutions Law restricts the amount of capital a subsidiary can transfer abroad to their parent bank to less than 50% of Tier 1 capital, which helped keep the domestic banking sector more stable during the crisis. The strong position of domestic banks could potentially help to absorb the loss of external financing and smooth out the credit results for borrowing firms.

Of loans made by domestic banks, the share denominated in foreign currencies was historically just below 20% prior to 2003, but has since dropped to just under 10% since 2005 (Hardy, 2018). Banks in Mexico are required to keep their open FX position below 15% of Tier 1 capital maintained on their balance sheet.

However, my sample consists of large and globally active firms who do a large share of the FX borrowing in the economy (in addition to their Peso borrowing). Thus, this sample is pertinent for studying balance sheet effects of depreciation shocks.

It is possible that these firms have derivatives positions that hedge their exposure. However, their on-balance-sheet net derivatives positions appear to be small. Figure 2.6 plots the sample average net derivatives position relative to total assets. Any derivatives positions that would hedge against exchange rate movements would be revealed after the exchange rate depreciates at the end of 2008. For non-exporters, hedged positions at this time amount to only half a percent of assets, compared to the nearly 10% exposure that these firms had at the time and the 33% depreciation they experienced. Exporters may have a natural hedge of FX revenues, but their derivatives positions turn negative on average following the shock. This is due to several listed firms engaging in risky derivatives contracts that essentially bet against a large depreciation of the peso (Chui, Fender, & Sushko, 2014; Sidaoui et al., 2010).

Why would non-exporting firms take the risk of unhedged FX exposure on their balance sheet? As is common in many emerging markets, deviations from uncovered interest rate parity (UIP) make FX loans relatively attractive despite the risk.[34] Figure 2.7 plots deviations from UIP, where $=1$ means UIP holds, and >1 indicates that FX loans are relatively cheaper than peso loans. There are

[34] See Salomao and Varela (2016) for evidence of UIP deviations in European countries and the correlation of FX loans with UIP.

consistent deviations from UIP that make FX loans attractive for even unhedged firms to borrow in. Thus, firms will take unhedged FX positions, exposing themselves to potential future balance sheet shocks.

2.5 Firm-Bank Level Loan Outcomes

2.5.1 Identification Strategy

A key component to my identification strategy is an exogenous shock to firms' balance sheets. The sharp depreciation of the peso at the end of 2008 provides such a shock, as discussed earlier and shown in Figure 2.4. While this shock provides a movement in the exchange rate that is exogenous to Mexico's fundamentals, there could be other macroeconomic effects that occurred simultaneously with the global financial crisis. Of particular concern are changes in trade, which affect foreign currency revenues, and capital inflows, which affect the credit supply.[35] To address the first concern, I split the sample into exporting firms (defined as those whose median sales share of exports is above 15%) and non-exporting firms. Non-exporting firms are of particular interest because they do not have the same "natural hedge" of FX revenues as exporting firms.

Financial markets worldwide were shocked following the collapse of Lehman Brothers (concurrent with the depreciation). Credit supply shocks to a firm's bank could bias the estimated effect of the shock if banks that lend more in foreign

[35]While a depreciation is usually associated with increased exports due to the terms-of-trade improvement, the recession in the US (Mexico's primary trading partner) led to a reduction in demand that overpowered the improved competitiveness.

currency or lend more to exposed firms are affected differently from the shock. My identification strategy addresses this by exploiting the matched nature of my dataset between firms and banks. Firms often maintain multiple bank relationships, and banks lend to many firms. By comparing multiple firms that borrow from the same bank in the same currency, I am able to control for credit supply shocks to a specific bank in that currency. In particular, I estimate separate regressions for FX and Peso loans, and control for bank-time fixed effects, which accounts for all variation in outcomes from observed and unobserved time-varying bank factors. This leaves variation in loan outcomes coming from firm characteristics, with FX mismatch as the main characteristic of interest.

The shock period is from 2009q1-2010q4, capturing the 2 years following the large peso depreciation.[36,37] $Shock_t$ takes a value of 1 during this period and 0 otherwise. Defining the shock in this manner allows for flexibility in the timing of the impact for each firm, as firms may not need to roll over debt or adjust their investment in every quarter. I take the average of my FX exposure measure ((FX Liabilities - FX Assets)/Total Assets) over 2008 to get a time invariant measure of exposure just prior to the shock period. I winsorize this measure for two outlier firms, which have an unusually large stock of FX assets.[38] I interact this measure

[36] Results are robust to adjusting the length of the shock period to end 2 or 3 quarters earlier, or start 1 quarter earlier. Given that the exchange rate is both at a higher level and more volatile following the Lehman collapse, I also check results using just a sample from 2009q1-2013q1 (comparing the immediate aftermath of the shock with normal times after the shock). Results are robust.

[37] The "Taper Tantrum" episode in 2013 also sparked a depreciation of the peso, but this depreciation was a steady, prolonged episode, and so it is less plausible as an unexpected shock unrelated to Mexico's fundamentals. Hence, my main sample of interest ends before that period, spanning 2008q1-2013q1.

[38] Results are stronger with the inclusion of non-winsorized outliers. I prefer a winsorized specification to ensure that results are not driven by these two firms.

with the shock dummy to capture the balance sheet shock. Using a time-invariant pre-shock measure of FX exposure avoids possible endogenous adjustment of the firm's FX position in response to the shock.

My identification assumption is that, conditional on firm fixed effects and additional time-varying firm controls, firms with different FX exposure who borrow from the same bank in the same currency do not differ from each other in a way that is correlated with the difference in their loan growth outcomes following the shock. This improves on the existing literature, which assumes that firms are exposed to the same credit supply shocks. The primary threat to this identification will be latent firm characteristics that are correlated with exposure and that affect loan outcomes through some other channel during the shock period. I discuss and address these threats in Section 2.5.2.1.

I implement my empirical strategy using the following baseline regression for non-exporting firms, run separately by currency:

$$\Delta \log(Loan^{c}_{f,b,t}) = \alpha_f + \alpha_{b,t} + \beta_0 Exposure_f \times Shock_t + \Phi X_{f,t-1} + \epsilon^{c}_{f,b,t} \tag{2.2}$$

where $\log(Loan^{c}_{f,b,t})$ is the log value of the loans outstanding at firm f from bank b at time t (quarterly data) in currency c. The dependent variable is loan growth, measured by $\Delta \log(Loan^{c}_{f,b,t}) = \log(Loan^{c}_{f,b,t}) - \log(Loan^{c}_{f,b,t-1})$, which compares the loans outstanding between the same firm-bank pair in the same currency over time.[39] Bank-quarter $\alpha_{b,t}$ and firm α_f fixed effects control for time-varying credit supply factors and time-invariant firm heterogeneity.[40] In some specifications, I also include sector dummy interactions or sector-year fixed effects to account for trends in each sector that could be correlated with the exchange rate shock, such as changes in demand or input cost.[41]

$X_{f,t-1}$ is a vector of time varying firm controls, lagged one period to avoid simultaneity, which captures any remaining determinants of loan outcomes not associated with the balance sheet shock. These include firm size measured by log assets, the ratios of cash to assets, bond debt to assets, total liabilities to assets, sales to assets, and net derivatives position relative to liabilities, as well as the share of sales to foreigners (which includes both exports and sales by foreign subsidiaries).[42] Since my independent variable of interest varies only at the firm-time level, but my outcome variable varies at the firm-bank-time level, I cluster the standard errors at the firm level.[43] The regressions are weighted by the lagged

[39] This is winsorized at 1% to reduce the influence large outliers in terms of loan outcomes, but results are robust to not winsorizing.

[40] Any common effects from macroeconomic conditions varying at the quarterly level are subsumed in the bank-quarter fixed effects.

[41] Sectors are broad categories: Construction, Energy, Health, IT, Manufacturing, Real Estate, Restaurants and Hotels, Retail and Wholesale, Telecom, and Transportation.

[42] These variables are winsorized as necessary to avoid the influence of outliers, but results are robust to either including non-winsorized controls and excluding controls.

[43] While clustering may be appropriate, some of the regressions have a lower number of clusters (e.g. 34) which casts doubt on the asymptotic properties of the estimator. However, results are robust to pooling the exporters and non-exporters together (for more clusters) and including an exporter dummy interaction with the main variables of interest. For presentational convenience, results are presented separately by export status. Results are also robust to using Huber-White robust errors instead of clustered errors.

value of log loans, $\log(Loan^c_{f,b,t-1})$.[44,45]

It is possible that we would not observe a significant effect because firms may receive a balance sheet shock but not hit their borrowing constraint. The effect of a given shock should be more relevant for firms that are more vulnerable or have less collateral, such as smaller firms. Thus, I add an interaction of the shock with a dummy for small firms, defined as having average size (measured by log assets) below the sample median.[46]

$$\Delta \log(Loan^c_{f,b,t}) = \alpha_f + \alpha_{b,t} + \beta_1 Exposure_f \times Shock_t + \beta_2 Small_f \times Shock_t + \beta_3 Exposure_f \times Small_f \times Shock_t + \Phi X_{f,t-1} + \epsilon^c_{f,b,t} \quad (2.3)$$

In this specification, β_1 represents the impact of the shock for large firms, while $\beta_1 + \beta_3$ is the impact of the shock for small firms. Note that the sample consists of some of the largest firms in the economy, so small is a relative term, but it is useful to separate out these firms from the ultra-large firms since extreme size may enable such firms to access capital readily despite increased risk.

My identification strategy follows a difference-in-difference framework. I check the validity of this approach by examining pre-period placebos (to check

[44]This weighting allows larger loans to be given more weight in the results, so the movements of smaller, less meaningful loans do not drive the results, but with a decreasing returns to size, so idiosyncrasies in ultra large loans are not given undue influence on the estimates. Results are robust to not weighting.

[45]All regressions are produced in STATA using reghdfe (Correia, 2016).

[46]Results are robust to defining the small firm dummy as being in the bottom third instead of the bottom half.

the parallel trends assumption), and firm specific time trends (to control for any differential trends for each firm).

2.5.2 Results

I focus on non-exporters in my main analysis, but results for exporters can be found in the Appendix in Tables A.4 and A.9. Table 2.7 presents my main results at the firm-bank level. In columns (1)-(4), I find that firms with a higher level of FX mismatch have lower growth in FX loans following the depreciation. This result holds after including bank-quarter fixed effects in column (3). Of note is the difference between columns (2) and (3). Column (2) uses the same sample as column (3), but does not include the bank-quarter fixed effects.[47] Failing to control for changes in bank credit supply can bias the main coefficient of interest downward because firms that have a currency mismatch and borrow in FX are likely to be borrowing from larger, stronger banks. Omitting this control in column (2) results in an estimate that is nearly 40% smaller in absolute value, though still significant. The drop in FX loan growth appears to be general among both small and large firms, as seen in column (4). The JointTest row at the bottom of the table shows the p-value on the joint significance test of $Exposure_f \times Shock_t$ and $Exposure_f \times Shock_t \times Small_f$ ($H_0 : \hat{\beta}_1 + \hat{\beta}_3 = 0$). Thus, smaller firms have a statistically significant, though smaller in magnitude, drop in their FX credit growth, though the smaller magnitude is not statistically different from the larger effect

[47] Including the bank-quarter fixed effects reduces the sample size for FX loans because there are many foreign banks that lend only to one firm in the sample, so their observations are wiped out with the bank-quarter fixed effects.

on the large firms.

Columns (5)-(8) shows the results for Peso loans. In Columns (5)-(7), firms with more exposure have a higher loan growth than less exposed firms following the shock. Here, accounting for credit supply shocks does not appear to be as important, as reflected in the coefficients in columns (6) and (7). The interesting difference comes in column (8), where we see that the large increase in peso borrowing is driven by larger firms, while smaller firms see a mild (though insignificant) decrease in Peso loan growth. Thus while all mismatched firms have lower loan growth in FX, only the large firms increase their Peso borrowing to compensate. Results are robust to alternate specifications of loan growth and of exposure,[48] adjusting the length of the shock period, and adjusting the cutoff for exporter and small firm designations.[49]

How large are these effects? I use columns (4) and (8) of Table 2.7 to calculate the estimated effects for small and large firms separately. For small firms, the net impact on their FX loan growth following the shock from the FX exposure is -0.264 and the net impact on their Peso loan growth is -0.121. If a small firm increases their FX exposure by 10% of assets (about equivalent to increasing from the median to the 75^{th} percentile), then their FX loan growth will fall by 2.64% and their peso loan growth will fall by 1.21%. For a small firm with 33% of its loans in FX (the pre-shock average), this results in a 1.68% drop in total loan growth. For a large firm, the estimated impact of the shock is -0.691 for FX and 0.899 for Peso.

[48] See Table A.5, which examines exposure measured by short term FX liabilities over assets, standard growth measures, and growth measures that admit entry and exit of firm-bank relationships.

[49] Available upon request.

A 10% increase in exposure for a large firm results in a drop of 6.91% in their FX loan growth and an increase of 8.99% in their Peso loan growth. For a large firm with 56.5% of its loans in FX, these effects will cancel out. The pre-shock average large non-exporting firm had 27% of its loans in FX, which would result in a total increase in loan growth of 4.7%.

To put the 1.68% drop for small firms and 4.7% increase for large firms in perspective, the average loan growth rates in 2008 were 11% and 25% for small and large firms, respectively, while the median rates were 5% and 2.8%, respectively.[50] Thus, for the typical small firm (in terms of loan growth), increasing their initial FX exposure could completely stall their loan growth after the depreciation shock. The increase for large exposed firms is large, more than doubling loan growth for the typical large firm. The effects of balance sheet shocks are thus important to the overall financial outcomes of the firm.

It could be the case that the the FX and Peso results for large firms are driven by different sets of firms, rather than the same firms moving from FX to Peso. In Table 2.8, I pool FX and Peso loans together in the same regression, and add an interaction with an FX dummy variable to examine the relative difference between FX and Peso borrowing for each firm. In this pooled specification, I can include firm-quarter fixed effects in order to compare the relative loan growth of FX vs

[50]These numbers for 2011 were 16.8% and 9.5% for small and large average, and -0.2% and 0.8% for small and large median.

Peso within firm. The regression takes the form:

$$\log(loan^{c}_{f,b,t}) = \alpha_{f,t} + \alpha_{b,t,c} + \delta_0 Exposure_f \times FX_c + \delta_1 Exposure \times Shock_t \times FX_c + \epsilon^{c}_{f,b,t} \tag{2.4}$$

where c indexes currency (domestic or foreign). While this specification can control for all time-varying firm heterogeneity, it relies on variation only from firms who borrow both in FX and Peso. In columns (1) and (2), I include firm fixed effects and bank-quarter-currency fixed effects, the latter to account for different credit supply shocks for each currency, and I add in the firm-quarter fixed effects in columns (3) and (4). These results, while more difficult to interpret with the extra interactions, reveal that there is a significant within firm difference between Peso and FX borrowing for large exposed firms following the shock. Note that the difference for small firms (the sum of the coefficients on $Exposure_f \times Shock_t \times FX_c$ and $Exposure_f \times Shock_t \times Small_f \times FX_c$) is close to zero and statistically insignificant, as small firms have declines in both FX and Peso growth.

Is the overall effect on loan outcomes positive or negative for large and small firms? Table 2.9 presents results with FX and Peso loans pooled together. Note that there are very few firms that borrow from the same bank at the same time in both currencies. Controlling for bank supply shocks in column (1), we see that large exposed firms do have a large and positive impact on their loan growth, whereas small exposed firms have a negative, though not statistically significant, impact. Controlling for credit supply shocks by currency in columns (2) and (3) reveals a significant decline in loan growth for small firms. Thus, it appears that after controlling for supply shocks that small firms hit with a balance sheet shock indeed appear to hit their borrowing constraint and decrease their overall loan growth.

Table A.6 in the Appendix considers differences in outcomes by the remaining maturity of the loans. While this measure does not capture maturity at origination, we see that most of the reduction in FX borrowing comes from short-term FX loans for larger firms. Small exposed firms have a significantly larger decline in their long-term FX borrowing, as compared to large exposed firms. On the Peso, side, most of the increase in loan growth for large firms occurs in long term Peso borrowing.

The mechanism for these effects on loan volume could work through changes in the interest rates charged on firm borrowing. Table 2.10 presents the results with the log of (1+ the real or nominal interest rate) as the dependent variable.[51] Interest rates are loan weighted within a firm-bank-currency triplet in each period (when aggregating the data to the firm-bank-currency level), and the regressions are weighted by contemporaneous $\log(Loans^c_{f,b,q})$. The regression takes the form:

$$\begin{aligned}\log(1+i^c_{f,b,t}) = \alpha_{f,b} + \alpha_{b,t} + \beta_1 Exposure_f \times Shock_t + \beta_2 Small_f \times Shock_t \\ + \beta_3 Exposure_f \times Small_f \times Shock_t + \Phi X_{f,t-1} + \epsilon^c_{f,b,t} \quad (2.5)\end{aligned}$$

where $\alpha_{f,b}$ captures any time invariant variation in interest rates that is specific to

[51]Real rates subtract the 1-year expected inflation rate of the Peso and add on expected 1-year Peso depreciation to FX loans. Both forecast series are from the Bank of Mexico's survey of inflation and exchange rate forecasts.

a given firm-bank pair. This controls for any preferential or unusual banking relationships that may determine the interest rate. A caveat to this analysis is that interest rates reflect all outstanding loans in the period, not just newly granted loans. Columns (1) and (3) show evidence of a mildly significant increase in interest rates on FX loans, though the relationship is not robust in columns (2) and (4) when the small firm interaction is included. Peso loans have coefficients similar in magnitude, but none are significantly different from 0.

If there is a change in the interest rate differential, this could affect firm borrowing in FX relative to Peso (and thus potentially explain the finding that large exposed firms switch to Peso). Table 2.11 pools the FX and Peso loans together, and considers the following regression:

$$\begin{aligned}\log(1 + r^c_{f,b,t}) =& \alpha_{f,b} + \alpha_{f,t} + \alpha_{b,t} + \eta_0 FX_c + \eta_1 FX_c \times Shock_t \\ &+ \eta_2 FX_c \times Exposure_f + \eta_3 FX_c \times Shock_t \times Exposure_f + \epsilon^c_{f,b,t}\end{aligned} \tag{2.6}$$

where r is the real interest rate. In this specification, I can control for all time varying firm and bank characteristics, and time-invariant firm-bank match characteristics that may determine the terms of these loans. In columns (1)-(2), I find a decrease in the differential price of FX vs. Peso loans following the depreciation, though this effect is not significantly different for firms who are more exposed following the shock. The significant and negative FX coefficient indicates that there is a premium on the interest rates for Peso loans at the individual level, even after controlling for all observable and unobservable time varying characteristics of both firm and bank. This premium is only reduced by 30% following the shock. This confirms the failure of UIP seen at the aggregate level, and suggests that FX loans are still attractive for firms (relative to Peso) following the shock if they are able to obtain such a loan.

In column (3), we see that the increase in the real interest rate on FX loans is driven by loans to small firms. That is, firms in the smaller half of the sample face more expensive FX borrowing in real terms following the shock. This is important as it means that a change in the interest rate differential cannot explain why large firms switch to Peso borrowing following the shock. Indeed, given that the increase in the FX interest rate is driven mainly by small firms, we would expect that those firms would have a higher propensity to switch to the local currency. Column (4) controls for time-vayring bank-specific factors in each currency via bank-quarter-currency fixed effects. Fully controlling for credit supply shocks in both currencies removes the significance of the effect for small firms and reduces the coefficient by nearly two-thrids. This may be due to soaking up too much variation with a heavy fixed effect specification, but shocks to bank credit supply in each currency may play more of a role in determining the change in the interest rate differential than does firm-specific risk.

2.5.2.1 Threats to Identification

Given my empirical setup, the primary threats to identification are firm characteristics that are correlated with FX mismatch and are affected by macroeconomic changes that occur during the shock period. I test my identification assumption by comparing my interaction of interest, $Exposure_f \times Shock_t$ with competing interactions of $Shock_t$ with other firm characteristics, similarly defined as time-invariant pre-depreciation averages. Tables 2.12 and 2.13 show these regressions, for FX and Peso loans respectively, for six firm characteristics that are potentially correlated with exposure or determine firm outcomes following the depreciation: ratios of exports to sales, cash holdings to assets, sales to assets, net derivatives to liabilities, and leverage (liabilities to assets, as well as firm size (log assets).[52] Exports and size affect the main coefficient of interest the most, but in every case the sign and significance of the coefficient on $Exposure \times Shock_t$ are robust to including these competing interactions.

As noted earlier, firms in some sectors tend to be more exposed to currency shocks than others. It is possible that firms in different sectors are impacted differently during the shock period for other reasons, either due to differences in the change in demand, the change in input costs, or the change in investment opportunities, so the exposure measure could simply be capturing differences in outcomes by sector. In Tables 2.14 and 2.15, I explicitly include interactions of

[52]Note that since non-exporters are defined as having their median share of sales to foreigners as less than 15% of total sales, some firms in the non-exporting sample will have some export revenue.

$Shock_t$ and $Exposure_f \times Shock_t$ with sector dummies, in order to see if see if the balance sheet shocks differ by sector or if a single sector is driving the results. These regressions include sector dummies one by one, with the column heading indicating which sector is in the interaction term $Sector_f$. Since the difference between small and large is important for Peso loan outcomes, Table 2.15 includes interactions with size as well. While some of the sectors do appear to be differentially affected during the shock period, none of the interactions appreciably affect the significance or magnitude of the exposure interaction.[53]

Table 2.16 further tests for robustness to sectoral differences using alternative fixed effects specifications. In columns (1) and (5), I include sector-year fixed effect as a more comprehensive way to account for trends that may affect certain sectors and thus contaminate my identification.[54] Alternatively, it is possible that banks may differentially adjust their credit supply following the shock depending on the sector of the firm. This would violate my identification assumption that firms borrowing from the same bank in the same currency are exposed to the same credit supply shock in each period. Columns (2) and (6) include bank-

[53]The exception is column (6) of Table 2.15. Firms in the construction sector appear to have larger impacts on their peso borrowing (larger positive for large firms, larger negative for small firms) than firms generally. Nevertheless, the results for construction and non-construction firms point in the same direction. Note that some of the triple and quadruple interactions in Table 2.15 are missing due to collinearity.

[54]My non-exporter sample largely is not exposed to changes in export revenues associated with the exchange rate change. However, they could be negatively exposed if they import intermediate goods which would become more expensive with the change in terms-of-trade. Exporting firms do a lot of importing (see Blaum (2017) for evidence of this from Mexico), so the exporter sample would be more affected by this issue, but the sector-year fixed effects do capture sector wide changes in import cost over the shock period. For a very limited sample of firms, I compute the share of production costs accounted for by imported inputs. Including this measure as a control captures relevant variation (as indicated by the increase in the within-R^2), but does not change the estimated coefficient. These results are available upon request.

sector-year fixed effects to account for this possibility. Additionally, there could be unobservable characteristics of each firm-bank match that are correlated with exposure and affect lending outcomes. For instance, higher mismatch firms may match with banks that are more exposed to exchange rate shocks. Columns (3) and (7) address this possibility by including firm-bank fixed effects. Further, differences in the effect of exposure between large and small firms could be driven by sector rather than by size. Indeed, most of the large manufacturing firms are exporting firms, while the small manufacturing firms are non-exporters. Hence, it is important to check that the differential behavior of small vs. large firms is not driven by manufacturing firms in my sample being primarily small. Columns (4) and (8) introduce a competing triple interaction of $Exposure_f$, $Shock_t$, and a manufacturing dummy.[55] In all of these cases, the main results concerning the interaction of $Exposure_f$ and $Shock_t$ are robust.[56]

My regression approach follows a difference-in-difference specification. I test the validity of the parallel trends assumption underlying this approach in Tables A.3 for loan outcomes and A.8 for real outcomes. The first two columns in either table highlight that the pre-periods show no significant differences in outcomes by level of exposure leading up to the shock. The second two columns show that the results are robust to the inclusion of firm-specific linear time trends.[57]

[55]Note that this is competing with the small firm dummy, unlike in Tables 2.14 2.15 where it is competing with the exposure measure.

[56]The coefficient on the triple interaction of Exposure*Shock*Small is affected in the Peso regression, but the net effect for large firms is only mildly affected and the net effect for small firms remains statistically insignificant.

[57]The exception is employment outcomes in column (3) of Table A.8, which are no longer significant after including firm specific time trends. Nevertheless, the coefficients are of approximately the same magnitude as the main specification, or larger.

Table A.7 presents results from a few alternative specifications. First, 42% of the loans to sample firms originate from cross-border banks. Thus, these changes in loan outcomes may be driven by cross-border banks reacting more strongly to the firm balance sheet shocks, as cross-border banks may differ in their access to FX financing and exposure to the financial crisis. In columns (1) and (3), I restrict my firm-bank sample to just banks resident in Mexico and find that the results are robust.[58] Second, the period following the depreciation was characterized by higher volatility of the exchange rate. Thus, the results could be driven by an increase in volatility and uncertainty about the exchange rate, rather than the actual depreciation shock. Restricting the sample to include just the period after the shock, comparing the immediate aftermath of the depreciation with the later post period, delivers the same results as shown in columns (2) and (5). Lastly, I conduct a placebo test, replacing the original shock variable with a dummy that equals 1 from 2010q3-2011q2, a period in which there were no large exchange rate movements, when firms should not be differentially affected by the exchange rate. This specification delivers the expected null result.[59]

Overall, I find strong evidence for a balance sheet effect, whereby a deterioration in net worth affects firms' ability to borrow. This constraint on borrowing appears to be tighter for loans in FX, and more binding generally on smaller firms. This is important, as my small firms are still quite large, so the negative effects could be larger still for out of sample firms. My results are further sugges-

[58] Mexico's banking sector is dominated by several large foreign banks, but these banks are limited by law as to the amount of assets they can transfer to their parent bank, effectively making them operate more independently.

[59] Note that results are robust to adjusting the shock period length shorter by a few quarters.

tive that liquidity in the domestic currency may be an important factor to offset the negative impact of FX mismatch shocks for larger firms, though the general equilibrium repercussions of the switch from FX to Peso borrowing are less well understood.

2.6 Firm Level Outcomes

When analyzing balance sheet shocks, we are ultimately interested in their effects on real outcomes. Real economic activity does not vary at the loan level, so analysis of real outcomes necessitates working at the firm level. This section presents the empirical approach and results for my firm level analysis. I focus on employment and investment outcomes for the baseline sample of non-exporting firms.

2.6.1 Identification Strategy

Working at the loan level allows me to control for bank shocks (via bank-time fixed effects) to isolate the impact of firm-level characteristics. When examining firm-level outcomes, controlling for bank shocks would be equally valuable. In order to do so, I construct a control for variation in bank credit supply that varies at the firm level. This is in line with the work ofAlfaro et al. (2016); Amiti and Weinstein (in press); Greenstone et al. (2014); Niepmann and Schmidt-Eisenlohr (2017b). I first estimate the following regression at the firm-bank level:[60]

$$\Delta \log(L_{f,b,t}) = \alpha_{f,t} + \alpha_{b,t} + \epsilon_{f,b,t} \tag{2.7}$$

This regression separates loan growth into bank- and firm-specific factors.[61] Note that if the firm-time fixed effects are not included, the bank-time effects will be biased, as they will attribute all of the time-variation in loan growth to the bank; certain banks may have high loan growth because they are lending to high loan growth firms.

I construct a firm-specific bank shock as the (loan) weighted sum of the estimated bank shocks $\hat{\alpha}_{b,t}$ for each bank that the firm borrows from. Formally,[62]

$$BS_{f,t} = \sum_{b \in B_{f,t}} \left(\frac{L_{f,b,t-1}}{\sum_{b \in B_{f,t}} L_{f,b,t-1}} \hat{\alpha}_{b,t} \right) \tag{2.8}$$

I then include this variable as a control in the firm level regressions:

$$\log(Y_{f,t}) = \alpha_f + \alpha_t + \gamma_1 Exposure_f \times Shock_t + \gamma_0 BS_{f,t-1} + X_{f,t-1}\theta + e_{f,t} \tag{2.9}$$

[60]Note that I have combined FX and Peso loans to get the evolution of total loans from the bank.

[61]These effects are computed using the felsdvreg command in STATA (Cornelissen, 2008). See Alfaro et al. (2016) for more discussion on this approach, which extends methodology originally developed in Abowd, Kramarz, and Margolis (1999).

[62]This formulation is similar to the Bartik instrument.

$$\log(Y_{f,t}) = \alpha_f + \alpha_t + \gamma_1 Exposure_f \times Shock_t + \gamma_2 Small_f \times Shock_t$$
$$+ \gamma_3 Exposure_f \times Small_f \times Shock_t + \gamma_0 BS_{f,t-1} + X_{f,t-1}\theta + e_{f,t} \quad (2.10)$$

where $Y_{f,t}$ is either physical capital, measured as property, plant, and equipment (PPE), or employment, with $\log(Y_{f,t})$ winsorized at 2% to reduce the influence of outliers; α_f is a firm fixed effect; α_t is a time fixed effect; and the other variables and controls are defined as in the firm-bank level regressions. Similar to those regressions, the firm-level regressions compare outcomes for firms with differing levels of exposure following the large depreciation shock.

There is an important econometric issue to address when using the bank shock control. Consider a single period version of Equation 2.7:

$$\Delta \log(L_{f,b}) = \alpha_f + \alpha_b + \epsilon_{f,b} \quad (2.11)$$

When both firm and bank fixed effects are included, each set of fixed effects will span the whole space. Thus, one individual fixed effect must be omitted due to collinearity, and the remaining fixed effects in this set are then measured relative to the omitted group. This would be true for each period in which we run this regression. If we expand back to the multiple period regression in Equation 2.7, we see that in each period, one fixed effect group will be omitted, and so the remaining fixed effects will all be estimated relative to the omitted group.

Since the effects in each period are measured relative to their own omitted group, the estimates of the effects cannot be compared across time.[63]

This means that my constructed bank shock measure is also not comparable over time. To address this issue, the following proposition will prove useful:

Proposition 2.6.1. *Time demeaned values of the estimated $\hat{\alpha}_{f,t}$ and $\hat{\alpha}_{b,t}$ are the same as the time demeaned values of a hypothetical $\hat{\alpha}^*_{f,t}$ and $\hat{\alpha}^*_{b,t}$ which have all of the fixed effects measured relative to the same benchmark (e.g. 0). Further, the constructed $BS_{f,t}$, when time demeaned, has the same value as a time demeaned hypothetical $BS^*_{f,t}$ constructed using $\hat{\alpha}^*_{b,t}$.*

Proof: *See Appendix A.2*

Proposition 2.6.1 indicates that by including time fixed effects in the firm level regression (and thus time demeaning the data), the coefficient on the bank shock in Equation 2.9 is exactly the same as it would be if all of the fixed effects were estimated relative to 0 rather than relative to an omitted category. This result is useful generally when using connected datasets (such as credit registry data or bilateral trade data) to construct similar shock estimates for use in collapsed regressions. So long as the appropriate regression specification includes a time

[63]More generally, the effects are only consistently identified within a connected group of firms and banks. A group is connected if any firm borrows from at least one bank in the group and any bank lends to at least one firm in the group. A group is separate from another group if no firms in the first group borrow from any banks in the second, and no banks in the first group lend to any firms in the second. When you estimate two sets of fixed effects, both sets will span each connected group and so be collinear. Hence, one effect in each group will need to be omitted to avoid the dummy variable trap. Since each connected group has a different omitted effect, the estimates of the fixed effects are all measured relative to different reference points. These effects are therefore consistently estimated and comparable within a connected group, but not necessarily comparable across groups. In the data, around 98% or more of observations in each period are in the same connected group. The handful of observations not in the main group in each period are dropped from this construction.

fixed effect,[64] the fixed effect estimates from the matched data can be used in that regression.[65]

2.6.2 Results

I first examine potential substitution at the firm-level to other sources of funding besides loans (such as bonds and trade credit). These results are presented in Table 2.17. Columns (1)-(3) present results where the dependent variable is non-bank liabilities (either total, FX, or Peso). These results mirror the bank borrowing results: large firms increase their funding, whereas small firms do not. The increase for large firms is driven by their Peso borrowing. One specific area of concern is that the large firms may be switching to FX bond debt in order to replace their lost FX bank debt (in addition to using more Peso borrowing). Columns (4)-(6) shows that this is not the case. Though not significant, the coefficient on the main interaction is negative for bond debt, particularly FX bond debt, indicating that the effect of the balance sheet shock on bonds is either unchanged or possibly negative.

Table 2.18 presents my main results at the firm level. Consistent with the firm-bank level results, I find that while there is no measured effect of the balance sheet shock across all firms on average, there is a difference in outcomes for large vs. small firms. In columns (1) and (2), I show results for total bank borrowing of

[64] Or more generally, a fixed effect that aligns with each connected group.

[65] This does not absolve more general issues associated with using an estimated factor in the regression, such as measurement error. A relatively small sample size makes bootstrapping the errors less feasible, but the results are robust to excluding the bank shock control, so any measurement error in the bank shock does not appear to be biasing the coefficients of interest.

these firms. Large exposed firms see an increase in their bank borrowing relative to large, less exposed firms, reflecting the increased access to Peso credit, while small exposed firms have a net negative effect, though not statistically significant. In columns (3) and (4), the difference in employment is similar, with exposed large firms seeing a mild increase while small firms do not. Columns (5) and (6) examine growth in physical capital. Here, large exposed firms again see an increase, but smaller exposed firms see a decrease in growth.

While the total effects for small exposed firms measure as a statistical zero for bank credit and employment, there is a significant decrease in growth of physical capital for these firms. An increase in exposure of 10% of assets for a small firm would result in a decrease in physical capital growth of 1.14%. For the median small firm, pre-shock capital growth was on the order of 0.2%, so this shock could represent a substantial decline for some firms, or a significant reduction relative to their previous expansion path for others.

These results are again robust to horseraced interactions with other firm characteristics. These results are shown in Tables 2.19 and 2.20 for employment and capital respectively. The results are further largely robust to alternative specifications of exposure and growth measurement, shown in the appendix in Table A.10, and to interactions with sector dummies, shown in Tables 2.21 and 2.22.[66] Thus for smaller firms with a large currency mismatch, balance sheet shocks can have negative real consequences as well as negative financial con-

[66] The effects on employment appear to be driven in part by the construction sector. In column (6) of Table 2.21, balance sheet shocks to large construction firms result in positive outcomes, but balance sheet shocks to small construction firms result in large negative outcomes. The direction of the effect for other sectors remains the same, but is statistically insignificant.

sequences. This provides corroborating evidence that currency mismatch and balance sheet effects can lead to negative real outcomes via binding borrowing constraints.

The 75th percentile firm in terms of FX exposure (for either small or large) experienced a drop in net worth of 3.33% of assets. The median firm (either small or large) experienced a 1.1% drop in net worth. Using the estimates from Table 2.18, a small firm that experiences a drop in net worth of 1% of assets experiences a decline in physical capital of 0.34%. For a large firm, a drop in net worth of 1% of assets results in an increase in employment of 0.48% and an increase in physical capital of 0.38%. If FX debt in the economy at large is primarily concentrated among the listed firms, then the aggregate implication is that there is not much of a net effect of the balance sheet shock on aggregate investment, as the smaller firms decrease investment while the larger firms increase investment.[67] However, direct and indeirect impacts on firms outside of my sample may be important sources of negative real outcomes. These are discussed in Sections 2.7.4 and 2.8.

How important is it to capture the firm's full on-balance sheet exposure to FX, rather than relying on more limited measures (e.g. FX debt only)? Table 2.23 reports coefficients from the investment and employment regressions using alternative measures of FX exposure. Column (1) augments the main measue used in this paper with an estimate of FX hedging. This is done by taking the value of the

[67] In unreported results, exporting firms with FX exposure are largely unaffected in their borrowing and investment behavior, suggesting their positions are fully hedged.

net derivatives position just after the depreciation (2009q1) and subtracting the net derivatives position just before the depreciation (2008q3). This captures the fact that if firms were using derivatives to hedge the exchange rate shock, these positions would turn into assets with the sharp exchange rate movement. As seen in Figure 2.6, non-exporting firms on average did see their net derivatives position turn positive (to an asset), suggesting some derivatives use, though in magnitude much smaller than their average exposure. Comparing columns (1) and (2) suggests that accounting for firm derivative usage, albeit imperfectly, does not appreciably alter the estimates.

Column (3) removes FX assets from the measure, as many studies rely on just information about FX liabilities. Here the magnitude for the effect on employment at large firms decreases, while for physical capital the magnitude for both large and small is halved. This suggests that firms holding FX liabilities may often also hold some FX assets, so we would measure a smaller than true effect because we over estimate their exposure. Some studies rely just on one source of debt to get FX exposure, such as loans or bonds. Column (4) uses just FX loans in the numerator of the exposure measure. Thea measured effects on employment in Pane A and attenuated downwards and all estimates lose significance. The estimates for investment remain similar to those of column (3), still underestimating the impact, but recording a negative net impact for small firms. Column (5) uses just FX bond debt in the numerator of the exposure measure. With just this piece, we lose all significance for the investment regression in Panel B. Panel A on employment, however, shows a large positive (though statistically insignificant) effect for large firms, and a large negative and significant effect on small firms. These results together highight the importance of having a more comprehensive measure of firm FX exposure in order to accurately measure the balance sheet effects of exchange rate shocks.

The result that large firms with a negative balance sheet shock actually have higher growth in terms of debt, employment, and physical capital than less exposed firms has been found previously in the empirical literature, yet is contrary to the standard model. We would expect either a negative effect, if the firm is constrained, or a null effect, if the firm is unconstrained. The positive effect of a balance sheet shock suggests that there may be some other factors at play, possibly an omitted variable that is correlated with FX exposure and leads to positive outcomes. A large variety of observable firm characteristics fail to explain this relationship. To address this result, I turn to a stylized model in the next section to help rationalize this result along with my other findings.

2.7 Model

My results suggest that firms are subject to a constraint on their total borrowing and a second, tighter constraint on their FX borrowing, which gives the balance sheet shocks real impacts. In this section, I present a stylized 3 period model which serves to illustrate qualitatively how this mechanism can generate the behavior observed in the empirical results. The model is partial equilibrium in nature to focus on the decisions of the firm.

The key to the model is that firms, in addition to being constrained in their total debt, are subject to a second borrowing constraint specifically on their FX borrowing. These constraints both depend on the net worth of the firm, which in this model is directly related to firm size. This assumption is justified in Figure 2.8, which plots the bank debt of non-exporting firms in my sample in Peso and FX against their size (log assets). As firms get larger, they increase their leverage in Peso before increasing their leverage in FX.[68] This is striking as the lower price of FX debt and failure of UIP suggests that firms would desire to do the opposite.

The constraint on total borrowing that the firm faces can be derived from an incentive compatibility constraint, in which the firm should not have the incentive to default on their debt (under most realizations of the exchange rate). The additional constraint on FX borrowing reflects the risks faced by the bank. Niepmann and Schmidt-Eisenlohr (2017a) provide evidence that firms that borrow more in FX have a higher probability of defaulting on their loans (both FX and Peso) in the event of a depreciation. Further, most collateral backing loans to firms is denominated in local currency (see Calomiris, Larrain, Liberti, and Sturgess (2017) and Fleisig, Safavian, and de la Peña (2006) for evidence that immovable collateral is frequently required to secure lending in emerging markets). That means that when a loan is made in FX and the exchange rate depreciates, the bank recovers a smaller share of the loan value in the event of default, increasing

[68] Size based borrowing constraints (as in Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017)) may match the data better, but are not necessary to generate the qualitative results observed in my analysis.

their downside risk. Thus, the bank has an incentive to limit FX borrowing in addition to limiting total borrowing.[69]

2.7.1 General Framework

There are 3 periods $t \in \{0, 1, 2\}$. The economy is populated by firms (or entrepreneurs) who seek to maximize their period 2 wealth. Firms are endowed with initial wealth w_0. Firms are risk neutral and produce using technology $y_t = f(k_t) = zk_t^\alpha$. Capital depreciates fully upon use.

The timing works as follows: at $t = 0$, firms inherit their initial wealth (their size) and make borrowing and investment decisions. At the beginning of $t = 1$, a depreciation shock is realized. Firms produce and repay their debt (which may be affected by the depreciation), or default and exit if they are unable to repay, and then use the remaining profits to make borrowing and investment decisions. At the beginning of $t = 2$, uncertainty about the exchange rate is again resolved, firms produce, repay their debt or default, and consume their profits.

Firms can borrow in Peso and FX, but the rate of currency depreciation is uncertain, and UIP fails such that FX debt is attractive.[70] UIP failure takes the following form: $E[1+\phi] = \frac{1+r}{1+r^*}\frac{1}{\gamma}$, where $\gamma > 1$ captures the deviation from UIP, $r > r^*$ are the interest rates on local and foreign currency loans, respectively, and ϕ is the rate of depreciation of the local currency. Firms are subject to constraints

[69] This incentive may strengthen if the bank faces higher penalties for not repaying its FX creditors as compared to domestic Peso creditors. In this model, I leave the explicit problem generating this constraint un-modeled.

[70] UIP failure is shown in the aggregate in Figure 2.7 and in the microdata at the firm level in Table 2.11.

on their total borrowing and on their FX borrowing.

2.7.2 Firm's Problem at $t = 1$

The problem is solved recursively. At the end of $t = 1$, firms take as given wealth w_1 and solve the following problem:[71]

$$\max_{d_2, d_2^*} z_2 k_2^{\alpha} - (1+r)d_2 - (1+r^*)E[1+\phi_2]d_2^* \tag{2.12}$$

s.t.

$$k_2 = w_1 + d_2 + d_2^* \tag{2.13}$$

$$0 \leq d_2 + d_2^* \leq \kappa_0 w_1 \tag{2.14}$$

$$0 \leq d_2^* \leq \kappa_1 w_1 \tag{2.15}$$

where d is Peso debt, d^* is FX debt, z is the (potentially firm specific) productivity, and k is investment in physical capital. $\kappa_1 < \kappa_0$, which means that the borrowing constraint on FX loans is tighter than for the firm's overall borrowing. Solving the $t = 1$ problem leads to decision rules $d_2(w_1)$, $d_2^*(w_1)$, and $k_2(w_1)$, which depend on wealth carried intro period 1. Note thatthe firm maximizes expected period 2 profit, where the only source of uncertainty is the period 2 exchange rate realization.

The solution consists of several cases and is fully laid out in Appendix A.3. Figure 2.9 illustrates the relationship between wealth w_1 and investment k_2. The

[71]This formulation is similar to that in Aghion, Bacchetta, and Banerjee (2001).

different cases are determined by which constraints are binding and the funding source (Peso, FX, or own wealth) with which the marginal unit of investment is financed.

Starting from 0 in Figure 2.9, as a firm increases in w_1, investment k_2 increases since higher wealth relaxes the total borrowing constraint. While the marginal debt is denominated in pesos, the optimal investment level is $\left(\frac{z\alpha}{1+r}\right)^{\frac{1}{1-\alpha}}$. Once wealth is sufficiently large, the firm can make this level of investment, so investment is flat though FX debt increases with increasing wealth, which relaxes the FX borrowing constraint. Once the marginal unit of debt switches to FX, the optimal level of investment increases to $\left(\frac{z\alpha\gamma}{1+r}\right)^{\frac{1}{1-\alpha}}$, so firms increase FX debt with increasing wealth (which relaxes their FX debt constraint). Once wealth is sufficiently large, the firm makes the new optimal level of investment. When the marginal unit of investment is purchased solely with wealth, then investment increases one-for-one with wealth.

The purpose of this model is to rationalize the patterns of borrowing and investment outcomes for small firms and large firms after a balance sheet shock. Small firms are constrained in their total borrowing, while large firms may be constrained only in their FX borrowing. Therefore, I focus my analysis on the first two cases, given by wealth cutoffs W_1 and W_2 corresponding to the first increasing slope and flat segment of the investment curve in Figure 2.9.[72,73]

[72]Note, however, that the pattern from the other cases matches the data plotted in Figure 2.8: as the firm gets bigger, the firm levers up in peso, decreases total borrowing while shifting to FX debt, then levers up in FX debt, and finally decreases bank debt as firm size becomes extremely large.

[73]There is also a case 0, where firms default in period 1 and exit, and so does not involve any decisions for period 2.

For illustration, consider two firms that have the same initial wealth w_0 and investment k_1, but for random reasons differ in terms of the FX share of initial debt $\frac{d_1^*}{d_1+d_1^*}$.[74] A large depreciation will lead to a larger decrease in w_1 for the more exposed firm. Proposition 2.7.1 summarizes the response of borrowing and investment to a shock to w_1 for firms in the first two cases.

Proposition 2.7.1. *If* $0 < w_1 \leq W_1$, *then a negative shock to* w_1 *results in lower FX debt, Peso debt, and investment. That is,* $\frac{\partial d_2^*}{\partial w_1} > 0$, $\frac{\partial d_2}{\partial w_1} > 0$, *and* $\frac{\partial k_2}{\partial w_1} > 0$.

If $W_1 < w_1 \leq W_2$, *then a negative shock to* w_1 *(such that* w_1 *remains above the lower threshold) results in lower FX debt, higher peso debt, higher total debt, and unchanged investment. That is,* $\frac{\partial d_2^*}{\partial w_1} > 0$, $\frac{\partial d_2}{\partial w_1} < 0$, $\frac{\partial (d_2+d_2^*)}{\partial w_1} < 0$, *and* $\frac{\partial k_2}{\partial w_1} = 0$

Proof: See Appendix.

The intuition for the first case is straightforward: the firm is constrained in their borrowing, and a negative shock to net worth causes that constraint to bind more tightly, so the firm must borrow and invest less. The intuition for the second case is as follows: the firm is constrained in their FX debt, so the negative shock forces them to reduce their FX debt. They remain unconstrained in their total debt. So, the firm makes up for the lost wealth and lost FX debt with an increase in Peso debt. The increase in Peso debt is thus larger than the decrease in FX debt, so total debt rises.

This matches most of my key empirical results shown in Table 2.7 and Table 2.18. However, the model does not explain why large exposed non-exporters

[74] The depreciation is quite unexpected, so this assumption could be justified that small and random differences may generate differences in exposure orthogonal to other firm characteristics.

have higher investment and employment following the shock, rather than unchanged real outcomes.[75] Further, I have assumed firms of the same size randomly have different levels of FX mismatch. If I relax this assumption, firms of the same size would choose exactly the same exposure in period 0. To address these two issues, I allow firms to differ from each other in terms of their period 1 and 2 productivity (z_1, z_2).[76] I next describe the firm's period 0 problem and the role of productivity in determining FX exposure and real outcomes.

2.7.3 Firm's Problem at $t = 0$

At $t = 0$, firms solve the following problem, taking the decision rules $d_2(w_1, z_1, z_2)$, $d_2^*(w_1, z_1, z_2)$, and $k_2(w_1, z_1, z_2)$ and initial wealth w_0 as given:

$$\max_{d_1, d_1^*} E[z_2 k_2(w_1, z_1, z_2)^\alpha - (1+r)d_2(w_1, z_1, z_2) - (1+r^*)(1+\phi_2)d_2^*(w_1, z_1, z_2)] \tag{2.16}$$

s.t.

$$w_1 = z_1 k_1^\alpha - (1+r)d_1 + (1+r^*)(1+\phi_1)d_1^* \tag{2.17}$$

$$k_1 = w_0 + d_1 + d_1^* \tag{2.18}$$

$$d_1 + d_1^* \leq \kappa_0 w_0 \tag{2.19}$$

[75] This is also found empirically elsewhere in the literature. See for example Kim et al. (2015).

[76] This need not be the only way to generate these results, but it is useful as a simple extension to the model. Note that the main empirical results that exposed firms decrease FX borrowing, exposed small firms decrease investment, and large exposed firms increase Peso (and total) borrowing, do not require this additional assumption of differences in future productivity.

$$d_1^* \leq \kappa_1 w_0 \tag{2.20}$$

(z_1, z_2) are known at $t = 0$. The solution for d_1 and d_1^* depends on the distribution of $1 + \phi$ and may not have a closed form depending on the functional form of the CDF, $G(\cdot)$.

Differences in productivity have a couple of key effects that can generate the patterns observed in the empirical analysis. The first concerns the cross-sectional difference in firm productivity, highlighted by Proposition 2.7.2

Proposition 2.7.2. *For a given initial wealth w_0, firms that are more productive in period 1 borrow more in FX in period 0 than firms that are less productive in period 1: $\frac{\partial d_1^*}{\partial z_1} \geq 0$.*

Proof: See Appendix.

The intuition is that higher d_1^* increases your probability of being constrained, but higher z_1 decreases your probability of being constrained or defaulting. So, firms that have higher z_1 can borrow more in the cheaper currency while maintaining an equal or lower probability of default than firms with lower z_1.[77] This mechanism is modeled more fully in Salomao and Varela (2016), which presents a model of firm dynamics that generates more productive firms selecting into FX borrowing. They confirm this prediction with data for firms in Hungary.[78]

[77] Since borrowing decisions made in period 0 affect how binding constraints will be for period 1 borrowing decisions, the FX borrowing constraint may be slack in period 0 for lower productivity firms.

[78] In my data, large non-exporting firms with higher income and more productive capacity (higher levels of physical capital) tend to have larger FX mismatches. However, I do not have data on hours worked or wage bill, so I cannot compute standard measures of total factor productivity directly. While exposed firms tend to have higher absolute income and higher levels of physical capital, those characteristics do not explain the positive results for exposed large firms following the depreciation. Thus, modeling this as an unobserved future opportunity is appropriate and is one possibility that rationalizes the fact found here, and elsewhere in the literature, that large exposed firms sometimes do better following a depreciation.

The second effect of productivity differences concerns the increase in productivity over time. Increased future productivity increases the optimal scale of current investment. If the firm is unconstrained in period 1 and future productivity is higher than current productivity ($z_2 > z_1$), the firm will increase investment k_2 up to the new optimal level. Note that, all things equal, the probability of being constrained increases with higher future productivity as the optimal investment size gets larger, requiring more debt: $\frac{\partial Pr(w_1 < W_i)}{\partial z_2} > 0 \; \forall \; i \in \{0, 1, 2, 3, 4\}$, where W_i's are the cutoffs for the different cases of the solution, detailed in Appendix A.3. Higher future productivity decreases your probability of default.

Combining the cross-sectional and dynamic differences in productivity generates the desired results. Firms with higher productivity in period 1 select into FX debt in period 0, but if there is a negative balance sheet shock in period 1, only the firms who initially had more wealth will be unconstrained. These unconstrained firms will be able to increase their investment k_2 up to a higher optimal level, relative to firms who are less productive in period 1 (and so chose less FX exposure). I assume that $Corr(z_1, \frac{z_2}{z_1}) > 0$, so that currently more productive firms are also more likely to have productive future investment opportunities. Formally, I consider two types of firms: unproductive firms who have productivity $\bar{z}$ in both periods, and productive firms who have productivity z_1 and z_2 such that $\bar{z} < z_1 < z_2$.[79] Proposition 2.7.3 gives the conditions whereby a firm with increasing productivity would choose a higher proportion of their debt in FX:

[79] The results are similar if firms differ in their initial productivity z_1, while all firms face the same productivity growth rate: $z_2 = (1 + g_z)z_1$.

Proposition 2.7.3. *Let $\bar{z}$ be the productivity level of unproductive firms in both periods and z_1, z_2 be the productivity of highly productive firms, such that $\bar{z} < z_1 < z_2$. Then $d_1^*(w_0, z_1, z_2) \geq d_1^*(w_0, \bar{z}, \bar{z})$ when $\frac{z_2^{\frac{1}{1-\alpha}} - \bar{z}^{\frac{1}{1-\alpha}}}{z_1 - \bar{z}} < X_1 k_1^{\alpha}$, for a given constant X_1.*

Proof: See Appendix.

This condition implies that the increase in z_2 over z_1 cannot be too large, or the firm will avoid FX debt in period 0 because their constraint (for the higher level of investment) would be more likely to bind in period 1. Under these conditions, highly productive firms will borrow more in FX in period 0. Thus, the result in the data that large exposed firms do better following the depreciation can be explained in the model by selection into exposure in period 0 by firms with higher current productivity and increasing future productivity (that is, they have productive future investments to make). These firms borrow more in FX initially and experience a large balance sheet shock. Highly productive but small firms (in terms of initial wealth w_0, which implies smaller k_1) are constrained as before, while larger firms are unconstrained, and so they can increase their investment up to the new optimal level.

For illustration, suppose that the realized depreciation is large enough that the productive firms (who borrow more in FX in period 0) end up with lower w_1 than unproductive firms of the same initial w_0.[80] This is not necessary, but serves as a useful demonstration that these results are not due to more productive firms making more money in period 1 than their less productive counterparts. The ef-

[80]This occurs when $(1+\phi) > \frac{k_1^{\alpha} - (1+r)\frac{\partial d_1}{\partial z_1}}{(1+r^*)\frac{\partial d_1^*}{\partial z_1}}$.

fects on period 1 decisions are illustrated in Figure 2.10. Consider 4 firms with high or low productivity and high or low initial wealth: $\{(w^H, z^H)$, (w^H, z^L), (w^L, z^H), $(w^L, z^L)\}$. For firms with lower initial wealth, the drop in net worth that the productive firms experience (given their higher FX exposure) leads to lower borrowing and investment, relative to less exposed firms, due to the binding borrowing constraint. For large (high wealth) firms, the negative shock to net worth leaves them in the unconstrained range, and so they are able to increase borrowing and investment up to the new optimal level k_2, but decrease FX borrowing and increase Peso borrowing to do so. Thus, comparing exposed firms to less exposed firms of the same w_0 size following the shock, the large firms invest more but the small firms invest less.

2.7.4 Other Explanations

While productivity differences with selection into FX exposure is a plausible explanation for the increase in real outcomes for more exposed large firms, one important caveat with the preceeding discussion is that these differences imply that more productive large firms would increase their real activity regardless of the exchange rate shock. This would violate the parallel trends assumption in the empirical section. Thus, while the proposed model may be a useful framework, especially for understanding the reallocation of debt by currency, other explanations are important to pursue.

One possibility is that the exchange rate movement itself changes the opportunity set of large vs small firms. For example, large firms may have their revenues tied to the US dollar via production chains where they serve as suppliers to exporting firms. For firms in my sample, the large non-exporting firms with large FX exposure tend to be in services or the construction industry. Thus, this explanation is possible in principle, though less likely in practice for my sample.

A more promising explanation relies on general equilibrium effects. In the event of a negative capital shock, banks may reallocate their resources to safer borrowers (e.g. very large firms). Carabarín, de la Garza, and Moreno (2015) find for Mexico that as alternative sources of funding (FX bond markets) open up for these large firms, that frees up capital in the banking sector to lend more to small and medium sized firms. The converse could certainly be the case. General equilibrium effects could also operate through changes in demand during the recession that favor larger firms. For example, the construction firm HOMEX reported to their investors following this episode that while government contracts had generally declined in the aggregate, their firm actually saw an increase in the number of government contracts won. These mechanisms appear to be promising avenues to pursue for future research in a general equilibrium model of FX borrowing and investment.

2.8 Conclusion

In this paper, I estimate the effect of balance sheet shocks following a depreciation for firms with currency mismatch. I construct a unique dataset of listed non-financial firms in Mexico that combines firm balance sheet data, including data on real outcomes, export revenues, and currency exposures, with loan level data for each firm that includes the currency of borrowing as well as the identity of the lending bank. I exploit an exogenous and sudden depreciation episode connected with the financial crisis in the US as an experiment. Using matched firm-bank data, I control for bank credit supply shocks with bank-quarter fixed effects and isolate the impact of pre-existing differences in firm characteristics on responses to the depreciation. I thus identify the mechanism of the balance sheet shock, and differentiate these effects by currency. I estimate bank credit supply shocks at the firm level, and show how to include this measure as a time-varying control in firm-level regressions. I then examine the effect of the balance sheet shock for real firm-level outcomes, focusing on employment and investment.

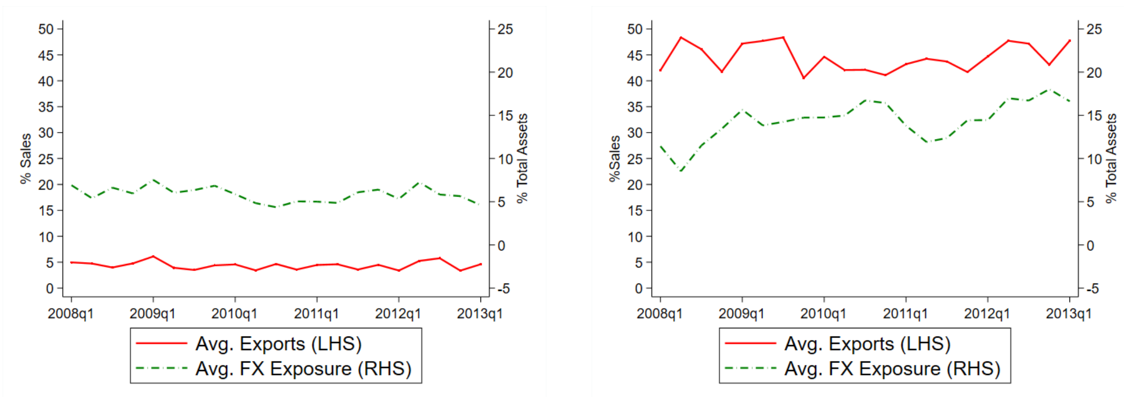
I find that non-exporting firms with a higher currency mismatch on their balance sheet have slower loan growth in FX following the depreciation shock. However, large firms with higher FX exposure compensate for this by increasing their Peso borrowing, while smaller exposed firms do not. These results are robust to numerous alternative specifications and controls. While the borrowing costs for FX loans relative to peso increase following the shock, compressing the interest rate differntial, the decrease in the real interest rate differential between FX and Peso loans was driven by the small firms who did not switch. FX loans remain cheaper in real terms for all firms, but this result suggests that FX loans were still as attractive as before to large firms in terms of the cost advantage they afford.

At the firm level, I find that total bank borrowing by large non-exporters with a mismatch increases, while smaller non-exporters with a mismatch do not increase the growth of their bank debt. Larger firms consequently see higher growth in their investment and employment, while smaller firms do not see higher employment growth and experience lower investment growth. Together, these results suggest that balance sheet effects can lead to binding borrowing constraints, that these constraints may bind more tightly on FX loans and smaller firms, and that these binding constraints can affect real outcomes. I explore the theoretical implications in a stylized 3 period model to highlight the role of the additional borrowing constraint in FX. This model helps to rationalize my empirical findings, including showing that selection into FX debt by productive firms can lead to the counterintuitive result that some firms with negative balance sheet shocks have higher growth outcomes.

This paper helps to harmonize and complement existing research by identifying and highlighting the roles of firm size and currency of debt for borrowing constraints. I show that the null or positive impact of balance sheet shocks found in some studies could be due to their focus on large firms that are able to substitute lost FX credit for domestic currency credit after the shock. This suggests that some firms can avoid a binding borrowing constraint after a shock if they are able to switch to Peso, but otherwise balance sheet effects can have real impacts on these firms. The stability and liquidity of the domestic banking sector could be a factor for emerging market policy makers to consider when assessing the risk posed by corporate borrowing in foreign currencies. Further, risk assessment should focus on the exposure of small and medium sized firms, as that is where the largest negative real impacts are likely to occur.

An important implication of my results is that the observed movement of the largest firms into the Peso credit market could have spillover effects for smaller firms (especially those not in my sample) by crowding them out of local currency borrowing. The converse result has been found for listed firms in Mexico by Carabarín et al. (2015), who find that when these large firms can increase their access to the FX bond market, that frees up the domestic banking system and leads to increased lending to smaller firms. Thus, negative aggregate effects that are often observed with large exchange rate shocks could be driven by a few different channels. First, negative effects could arise if FX borrowing is pervasive prior to the shock among the small and medium sized firms who are more likely to be constrained in the event of a shock. Second, negative effects could occur due to a misallocation of capital from risky to safe borrowers. This is an important area to study for future reserach. As most existing research relies on large firms for data and analysis of their FX debt, firm level studies may fail to examine the portion of the economy where negative effects might be stronger. A more complete look at the distribution of FX debt among the universe of firms and analysis accounting for general equilibrium channels should be a priority in this line of research.

Figure 2.1: Exports and Exposure

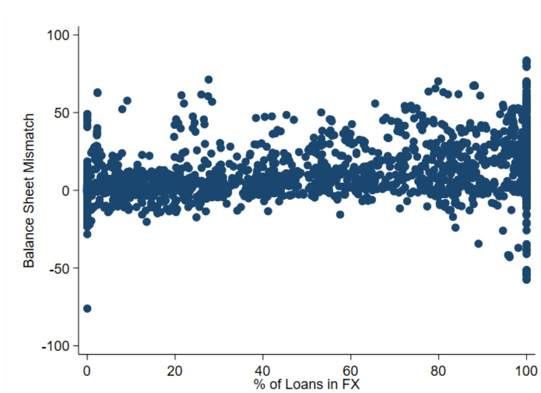


(a) Non-Exporters

(b) Exporters

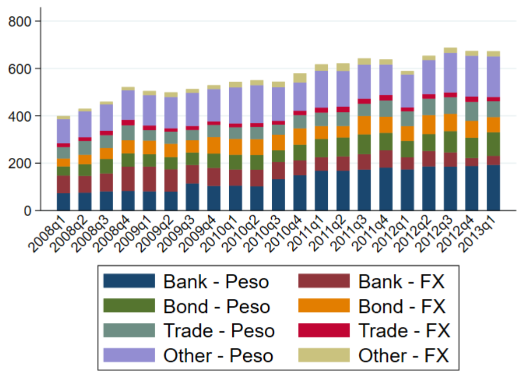
Source: Author's calculations. FX Exposure is (FX Liabilities - FX Assets)/Total Assets, right axis. Exports is share of external sales relative to total sales, left axis.

Figure 2.2: Exposure vs Loan Share

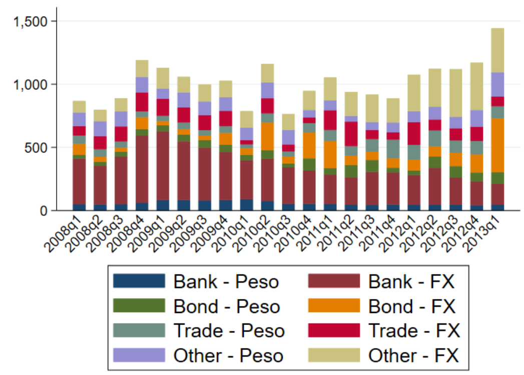


Source: Author's calculations

Figure 2.3: Aggregate Capital Structure, Billions Peso



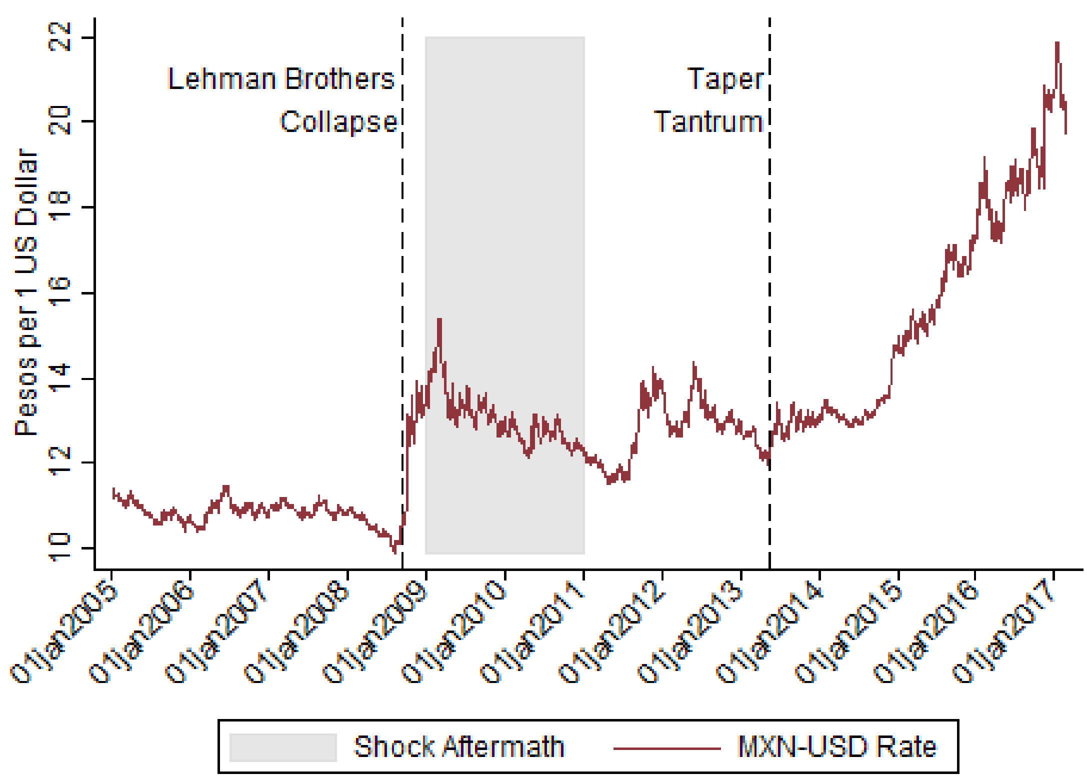
(a) Non-Exporters



(b) Exporters

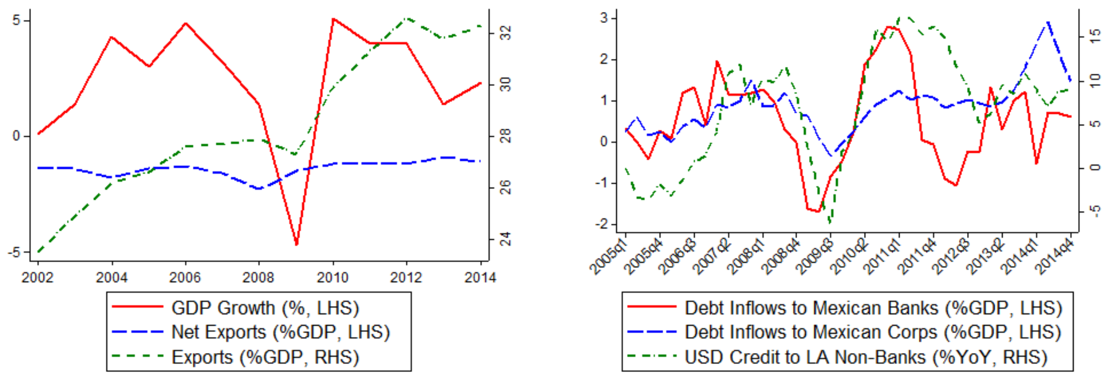
Source: Author's calculations

Figure 2.4: US Dollar - Mexican Peso Exchange Rate



Source: FRED. Data is daily.

Figure 2.5: Macroeconomic Trends of Mexico

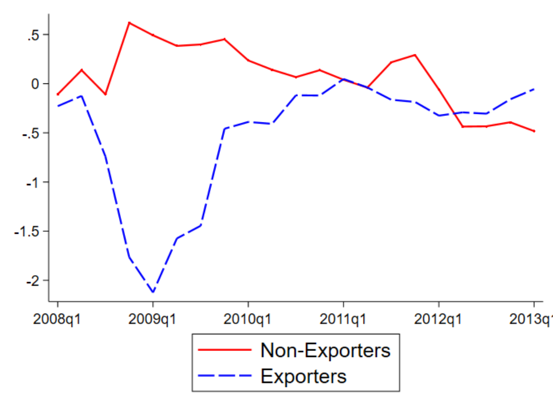


(a) Exports and GDP Growth

(b) Capital Inflows and Dollar Liquidity

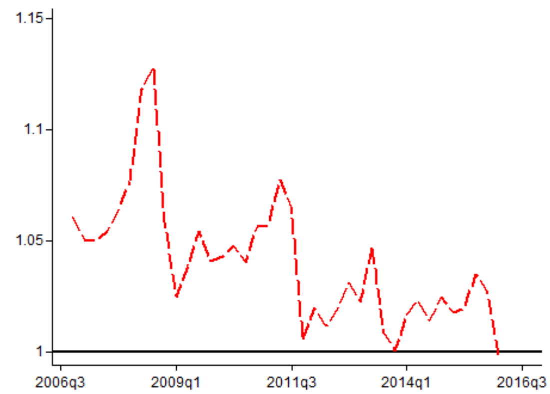
Source: World Bank WDI, Avdjiev, Hardy, Kalemli-Özcan, and Servèn (2017), BIS. Debt inflows is defined as portfolio debt inflows (e.g. bonds) plus other investment debt inflows (e.g. loans) capital flows from external creditors to resident banks or non-bank firms. USD credit to LA non-banks is total credit provided to non-bank institutions resident in Latin American countries.

Figure 2.6: Average Net Derivatives Position to Assets



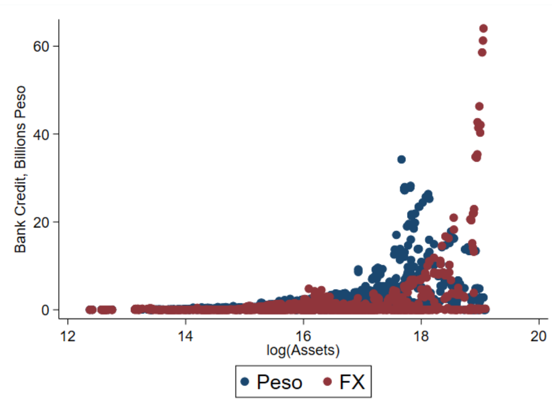
Source: Author's calculations. Figures expressed as percent.

Figure 2.7: UIP Deviations



Source: Banco de Mexico, FRED. UIP Deviation defined as $(s_t/E[s_{t+1}]) * ((1+r_t)/(1+r_t^*))$, where s_t is the exchange rate expressed as dollars per peso, $E[s_{t+1}]$ is the year ahead expected exchange rate (from survey of professional forecasters), and r and r^* are the the interest rates on 1 year treasury bills for Mexico and the U.S., respectively. All rates are period averages over each quarter.

Figure 2.8: Bank Debt vs Firm Size



Source: Author's calculations. Regression sample, non-exporters

Figure 2.9: Size and Investment

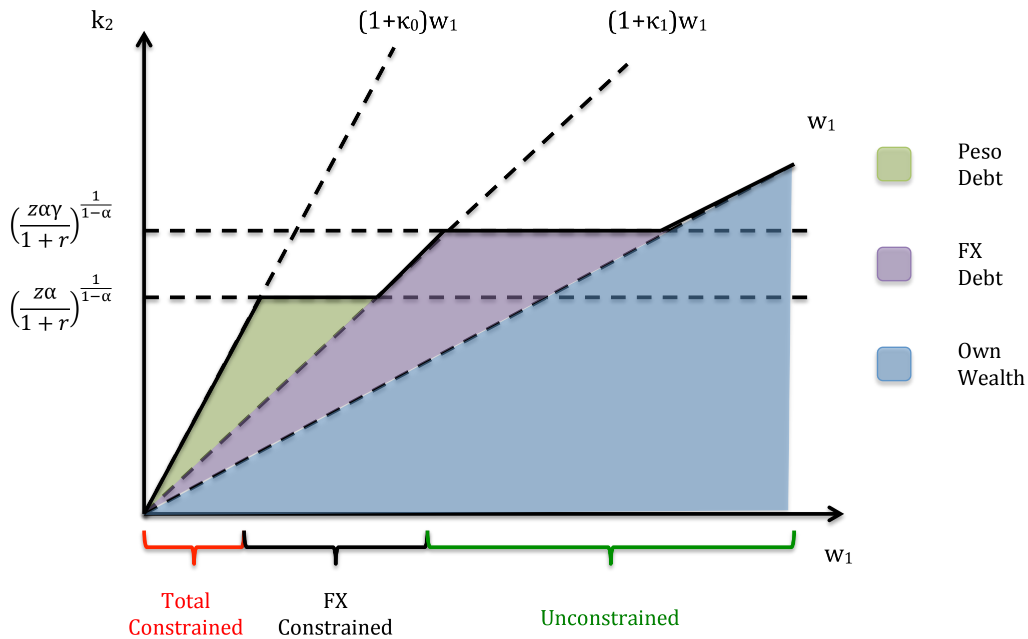


Figure 2.10: Size and Investment: Difference by Productivity

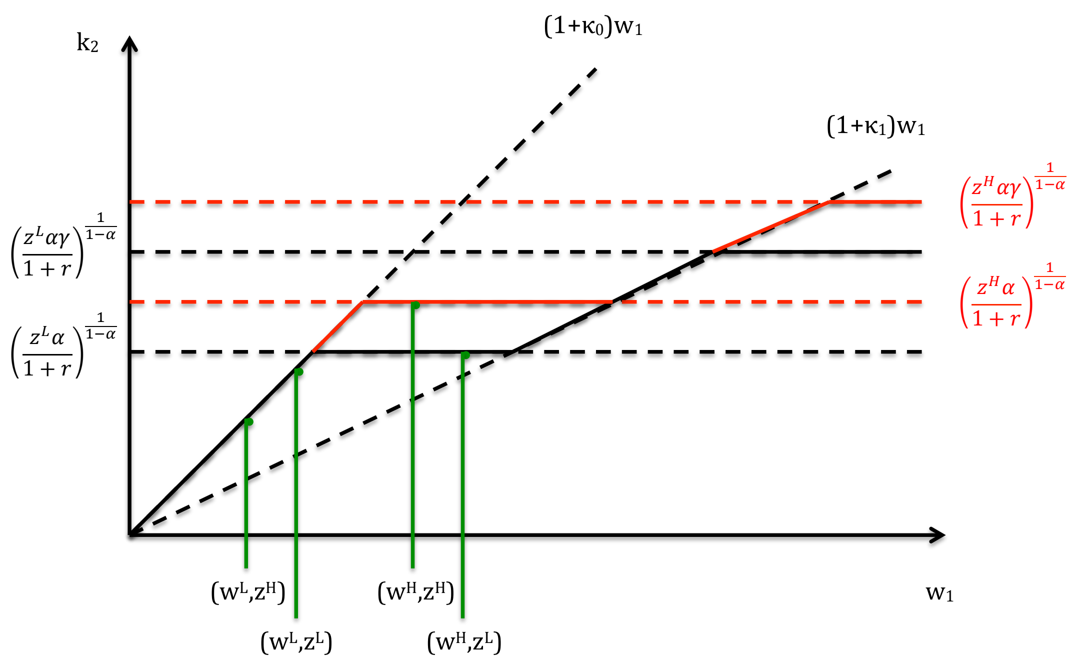


Table 2.1: Firms by Category

	Non-Exporters	Exporters	Total
Small	44	20	64
Large	28	32	60
Total	72	52	124

Firms are from the regression sample, which includes just firms with loan data from identifiable banks over 2008q1-2013q1. Exporters are defined as having their median share of external sales to total sales over the sample greater than 15%. Small firms are defined as having their average size (measured by log assets) below the sample median.

Table 2.2: Firms by Sector

Sector	Number of Firms	Firm-Bank Observations
Construction	14	2106
Energy	1	8
Health	5	294
IT	1	105
Manufacturing	60	7194
Real Estate	6	339
Restaurants	8	669
Retail and Wholesale	11	578
Telecom	12	1313
Transportation	6	464
Total	124	13 070

Firms are from the regression sample, which includes just firms with loan data from identifiable banks over 2008q1-2013q1.

Table 2.3: Firm-Bank Relationships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Firms: Multiple Bank Rels.					Banks: Multiple Firm Rels.			
	Firms	Num Firms	Firm Share	Loan Share	Av. No. Rel. per Firm	Banks	Num Banks	Bank Share	Loan Share	Av. No. Rel. per Bank
2008	94	80	0.851	0.995	7.280	221	94	0.425	0.732	3.095
2009	89	81	0.910	0.991	6.831	204	82	0.402	0.797	2.980
2010	94	77	0.819	0.957	6.638	220	84	0.382	0.742	2.836
2011	90	73	0.811	0.955	6.644	202	67	0.331	0.760	2.960
2012	89	77	0.865	0.943	6.798	186	82	0.441	0.876	3.253
2013	87	75	0.862	0.941	6.782	180	82	0.456	0.900	3.278
2014	88	75	0.852	0.936	6.898	191	93	0.487	0.902	3.178

This table presents annual (quarter 4) summary statistics on the frequency of different types of firm-bank relationships within the loan data using end-of-year data for the regression sample. Column (1) lists the number of firm; columns (2)-(4) deal with firms who borrow from multiple banks, listing the number of them, the share of firms, and the share of loans accounted for, respectively; column (5) gives the average number of bank relationships each firm in sample has; column (6) lists the number of banks; columns (7)-(9) deal with banks that lend to multiple firms, listing the number, the share of banks, and the share of loans accounted for, respectively; and column (10) gives the average number of firms each bank lends to in sample.

Table 2.4: Sample Summary

	Sample Means			Differences		
	Full Sample	Regression Sample	Fixed Effects Sample	Full-Reg	Reg-FE	Full-FE
Firms	74	54	51			
N	2537	1685	1493			
log(Assets)	16.27	16.37	16.50	-0.10^{*}	-0.14^{**}	-0.23^{***}
Liabilities/Assets	53.91	53.24	52.73	0.67	0.51	1.19
Cash/Assets	7.59	6.99	7.21	0.59^{***}	-0.21	0.38
PPE/Assets	39.39	39.03	37.94	0.37	1.09	1.45^{*}
Employment	18.09	16.77	18.68	1.32	-1.92^{*}	-0.60
Output/Assets	20.59	20.02	20.52	0.57	-0.50	0.75
External Sales/Sales	17.61	19.31	20.26	-1.70^{**}	-0.95	-2.65^{***}
FX Exposure	7.86	9.16	9.17	-1.31^{**}	-0.01	-1.31^{**}

Samples as described in the text. N reports the number of firm-time observations. The first 3 data columns are the means for each sample, with all figures expressed in percent, except Employment (measured in thousands of persons) and log(Assets) (where assets are measured in thousands of pesos). PPE is property, plant, and equipment. FX Exposure is defined as (FX Liabilities - FX Assets)/Total Assets. The last 3 data columns are the differences between those means, along with their statistical significance. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Firm-Bank Level Loan Summary

	Obs	Mean	Median	Std. Dev.	Min	Max
Panel A: Non-Exporters, Peso Loans						
Volume	3980	0.65	0.20	1.19	0.00	13.90
Interest Rate	3980	11.21	11.75	4.79	0	25.52
Short Term Share	3980	0.54	0.50	0.41	0	1
Panel B: Non-Exporters, FX Loans						
Volume	2040	0.64	0.09	2.57	0.00	43.00
Interest Rate	2039	9.24	8.74	4.75	0	35.43
Short Term Share	2040	0.55	0.49	0.41	0	1
Panel C: Exporters, Peso Loans						
Volume	1814	0.75	0.28	1.46	0.00	13.50
Interest Rate	1814	12.62	12.43	3.81	0	30.25
Short Term Share	1814	0.53	0.46	0.43	0	1
Panel D: Exporters, FX Loans						
Volume	5228	1.25	0.16	4.89	0.00	99.00
Interest Rate	5228	9.80	9.05	5.00	0	36.73
Short Term Share	5228	0.51	0.40	0.43	0	1

Loan volume is expressed in billions of Pesos. Interest rate is nominal. Short term share is the share of the loan that is due within 1 year divided by the total amount of the loan. The maximum loan volume is expressed in billions of pesos.

Table 2.6: Correlates with Exposure

Sector	Mean Exposure in 2008	Observations	Variable	Correlation Coefficient
Construction	1.99	35	Assets	0.08^{***}
Health	0.00	16	Employment	-0.03
IT	4.73	1	PPE/Assets	0.11^{***}
Manufacturing	5.71	85	Liabilities/Assets	0.45^{***}
Real Estate	-3.03	16	Profit/Assets	-0.03
Restaurants	0.65	20	Cash/Assets	-0.28^{***}
Retail and Wholesale	2.18	26	Sales/Assets	-0.05
Telecom	14.78	40	Exports/Sales	0.24^{***}
Transportation	3.27	20	Bond Debt/Assets	0.05^{*}
Total	4.78	259	N	1033

Sample is non-exporting firms over 2005-2008. Left side of the table show the average FX exposure in 2008 for each sector. The right side of the table shows the correlation coefficients of various firm characteristics with exposure over 2005-2008. Sample size for correlations is 1033, except for profits where it is 986. t-stat on significance is non-directional. PPE is property, plant, and equipment * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Growth in Bank Loans (%), Firm-Bank Level

	FX				Peso			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock_t	0.0553	0.0265			-0.0423**	-0.0397		
	(0.0353)	(0.0368)			(0.0210)	(0.0239)		
$\text{Exposure}_f \times \text{Shock}_t$	-0.402***	-0.322***	-0.542***	-0.691***	0.404**	0.464*	0.477*	0.899***
	(0.0825)	(0.103)	(0.108)	(0.209)	(0.196)	(0.256)	(0.250)	(0.279)
$\text{Small}_f \times \text{Shock}_t$				-0.288**				0.0710*
				(0.119)				(0.0389)
$\text{Exposure}_f \times \text{Small}_f \times \text{Shock}_t$				0.427				-1.020***
				(0.270)				(0.299)
Observations	1636	764	764	764	2818	2377	2377	2377
R^2	0.054	0.096	0.475	0.484	0.032	0.034	0.151	0.154
Firms	40	34	34	34	49	47	47	47
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	No	No	Yes	Yes	No	No	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest				0.0505				0.314

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Growth in Bank Loans (%), Firm-Bank Level - FX vs Peso

	(1)	(2)	(3)	(4)
$Exposure_f \times Shock_t$	0.449*	0.837***		
	(0.246)	(0.270)		
$Exposure_f \times FX_c$	0.396***	0.787***	0.185	0.542***
	(0.146)	(0.174)	(0.162)	(0.139)
$Exposure_f \times Shock_t \times FX_c$	-0.798***	-1.173***	-0.358*	-0.656***
	(0.260)	(0.255)	(0.206)	(0.238)
$Shock_t \times Small_f$		0.0653		
		(0.0397)		
$Exposure_f \times Shock_t \times Small_f$		-0.947***		
		(0.290)		
$Small_f \times FX_c$		0.235***		0.219***
		(0.0740)		(0.0642)
$Exposure_f \times Small_f \times FX_c$		-0.927***		-0.784***
		(0.244)		(0.194)
$Shock_t \times Small_f \times FX_c$		-0.281***		-0.275***
		(0.0765)		(0.0766)
$Exposure_f \times Shock_t \times Small_f \times FX_c$		1.046***		0.752*
		(0.315)		(0.378)
Observations	3142	3142	2964	2964
R^2	0.200	0.204	0.411	0.413
Firms	50	50	47	47
FirmFE	Yes	Yes	-	-
FirmQuarterFE	No	No	Yes	Yes
BankQuarterCurrencyFE	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	-	-

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. FX is a dummy equal to 1 if the loan is in foreign currency. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Growth in Bank Loans (%), Firm-Bank Level - All Loans

	(1)	(2)	(3)
$\text{Exposure}_f \times \text{Shock}_t$	0.553*	0.529*	0.324*
	(0.275)	(0.272)	(0.187)
$\text{Small}_f \times \text{Shock}_t$	0.0419	0.0348	0.0453
	(0.0375)	(0.0390)	(0.0406)
$\text{Exposure}_f \times \text{Small}_f \times \text{Shock}_t$	-0.724**	-0.789**	-0.565**
	(0.291)	(0.305)	(0.234)
Observations	3413	3142	3112
R^2	0.197	0.200	0.254
Firms	51	50	50
FirmFE	Yes	Yes	-
FirmBankFE	No	No	Yes
BankQuarterFE	Yes	-	-
BankQuarterCurrencyFE	No	Yes	Yes
FirmControls	Yes	Yes	Yes
JointTest	0.121	0.0129	0.0244

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Interest Rates, Firm-Bank Level

	Nominal FX		Real FX		Nominal Peso		Real Peso	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Exposure}_f \times \text{Shock}_t$	0.0175*	0.0106	0.0177*	0.0114	0.0117	0.0128	0.0123	0.0134
	(0.00892)	(0.00852)	(0.00905)	(0.00888)	(0.0151)	(0.0239)	(0.0158)	(0.0249)
$\text{Shock}_t \times \text{Small}_f$		0.00399		0.00342		0.00800		0.00832
		(0.00512)		(0.00521)		(0.00718)		(0.00751)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$		0.00882		0.00819		-0.0105		-0.0106
		(0.0193)		(0.0196)		(0.0302)		(0.0314)
Observations	884	884	883	883	2662	2662	2662	2662
R^2	0.942	0.943	0.967	0.967	0.893	0.894	0.892	0.893
Firms	34	34	34	34	48	48	48	48
FirmBankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.257		0.265		0.873		0.855

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1)-(2) is the log of 1 + the loan weighted nominal interest rate at the firm-bank level in each period. Depedent variable in columns (3)-(4) is the log of the nominal rate, plus the expected Peso depreciation rate for the foreign currency loans, minus expected Peso inflation rate. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. FX is a dummy variable equal to 1 if the loan is denominated in foreign currency. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Real Interest Rate Differential, Firm-Bank Level

	(1)	(2)	(3)	(4)
FX_c	-0.0503***	-0.0504***	-0.0459***	
	(0.00450)	(0.00531)	(0.00711)	
$FX_c \times Shock_t$	0.0154***	0.0154**	0.00645	
	(0.00468)	(0.00650)	(0.00767)	
$FX_c \times Exposure_f$		0.00347		
		(0.0244)		
$FX_c \times Shock_t \times Exposure_f$		-0.00151		
		(0.0264)		
$FX_c \times Small_f$			-0.00880	-0.00502
			(0.00892)	(0.00627)
$FX_c \times Shock_t \times Small_f$			0.0172**	0.00650
			(0.00809)	(0.00611)
Observations	4348	3860	4348	4003
R^2	0.909	0.904	0.909	0.971
Firms	59	48	59	58
FirmBankFE	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	-
FirmQuarterFE	Yes	Yes	Yes	Yes
BankQuarterCurrencyFE	No	No	No	Yes

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log of 1 + the loan weighted nominal interest rate at the firm-bank level in each period, plus expected Peso depreciation for foreign currency loans, minus expected Peso inflation rate. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. FX is a dummy variable equal to 1 if the loan is denominated in foreign currency. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Regressions are weighted by log loan. Errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Growth in FX Loans (%), Firm-Bank Level, Horseraces

	(1) Exports	(2) Cash	(3) Derivatives	(4) Size	(5) Leverage	(6) Sales
$\text{Exposure}_f \times \text{Shock}_t$	-0.399**	-0.592***	-0.549***	-0.487***	-0.557***	-0.565***
	(0.147)	(0.148)	(0.132)	(0.0962)	(0.157)	(0.111)
$\text{Horse}_f \times \text{Shock}_t$	-0.00355	-0.00282	0.00302	0.0193	0.000405	0.00485
	(0.00375)	(0.00535)	(0.0257)	(0.0251)	(0.00342)	(0.00487)
Observations	764	764	764	764	764	764
R^2	0.476	0.475	0.475	0.476	0.475	0.476
Firms	34	34	34	34	34	34
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Horse is the firm characteristic indicated in the column heading. Exports is the 2008 average of the firm's external sales (exports + sales by foreign subsidiaries) over total sales. Cash is the 2008 average of cash to assets, with 2 outlier firms winsorized. Derivatives is the 2008 average of the net derivatives position to liabilities. Size is the 2008 average of log of assets. Leverage is the ratio of liabilities to assets. Sales is the ratio of sales to assets. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: Growth in Peso Loans (%), Firm-Bank Level, Horseraces

	(1) Exports	(2) Cash	(3) Derivatives	(4) Size	(5) Leverage	(6) Sales
Exposure$_f$ × Shock$_t$	0.854***	0.998***	0.924***	0.898***	1.103***	0.885***
	(0.279)	(0.267)	(0.277)	(0.293)	(0.238)	(0.266)
Shock$_t$ × Small$_f$	0.0838**	0.264***	0.0610	-0.409	-0.116	0.115
	(0.0384)	(0.0646)	(0.0407)	(1.012)	(0.140)	(0.0845)
Exposure$_f$ × Shock$_t$ × Small$_f$	-1.332***	-1.305***	-0.975***	-0.846**	-1.210***	-1.012***
	(0.402)	(0.307)	(0.307)	(0.330)	(0.267)	(0.290)
Horse$_f$ × Shock$_t$	0.00654*	0.00694**	-0.00723	0.00124	-0.00403**	0.00101
	(0.00331)	(0.00283)	(0.0154)	(0.0502)	(0.00165)	(0.00224)
Horse$_f$ × Shock$_t$ × Small$_f$	-0.00140	-0.0304***	-0.0841	0.0309	0.00376	-0.00225
	(0.00506)	(0.00949)	(0.0538)	(0.0600)	(0.00288)	(0.00330)
Observations	2377	2377	2377	2377	2377	2377
R^2	0.155	0.157	0.154	0.154	0.156	0.154
Firms	47	47	47	47	47	47
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.134	0.0769	0.691	0.749	0.439	0.314

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Horse is the firm characteristic indicated in the column heading. Exports is the 2008 average of the firm's external sales (exports + sales by foreign subsidiaries) over total sales. Cash is the 2008 average of cash to assets, with 2 outlier firms winsorized. Derivatives is the 2008 average of the net derivatives position to liabilities. Size is the 2008 average of log of assets. Leverage is the ratio of liabilities to assets. Sales is the ratio of sales to assets. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14: Growth in FX Loans (%), Firm-Bank Level - Robustness To Sectors

	Telecom		Manufacturing		Construction		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Exposure}_f \times \text{Shock}_t$	-0.581***	-0.577***	-0.364**	-0.561***	-0.428***	-0.424***	-0.576***	-0.575***
	(0.117)	(0.171)	(0.166)	(0.181)	(0.111)	(0.106)	(0.107)	(0.107)
$\text{Shock}_t \times \text{Sector}_f$	0.0633	0.0677	-0.119	-0.252	0.130*	0.136**	-0.389***	-0.543***
	(0.0778)	(0.114)	(0.114)	(0.192)	(0.0767)	(0.0648)	(0.109)	(0.0802)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Sector}_f$		-0.0180		0.630		-0.113		1.449
		(0.364)		(0.508)		(0.646)		(1.003)
Observations	764	764	764	764	764	764	764	764
R^2	0.475	0.475	0.477	0.478	0.477	0.477	0.478	0.478
Firms	34	34	34	34	34	34	34	34
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Sector is a dummy variable taking a value of one if the firm is in the sector indicated in the column heading. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.15: Growth in Peso Loans (%), Firm-Bank Level - Robustness To Sectors

	Telecom		Manufacturing		Construction		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Exposure}_f \times \text{Shock}_t$	0.855**	1.614***	0.934***	0.936***	0.889***	0.417**	0.908***	0.907***
	(0.318)	(0.205)	(0.277)	(0.276)	(0.278)	(0.159)	(0.279)	(0.278)
$\text{Shock}_t \times \text{Small}_f$	0.0784*	0.0966**	0.0754*	0.0912**	0.0836	0.0561	0.0705*	0.0680*
	(0.0403)	(0.0393)	(0.0425)	(0.0437)	(0.0502)	(0.0515)	(0.0400)	(0.0395)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$	-0.963***	-1.703***	-1.163***	-2.132**	-1.111***	-0.551**	-1.042***	-0.998***
	(0.334)	(0.218)	(0.360)	(0.841)	(0.308)	(0.228)	(0.300)	(0.298)
$\text{Shock}_t \times \text{Sector}_f$	0.0531	0.125*	0.153***	0.157***	-0.0261	-0.0692	0.0777*	0.0512
	(0.0741)	(0.0675)	(0.0496)	(0.0494)	(0.0537)	(0.0510)	(0.0411)	(0.0402)
$\text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$	0.184*	0.173*	-0.117	-0.153	-0.0709	0.0300	0.0403	0.251***
	(0.109)	(0.102)	(0.0871)	(0.0931)	(0.0820)	(0.0687)	(0.0947)	(0.0714)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Sector}_f$		-1.283***				1.308***		-2.501**
		(0.327)				(0.292)		(0.978)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$				1.082		-4.377**		
				(0.872)		(2.164)		
Observations	2377	2377	2377	2377	2377	2377	2377	2377
R^2	0.155	0.157	0.155	0.155	0.155	0.158	0.154	0.155
Firms	47	47	47	47	47	47	47	47
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.370	0.471	0.330	0.153	0.123	0.336	0.275	0.455

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Sector is a dummy variable taking a value of one if the firm is in the sector indicated in the column heading. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.16: Growth in Bank Loans (%), Firm-Bank Level, Alternate Fixed Effects

	FX				Peso			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure$_f$ × Shock$_t$	-0.479**	-0.780**	-0.552***	-0.723***	0.817**	0.833**	0.717***	0.918***
	(0.231)	(0.324)	(0.133)	(0.214)	(0.359)	(0.388)	(0.185)	(0.276)
Shock$_t$ × Small$_f$				-0.212	0.0182	-0.0289	0.0768*	0.0697*
				(0.127)	(0.0442)	(0.0655)	(0.0393)	(0.0392)
Exposure$_f$ × Shock$_t$ × Small$_f$				-0.964	-1.145**	-1.117**	-0.821***	-1.791**
				(0.942)	(0.444)	(0.464)	(0.256)	(0.788)
Shock$_t$ × Manufacturing				-0.208				0.0644
				(0.182)				(0.0549)
Exposure$_f$ × Shock$_t$ × Manufacturing				1.843				0.578
				(1.123)				(0.781)
Observations	760	1511	749	764	2376	2690	2351	2377
R^2	0.500	0.354	0.560	0.486	0.165	0.182	0.215	0.155
Firms	34	40	33	34	47	49	47	47
FirmFE	Yes	Yes	N/A	Yes	Yes	Yes	N/A	Yes
QuarterFE	N/A	Yes	N/A	N/A	N/A	Yes	N/A	N/A
SectorYearFE	Yes	N/A	No	No	Yes	N/A	No	No
BankQuarterFE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
BankSectorYearFE	No	Yes	No	No	No	Yes	No	No
FirmBankFE	No	No	Yes	No	No	No	Yes	No
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest					0.118	0.115	0.523	0.270

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.17: Growth in Firm Level Non-Bank Financing (%)

	Non-Bank Liabilities			Bond Debt		
	(1) Total	(2) FX	(3) Peso	(4) Total	(5) FX	(6) Peso
Exposure$_f$ × Shock$_t$	0.331**	-0.425	0.814*	-0.179	-0.201	0.249
	(0.161)	(0.285)	(0.405)	(0.303)	(0.147)	(0.479)
Shock$_t$ × Small$_f$	0.0517	-0.167*	0.109*	-0.193**	-0.0321	-0.143
	(0.0365)	(0.0877)	(0.0595)	(0.0771)	(0.0515)	(0.0910)
Exposure$_f$ × Shock$_t$ × Small$_f$	-0.482**	0.335	-0.672	0.525	-0.122	0.176
	(0.211)	(0.330)	(0.434)	(0.438)	(0.320)	(0.556)
Observations	844	517	790	837	837	844
R^2	0.217	0.273	0.161	0.082	0.084	0.076
Firms	52	40	47	52	52	52
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.292	0.585	0.405	0.296	0.267	0.130

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1)-(3) is the log difference of non-bank liabilities outstanding at the firm level in each period, winsorized at 2%. Dependent variable in columns (4)-(6) is the log difference of bond debt at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.18: Growth in Firm Level Outcomes (%)

	Bank Debt		Employment		PPE	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Exposure}_f \times \text{Shock}_t$	0.250	0.479**	0.0672	0.160**	0.0325	0.128*
	(0.162)	(0.202)	(0.0477)	(0.0796)	(0.0579)	(0.0653)
$\text{Shock}_t \times \text{Small}_f$		0.0770*		0.00519		0.0166
		(0.0439)		(0.0146)		(0.0111)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$		-0.598**		-0.234**		-0.249***
		(0.239)		(0.108)		(0.0839)
Observations	848	848	765	765	787	787
R^2	0.206	0.210	0.162	0.168	0.198	0.207
Firms	52	52	51	51	52	52
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.391		0.340		0.0290

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1) and (2) is the log difference of bank credit outstanding at the firm level in each period, winsorized at 1%. Dependent variable in columns (3) and (4) is the log difference of employment at the firm level in each period, winsorized at 2%. Dependent variable in columns (5) and (6) is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.19: Growth in Employment (%), Horseraces

	(1) Exports	(2) Cash	(3) Derivatives	(4) Size	(5) Leverage	(6) Sales
$\text{Exposure}_f \times \text{Shock}_t$	0.169*	0.158*	0.180***	0.188***	0.158**	0.157*
	(0.0865)	(0.0798)	(0.0632)	(0.0558)	(0.0739)	(0.0798)
$\text{Shock}_t \times \text{Small}_f$	0.00368	-0.00277	0.00606	-0.460*	-0.00830	0.0272
	(0.0162)	(0.0194)	(0.0149)	(0.248)	(0.0304)	(0.0225)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$	-0.410**	-0.229**	-0.248**	-0.227**	-0.252**	-0.240**
	(0.184)	(0.112)	(0.0990)	(0.0959)	(0.112)	(0.103)
$\text{Horse}_f \times \text{Shock}_t$	-0.00104	-0.000195	-0.00575	-0.0180	0.0000479	-0.000113
	(0.00157)	(0.000805)	(0.00426)	(0.0109)	(0.000348)	(0.000410)
$\text{Horse}_f \times \text{Shock}_t \times \text{Small}_f$	0.00345	0.00145	-0.000449	0.0281*	0.000312	-0.00115
	(0.00244)	(0.00228)	(0.0146)	(0.0151)	(0.000630)	(0.000715)
Observations	765	765	765	765	765	765
R^2	0.170	0.168	0.169	0.170	0.168	0.171
Firms	51	51	51	51	51	51
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.134	0.381	0.395	0.627	0.296	0.248

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of employment at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Horse is the firm characteristic indicated in the column heading. Exports is the 2008 average of the firm's external sales (exports + sales by foreign subsidiaries) over total sales. Cash is the 2008 average of cash to assets, with 2 outlier firms winsorized. Derivatives is the 2008 average of the net derivatives position to liabilities. Size is the 2008 average of log of assets. Leverage is the ratio of liabilities to assets. Sales is the ratio of total sales to assets. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text, lagged one period. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.20: Growth in Physical Capital (%), Horseraces

	(1) Exports	(2) Cash	(3) Derivatives	(4) Size	(5) Leverage	(6) Sales
$\text{Exposure}_f \times \text{Shock}_t$	0.127*	0.131*	0.160***	0.145**	0.158**	0.119**
	(0.0656)	(0.0671)	(0.0513)	(0.0583)	(0.0694)	(0.0576)
$\text{Shock}_t \times \text{Small}_f$	0.0178	0.0175	0.0189*	-0.130	-0.0205	0.0500**
	(0.0115)	(0.0155)	(0.0103)	(0.190)	(0.0277)	(0.0198)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$	-0.347***	-0.251***	-0.284***	-0.279***	-0.295***	-0.251***
	(0.123)	(0.0860)	(0.0765)	(0.0809)	(0.0967)	(0.0743)
$\text{Horse}_f \times \text{Shock}_t$	0.000426	0.000299	-0.00932***	-0.0116	-0.000530	0.000798
	(0.000816)	(0.000593)	(0.00328)	(0.00893)	(0.000356)	(0.000526)
$\text{Horse}_f \times \text{Shock}_t \times \text{Small}_f$	0.000998	0.0000631	0.0108	0.00821	0.000805	-0.00177**
	(0.00149)	(0.00192)	(0.00835)	(0.0117)	(0.000661)	(0.000788)
Observations	787	787	787	787	787	787
R^2	0.208	0.207	0.212	0.208	0.209	0.212
Firms	52	52	52	52	52	52
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.0261	0.0387	0.0324	0.0211	0.0324	0.00984

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Horse is the firm characteristic indicated in the column heading. Exports is the 2008 average of the firm's external sales (exports + sales by foreign subsidiaries) over total sales. Cash is the 2008 average of cash to assets, with 2 outlier firms winsorized. Derivatives is the 2008 average of the net derivatives position to liabilities. Size is the 2008 average of log of assets. Leverage is the ratio of liabilities to assets. Sales is the ratio of total sales to assets. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text, lagged one period. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.21: Growth in Employment (%) - Robustness to Sectors

	Telecom		Manufacturing		Construction		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Exposure}_f \times \text{Shock}_t$	0.412***	0.363	0.390***	0.394***	0.411***	0.446***	0.397***	0.397***
	(0.145)	(0.229)	(0.129)	(0.128)	(0.110)	(0.0710)	(0.133)	(0.133)
$\text{Shock}_t \times \text{Small}_f$	0.00532	0.00513	0.0114	0.0212	0.00712	0.00343	0.00867	0.00891
	(0.0211)	(0.0209)	(0.0201)	(0.0218)	(0.0137)	(0.0141)	(0.0199)	(0.0201)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$	-0.425**	-0.378	-0.319*	-0.677**	-0.372**	-0.310**	-0.409**	-0.417**
	(0.183)	(0.248)	(0.177)	(0.296)	(0.159)	(0.126)	(0.176)	(0.184)
$\text{Shock}_t \times \text{Sector}_f$	-0.0228	-0.0281	-0.0209	-0.0206	0.0442	0.0434	0.00868	0.0101
	(0.0255)	(0.0212)	(0.0146)	(0.0145)	(0.0306)	(0.0293)	(0.0138)	(0.0140)
$\text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$	0.00385	0.00438	-0.0121	-0.0390	0.0194	0.0600*	-0.00835	-0.0233
	(0.0326)	(0.0324)	(0.0261)	(0.0273)	(0.0406)	(0.0338)	(0.0197)	(0.0363)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Sector}_f$		0.106				-0.0555		0.120
		(0.218)				(0.177)		(0.226)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$				0.551*		-1.552***		
				(0.298)		(0.360)		
Observations	526	526	526	526	526	526	526	526
R^2	0.238	0.239	0.240	0.244	0.252	0.260	0.237	0.237
Firms	43	43	43	43	43	43	43	43
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.914	0.905	0.583	0.298	0.742	0.218	0.924	0.885

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of employment at the firm level in each period, winsorized at 2%. Sector is a dummy variable taking a value of 1 if the firm is in the sector indicated in the column heading. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.22: Growth in Physical Capital (%) - Robustness to Sectors

	Telecom		Manufacturing		Construction		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Exposure}_f \times \text{Shock}_t$	0.205**	0.252*	0.214***	0.217***	0.204***	0.186***	0.214***	0.215***
	(0.0836)	(0.134)	(0.0760)	(0.0773)	(0.0626)	(0.0461)	(0.0776)	(0.0776)
$\text{Shock}_t \times \text{Small}_f$	0.00982	0.0100	0.0160	0.0235*	-0.00239	-0.00285	0.0103	0.00941
	(0.0128)	(0.0128)	(0.0123)	(0.0130)	(0.0133)	(0.0133)	(0.0122)	(0.0122)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$	-0.346**	-0.391**	-0.272*	-0.533***	-0.327**	-0.307**	-0.352**	-0.323**
	(0.156)	(0.190)	(0.160)	(0.169)	(0.141)	(0.132)	(0.156)	(0.154)
$\text{Shock}_t \times \text{Sector}_f$	0.0107	0.0157	0.0187	0.0191	-0.0221	-0.0225	0.00862	0.00333
	(0.0185)	(0.0187)	(0.0122)	(0.0123)	(0.0216)	(0.0214)	(0.00911)	(0.00905)
$\text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$	0.0252	0.0249	-0.0525*	-0.0728**	0.0442*	0.0453	-0.0103	0.0453
	(0.0229)	(0.0228)	(0.0274)	(0.0317)	(0.0253)	(0.0270)	(0.0272)	(0.0288)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Sector}_f$		-0.104				0.0350		-0.447**
		(0.145)				(0.112)		(0.189)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f \times \text{Sector}_f$				0.404**		-0.0664		
				(0.176)		(0.298)		
Observations	547	547	547	547	547	547	547	547
R^2	0.220	0.221	0.223	0.226	0.222	0.222	0.219	0.220
Firms	44	44	44	44	44	44	44	44
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest	0.276	0.281	0.678	0.0162	0.332	0.365	0.305	0.404

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Sector is a dummy variable taking a value of 1 if the firm is in the sector indicated in the column heading. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.23: Measures of FX Exposure and Growth in Firm Outcomes (%)

	Panel A: Employment				
Exposure Measure	$\frac{FXL-FXA-FXD}{Assets}$	$\frac{FXL-FXA}{Assets}$	$\frac{FXL}{Assets}$	$\frac{BankFXL}{Assets}$	$\frac{BondFXL}{Assets}$
Exposure$_f$ $\times$ Shock$_t$	0.184**	0.160**	0.105	0.021	0.442
Exposure$_f$ $\times$ Small$_f$ $\times$ Shock$_t$	-0.268**	-0.234**	-0.177**	-0.064	-0.707**
Total Effect (Small)	-0.084	-0.074	-0.072	-0.043	0.265**
	Panel B: Physical Capital				
Exposure Measure	$\frac{FXL-FXA-FXD}{Assets}$	$\frac{FXL-FXA}{Assets}$	$\frac{FXL}{Assets}$	$\frac{BankFXL}{Assets}$	$\frac{BondFXL}{Assets}$
Exposure$_f$ $\times$ Shock$_t$	0.128*	0.128*	0.079*	0.106	0.081
Exposure$_f$ $\times$ Small$_f$ $\times$ Shock$_t$	-0.253***	-0.249***	-0.140***	-0.179**	-0.28
Total Effect (Small)	-0.125**	-0.121**	-0.061*	-0.073*	-0.199

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in Panel A is the log difference of employment at the firm level in each period, winsorized at 2%. Dependent variable in Panel B is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Exposure variable in column (1) is FX liabilities minus FX assets minus estimated derivatives hedging (as described in the text), divided by total assets; in coplumn 2, FX assets minus FX liabilities, divided by total assets; in column (3), FX liabilities divided by total assets; in column (4), FX loans divded by total assets; in column (5), FX bonds divided by total assets. Exposure variables are all defined as the 2008 average. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. All regressions include firm fixed effects, time fixed effects, and time-varying firm controls consisting of one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. Total Effect (Small) reports the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small, with their estimated significance. All regressions also include Shock*Small. N=765 for PanelA, N=787 for Panel B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3: Gross Capital Flows by Banks, Corporates and Sovereigns

3.1 Introduction

International capital flows have nontrivial consequences for the transmission of real and financial shocks across borders and countries' own macroeconomic outcomes. The domestic macroeconomic environment and global shocks also affect the amount and direction of capital flows. It is apparent from the history of financial crises that the vulnerability to external shocks can vary greatly depending on which economic sector(s) are on the receiving side of capital inflows. For example, sovereign debt proved to be the Achilles' heel in the Latin American crises, while private sector debt financed by capital inflows was the key source of fragility in the Asian financial crises. During the latest global financial crisis, in the US, the culprit was the domestic household debt held by US and global banks. By contrast, in the European countries, sovereigns' and banks' external borrowing played the central role.

A great deal of empirical and theoretical work on capital flows has focused on the behavior of net flows, defined as the difference between purchases of domestic assets by foreign residents (gross capital inflows by foreigners) and the purchases of foreign assets by domestic residents (gross capital outflows by domestic agents). Researchers usually measure net flows as the current account balance with a reversed sign, sometimes excluding changes in reserves. There has been recent attempts to investigate the behavior of domestic and foreign investors separately, focusing on gross inflows and gross outflows around crisis events. Forbes and Warnock (2012), Broner, Didier, Erce, and Schmukler (2013), Milesi-Ferretti and Tille (2011), and Bluedorn, Duttagupta, Guajardo, and Topalova (2013), are some examples. These papers document that gross flows are much larger and more volatile than net flows, tend to be procyclical, and respond systematically to changes in global conditions. These properties make gross flows first order for financial stability issues.[1]

An important contribution of this paper is to introduce a new comprehensive dataset on *gross* capital inflows and outflows at the *quarterly* frequency for a balanced panel of 85 countries for inflows and 31 countries for outflows. We report total inflows and outflows and also the decomposition by borrower and lender sectors.[2]

We see two distinct advantages of our data. First, the large number of developing countries and emerging markets is a big advantage of our capital inflows

[1] See Caballero (2016), Obstfeld (2012), Catão and Milesi-Ferretti (2014), and Borio and Disyatat (2011).

[2] Galstyan, Lane, Mehigan, and Mercado (2016) use data after 2013 from IMF's CPIS to examine portfolio debt and portfolio equity stocks by the sectoral identity of the issuer and holder of the security. We focus on the flow of portfolio debt by sector over a much longer time horizon in quarterly data and analyze it in conjunction with other investment debt inflows by sector over the same time horizon. Arslanalp and Tsuda (2014b) and Arslanalp and Tsuda (2014a) decompose sovereign/government loan and bond debt by creditor, both foreign and domestic. They employ QEDS data to split by foreign and domestic and BIS data to identify external bank lenders, similar to our approach but only for the sovereign where we consider all three sectors: banks, corporates and the soveregins. Broner, Erce, Martin, and Ventura (2014) identify the creditors for external sovereign bonds using data derived from national sources and the OECD.

dataset relative to standard sources.[3] Second, our sectoral breakdown of debt inflows into 3 borrowing groups, sovereigns (government and central bank), banks, and corporates, is of utmost importance since increased financial integration increases the risk of crises through debt linkages.[4]

Debt flows are generally the largest component in total capital flows. Figure 3.1 illustrates this clearly.[5] Panel (a) shows the share of total debt in total external liabilities. Debt represents the majority of external liabilities globally and in advanced countries (AE). In emerging markets (EM), debt and non-debt liabilities are of similar magnitude. Panel (b) highlights that other investment debt (usually bank credit or loans) is the bulk of debt stocks. Portfolio debt (bonds) in panel (c) represents nearly half of AE external debt and around a third of EM external debt. Thus, it is important to consider both types of external debt.

In terms of sectoral composition of debt, panels (d)-(i) highlight the sectoral share of external debt stocks for each flow type and country group. In AE, banks hold the lion's share of external debt liabilities, whereas in EM, corporates, banks and sovereigns have more or less equal shares. This is interesting since in general it is thought that all types of agents enjoy easier access to international capital

[3]The set of countries in our 85 country capital inflows data includes 25 advanced, 34 emerging, and 26 developing economies from 1996q1 to 2014q4. If we go to an annual frequency, we can have 89 countries for inflows, adding 4 more developing economies. For capital outflows data we have 16 advanced and 15 emerging economies for 2004q1–2014q4. This is because of the fact that foreign assets of lender types are poorly recorded. For total outflows one can have of course more countries but our aim here is to decompose outflows by banks, corporates and sovereigns as we do inflows. We combine the general government and central bank sectors into a single public sector in order to increase data coverage.

[4]Lane (2013) discusses the importance and difficulty of analyzing sectoral financial positions for understanding and assessing risk. See also Lane (2015).

[5]This figure plots stocks. The flow version delivers a similar picture, though more noisy, and is plotted in Appendix B.6 in Figure B.1.

markets in AE than in EM. It seems that banks do most of the intermediation of external funds in AE, while corporates and sovereigns might be borrowing more domestically. What is more surprising is that the conventional wisdom that most other investment debt is owed by banks and most portfolio debt is owed by corporates holds for AE but not for EM. In the latter, most of the portfolio debt is attributable to sovereigns, and banks and corporates have equal shares in other investment debt.

The composition of external debt is remarkably stable over time, with few exceptions.[6] The share of other investment debt in total external liabilities is decreasing and the share of portfolio debt is increasing in AE over time. This seems to be partly driven by the global financial crisis: in these countries, the share of bank-held debt declines and that of sovereign debt increases following the crisis. For EM, sector shares are more stable over time, although prior to the crisis there is a declining trend in the share of debt vis-a-vis equity.

Figure 3.2 shows the counterpart of Figure 3.1 for the composition of external asset stocks in debt instruments, including reserves.[7] Panel (a) shows the share of debt in total external assets. Debt assets represents the majority of external assets; 80 percent in EM and 60 percent in AE on average during 2000s, though share of debt assets in total external assets is on a declining trend for both set of countries. Panel (b) highlights that other investment debt is the bulk of debt asset stocks in AE, whereas portfolio debt assets in panel (c) represents only

[6]We use a balanced sample of countries to prevent entry/exit of countries into the sample from distorting time series patterns in the composition of debt.

[7]There are not enough developing countries in the outflows sample to include an average for the group.

40 percent of the AE economies external debt assets. For EM, other investment debt assets represent half of the external debt assets, portfolio debt assets are not important, and the remainder consists of reserves.

In terms of sectoral composition, panels (d)-(i) highlight the sectoral share of external debt asset stocks for each flow type and country group. In EM the public sector is overwhelmingly the main lender to other countries. This is primarily driven by their accumulation of reserve assets, which are included in the total debt figure. In AE, as is the case for borrowing, banks do the lion's share of external lending, while corporates also have a big share of AE lending in portfolio debt assets. For EM, banks and corporates do about an equal share of lending in other investment debt, while corporates lead in terms of portfolio debt. The composition of external debt assets is also very stable over time, as in the case of debt liabilities.

These data patterns highlight the importance of separating external debt liabilities and assets by sector for a more complete understanding of the drivers of capital flows and lead us to a re-evaluation of conventional stylized facts on capital flows. Using our dataset we document four new stylized facts. First, the well-known positive correlation between capital inflows and outflows is driven by banking flows, mainly by global banks in advanced countries. The literature shows a high degree of correlation between capital inflows and outflows and an increase in this correlation over time (see Forbes and Warnock (2012), Broner et al. (2013) Bluedorn et al. (2013) and Davis and van Wincoop (2017), for example). We find that this correlation is driven mainly by the borrowing and lending patterns of global banks who are in general domiciled in advanced countries. This results holds both for unconditional correlations and correlations conditional on VIX and GDP growth.

To establish the other three facts, we run separate quarterly panel regressions of capital inflows and outflows on lagged global risk appetite (VIX) and countries' own lagged GDP growth. These regressions are country fixed effect specifications, which means we identify from within variation, that is from changes in VIX, GDP growth and capital flows.[8] We find that, during domestic economic downturns, inflows to domestic banks and corporates decline in all countries. In terms of outflows, banks in advanced countries invest less abroad, decreasing their outflows, whereas banks and corporates in emerging markets do not respond to their own recessions in terms of outflows. Results are symmetric and can be interpreted for boom periods as well. Hence, in terms of business cycle properties of capital inflows, banks' and corporates' inflows move procylically everywhere, but for outflows, only banks of AEs invest overseas proylically, increasing their outflows when their own economies experience a boom.[9]

[8] Cerutti, Claessens, and Puy (2015) uses quarterly BOP data aggregated for a group of emerging economies, and shows in time series regressions that VIX is negatively correlated with their estimated common factor for all types of capital flows. Nevertheless, the correlation is not robust to including GDP growth. Cerutti, Claessens, and Puy (2016) find that inflows to emerging economies have strong co-movement with VIX and that this link is stronger in bank flows.

[9] The results on the response of capital flows to GDP growth are robust and resonate with the theoretical and empirical results in Blanchard, Ostry, Ghosh, and Chamon (2015). These authors find, in a sample of 19 EM, that other investment debt flows are positively correlated with GDP growth and portfolio debt flows are negatively correlated or not robustly correlated. Due to their instrumentation strategy they interpret their results causally as loans (other investment debt flows) being expansionary, whereas bond flows (portfolio debt) being contractionary. Our results show that their result on other investment debt flows is driven by private sector inflows, both banks and corporates. We also explain their non-robust zero/negative correlation of bond flows (portfolio debt) with GDP growth in EM. This is due to the fact that in EM, public and corporate bond flows are correlated with GDP growth with opposite signs.

Our third fact is on the role of sovereigns.[10] In response to country-specific slowdowns, private and public inflows respond in opposite directions—a fact driven by emerging markets' sovereigns. While inflows to private sector decline, the sovereigns behave in a countercyclical manner by borrowing more from abroad and drawing down reserves in response to economic downturns in emerging markets. Another way to put these results is that advanced country sovereign's inflows are acyclical and emerging market sovereigns' inflows are countercylical with respect to own business cycles. Hence, public debt inflows seem to do most of the risk sharing when private debt markets collapse in emerging markets during recessions.

Our fourth fact is about the global shocks. In response to adverse global credit supply shocks, such as an increase in the VIX, inflows to domestic banks and corporates decline, while domestic banks and corporates invest less abroad, decreasing their outflows. Sovereigns do not respond to such supply shocks on average since our regressions condition on countries' own business cycle.[11,12]

[10] Aguiar and Amador (2011), Gourinchas and Jeanne (2013), and Alfaro, Kalemli-Özcan, and Volosovych (2014) separate public and private flows at an annual frequency. However, all these studies focus on *net* flows. These papers show, net capital might be flowing out of a country in the aggregate (i.e., the country may run a current account surplus), but one of the two sectors considered might still be engaging in net borrowing.This can also be the case for a particular asset class (capital flow type) instead of the borrowing sector. See, for example, Ju and Wei (2010), who show that FDI can flow in on net and reserves can flow out on net, generating two-way capital flows.

[11] Other investment debt inflows to emerging market sovereigns do respond positively and significantly to the VIX, but not their total debt inflows.

[12] Unconditional correlations of VIX with aggregate capital inflows, shown in Appendix B.6, deliver similar results in terms of sign of the relationship but different results in terms of size and significance. Two main differences driving this are the use of cross country variation in the panel regressions instead of aggregates in the unconditional correlations, and controlling for domestic GDP growth in the regressions. The correlations show that all private debt flows (that is, inflows to banks and corporates in both portfolio debt and other investment debt) are negatively correlated with global risk appetite, as measured by the VIX. By contrast, inflows to sovereigns are positively correlated with the VIX. Rey (2013) uses quarterly BOP data and shows that across all

These four facts are inconsistent with standard international macroeconomic models, which treat domestic and foreign investors symmetrically. In those models, all agents respond to a boom in the domestic economy by investing more in the domestic economy and vice versa for a bust. For global shocks, again, since all countries are affected, there is no difference in the way domestic and foreign agents respond to global shocks. Our results imply that foreign and domestic investors behave differently in response to domestic and global shocks, where our measure of "investors" are sectors such as banks, corporates and the public sector.

The rest of the paper is organized as follows: Section 3.2 describes the construction and coverage of our data; Section 3.3 illustrates descriptive patterns; Section 3.4 presents the results from our empirical analysis; and Section 3.5 concludes.

3.2 A New Dataset for Capital Flows Research

3.2.1 Data Construction

What is commonly called "gross flows" in the literature is actually more accurately described as "net inflows" and "net outflows". Net inflows are gross liability flows, net of repayments. Net outflows are gross asset flows, net of disinvestment. Capital flows data found in the BOP, which is based on residency

geographic regions, portfolio equity, portfolio debt, and other investment debt are all negatively correlated with the VIX. Nier, Sedik, and Mondino (2014) and Forbes and Warnock (2012) find similar results to Rey.

principle, conform to this definition. Thus, although these measures are often called "gross", they can be positive or negative. The separation of flows into asset and liability flows allows interpreting liability flows as net inflows from foreign agents, and asset flows as net outflows by domestic agents. This is the primary working definition of capital flows, which we use across all data sources for consistency.[13]

The focus of this paper is on the differentiation of capital flows by sector in the domestic economy. The term "sector" is used here to refer to institutional sectors: general government, central banks, depository corporations except the central bank ("banks"), and other sectors ("corporates").[14]

To build our dataset, we combine and harmonize several publicly available sources: Balance of Payments (BOP) and International Investment Position (IIP) statistics of the International Monetary Fund (IMF), Locational Bank Statistics (LBS) and Consolidated Bank Statistics (CBS) from Bank for International Settlements (BIS), International Debt Securities (IDS) from BIS, Quarterly External Debt Statistics (QEDS) of IMF and World Bank (WB), and Debt Reporting System (DRS) data of WB.[15]

Our base dataset is the Balance of Payments (BOP) data produced by the

[13]See Section B.1 in the appendix for more discussion about the definitions and terms associated with the capital flow literature and capital flow data.

[14]It should be noted that the BOP category "other sectors" is broader than what is captured than the term "corporates". Nevertheless, in most cases, there is fairly broad overlap between the two categories. That is why, in the rest of this paper, we use the two terms interchangeably for presentational convenience.

[15]It should be noted that, even though combining different data sources to complement BOP/IIP statistics is rarely done at the global level, this is exactly what many country-level BOP/IIP compilers do on a regular basis (e.g. many country BOP/IIP compilers use the BIS IBS data series on banks' cross-border deposit liabilities to the residents of their respective countries in order to enhance their BOP/IIP compilation).

IMF, which is the most comprehensive dataset on international capital flows. This data is reported to the IMF by country statistical offices. The BOP data captures capital flows into and out of a country. The accompanying stock measures of external assets and liabilities are captured in the IMF's International Investment Position (IIP) data. Capital flows are measured as asset flows (outflows), liability flows (inflows), and net flows. We focus on the financial account portion of the data and the BPM6 version. More details on the BOP data, along with its different presentations and versions, are given in Appendix B.2.[16]

In theory, each type of capital flow can be disaggregated by sector (borrower and lender type). In practice, however, the coverage tends to be sparse, especially for EM/developing countries and earlier years. To be absolutely clear, capital flow types (asset classes) are generally very well reported in aggregate terms in the BOP data, and the reporting of the sectoral breakdowns has improved in recent years. Nevertheless, for most emerging/developing countries and years before 2005 the reporting of the data by sector is much less exhaustive.

Figure 3.3 illustrates the structure of the BOP data. In simple terms, capital flows in the BOP are split into three main categories: direct investment, portfolio investment, and other investment.[17] Each of these categories can be split into debt and equity components. For portfolio investment debt and equity and other investment debt, the flows can be further subdivided by domestic sector: banks, corporates, government, and central bank. Other investment debt can also be

[16]See the 6th Edition Balance of Payments Manual Appendix 8 for more details on the differences between BPM5 and BPM6.

[17]Other categories include reserves (asset flows to the central bank) and financial derivatives (small and sparsely reported, previously a part of portfolio investment).

decomposed by instrument (loans, currency and deposits, trade credit and advances, and other accounts payable/receivable[18]) and then by sector.

To construct our capital inflows dataset, we start with BOP data by sector, and incorporate data from the BIS and the WB on external bond and loan flows to expand the limited quarterly sectoral coverage available in the BOP.[19] We similarly construct our dataset for outflows, and incorporate data from the BIS to complement coverage for portfolio debt and other investment debt outflows.

We undertake a "filling" exercise to complete the missing sectoral data on debt inflows in the BOP. Assuming missing data is zero may or may not be accurate depending on the country under consideration, so we fill missing values with data from other sources.[20] We start by identifying the appropriate variables from the BOP data. This is not as easy as it sounds since, unfortunately, in the public download of the BOP data the sector breakdown of other investment debt category is shown under other investment equity category.[21]

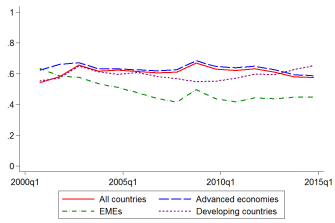
[18] Another instrument, insurance and pensions schemes, is also detailed, though it is very small and sparsely reported.

[19] The IMF's Coordinated Investment Portfolio Survey (CPIS) database also reports data on sectoral breakdowns for portfolio equity and portfolio debt flows. However, these breakdowns are available only since 2013 and, more importantly, the CPIS does not have data on other investment debt flows.

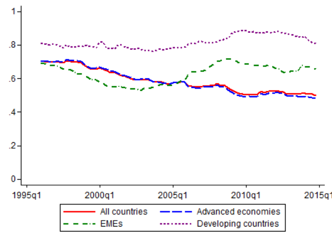
[20] It is difficult to distinguish missing from a true zero in the BOP data.

[21] In the public download of the BOP data, available from the IMF's website, the variables for other investment debt by sector are mislabeled, and so may be difficult to find. They are labeled as "...Other Investment, Other Equity..., Debt Instruments, ...". For example, the full label for other investment debt for Other Sectors (which we refer to as "Corporates") is "Financial Account, Other Investment, Other Equity, Net Incurrence of Liabilities, Debt Instruments, Other Sectors, US Dollars". The letter codes (EDD2 Codes) for these variables are BFOLOO_BP6_USD, BFOLOGFR_BP6_USD, BFOLODC_BP6_USD, and BFOLOCBFR_BP6_USD. On the asset flow side, these variables are BFOADO_BP6_USD, BFOADG_BP6_USD, BFOADDC_BP6_USD, and BFOADCB_BP6_USD.In reality, other investment equity (which is usually very small) is the only category within other investment that is not split by borrowing sector. We thank Gian-Maria Milesi-Ferretti and IMF Statistics for helping us uncover this.

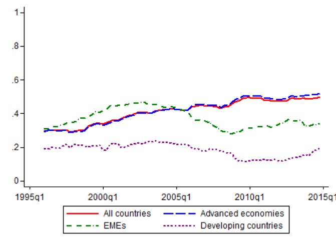
Figure 3.1: Composition of External Debt Liabilities: Share by Sector



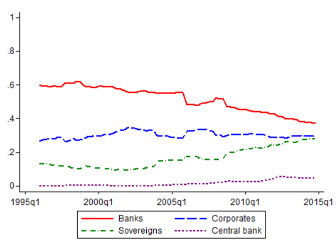
(a) Share of Debt in Total Stocks



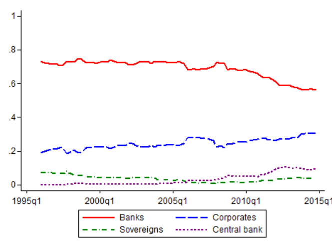
(b) Share of Other Investment in Total Debt Stocks



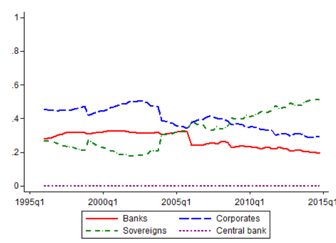
(c) Share of Portfolio Debt in Total Debt Stocks



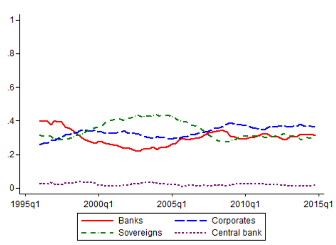
(d) Share of Sectors in Total Debt - Advanced



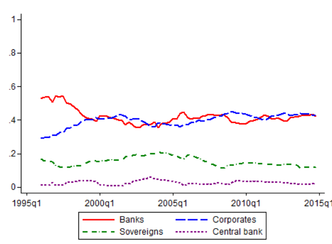
(e) Share of Sectors in Other Investment Debt - Advanced



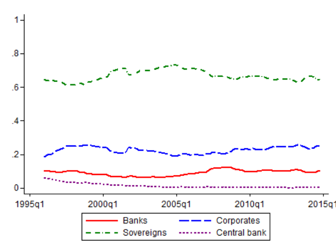
(f) Share of Sectors in Portfolio Debt - Advanced



(g) Share of Sectors in Total Debt - Emerging



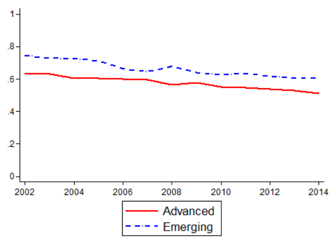
(h) Share of Sectors in Other Investment Debt - Emerging



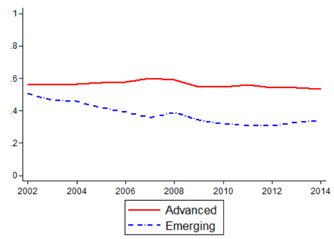
(i) Share of Sectors in Portfolio Debt - Emerging

Source: IIP, QEDS, and BIS, authors' calculations.

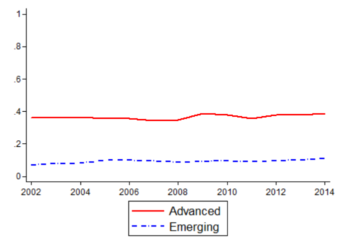
Figure 3.2: Composition of External Debt Assets: Share by Sector



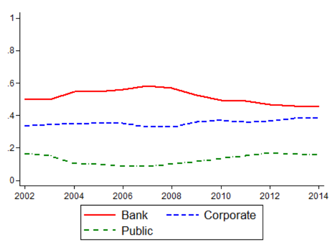
(a) Share of Debt in Total Asset Stocks



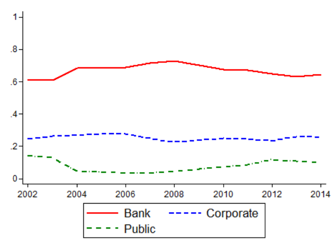
(b) Share of Other Investment Debt in Total Debt Assets



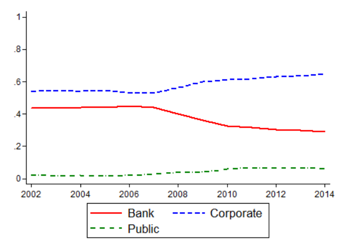
(c) Share of Portfolio Debt in Total Debt Assets



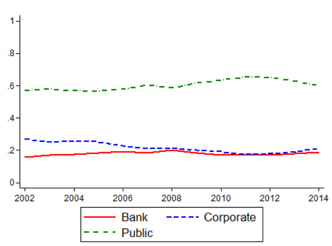
(d) Sector Shares of Total Debt Assets - Advanced



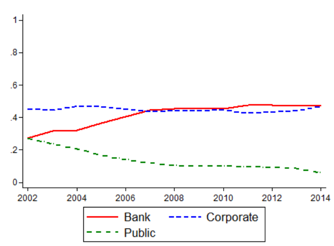
(e) Sector Shares of Other Investment Debt Assets - Advanced



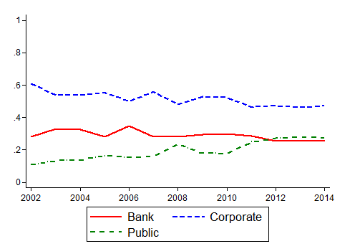
(f) Sector Shares of Portfolio Debt Assets - Advanced



(g) Sector Shares of Total Debt Assets - Emerging



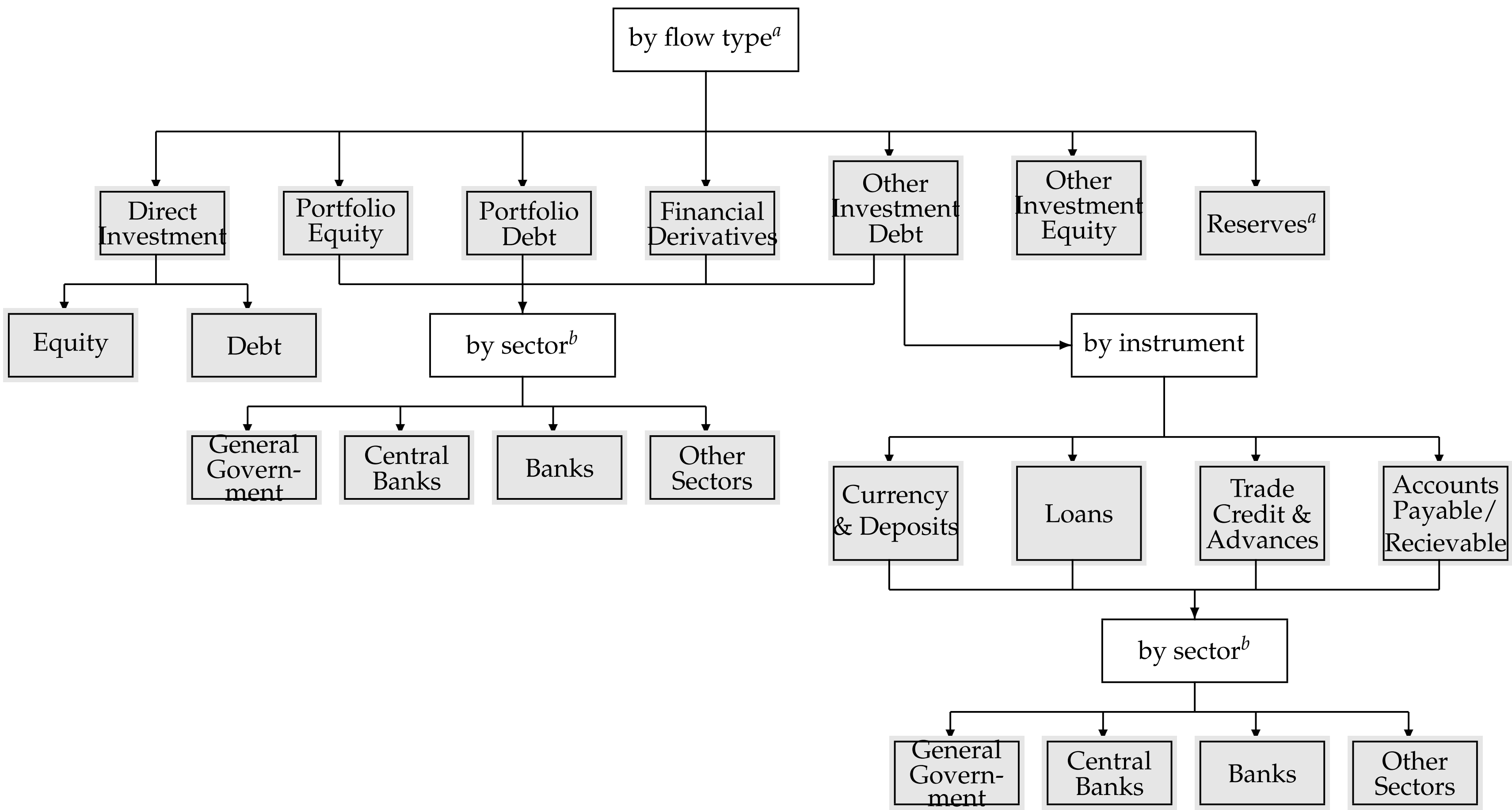
(h) Sector Shares of Other Investment Debt Assets - Emerging



(i) Sector Shares of Portfolio Debt Assets - Emerging

Source: IIP and BIS, authors' calculations. Total Debt includes official reserves. Note that Norway is dropped from the asset sample due to lack of stock data.

Figure 3.3: BOP Data Structure



[a] This structure is the same for inflows and outflows. Reserves are only classified as outflows.
[b] The breakdowns of these variables by sector exist in the BOP data but the coverage is sparse for many countries and quarters.

Other investment debt flows are important since the vast majority of external bank flows are in this category.[22] Crucially, this category also includes some cross-border loans to corporates and loans to sovereigns, such as IMF credit.[23] In most countries, sovereigns tend to borrow externally primarily via bonds, which appear under the portfolio debt category. When bond financing to emerging market borrowers, including governments, dries up, emerging market sovereigns rely more on loans.[24]

In order to get a larger, longer, and balanced panel of countries with debt flows split by sector, we proceed with the following methodology for our data filling exercise. When the BOP data reports the total for the category and reports data for 3 out of the 4 sectors, we take the total and subtract the 3 reported sectors in order to obtain the fourth sector. If there is still missing data, we construct measures of portfolio debt and other investment debt inflows by sector from several alternative datasets.[25] One such dataset is the data from BIS on debt securities issued in international markets, which we use to fill in portfolio debt flows. Another one is the BIS dataset on cross-border banking, which we use to fill the missing data under other investment debt.[26] Here, we only use loan lending by

[22] Milesi-Ferretti and Tille (2011) and Cerutti et al. (2015) separate out the banking sector within other investment debt category to investigate this category on its own.

[23] Other studies examining gross capital inflows using only BOP data sometimes exclude official reserves and IMF credit in order to focus on private inflows (see Forbes and Warnock (2012), Bluedorn et al. (2013), and Milesi-Ferretti and Tille (2011) for example). Milesi-Ferretti and Tille (2011) additionally exclude central bank loans and deposits. Bluedorn et al. (2013) analyze private flows by removing from reserves, IMF credit, and most government-related components included under the other investment debt category from total flows.

[24] Figure B.1 in Appendix B.6 shows that this is the case during the global financial crisis.

[25] The capital flight literature also uses techniques of internal filling with the BOP and external filling with other datasets in order to identify unreported private capital flows. See Chang, Claessens, and Cumby (1997) for a discussion. See also Claessens and Naudé (1993).

[26] Note that it takes a few steps to construct estimates by sector from the BIS loan data. We

BIS reporting banks, so as not to capture direct investment flows or debt securities holdings.[27,28] We then complement these loans with any other non-missing data from the BOP for particular instruments within other investment debt (trade credit, IMF credit, etc.) to get a more complete and accurate measure of other investment debt flows for each sector.[29,30]

While the BIS data has extensive coverage and captures a vast amount of capital flows, in some cases it may not match well with the BOP data.[31] In these cases, we rely first on measures derived from IIP, produced concurrently with the BOP data by the IMF, and the Quarterly External Debt Statistics (QEDS) data, produced jointly by the IMF and World bank. These data have the same sectoral and capital flow definitions and breakdowns, making them comparable to the BOP data. These are stock measures, which we first difference with a simple currency adjustment to approximate flows. While imperfect, these stock derived

detail this process in the Appendix. The BIS bank data captures the overwhelming majority of cross-border banking activity (BIS, 2015), but some banking flows between non-BIS reporting EM may not be captured (e.g. Chinese banks lending to Nigeria, etc.).

[27]Debt security flows would already be captured in portfolio debt (or the equivalent filling series). In principle, there could be an overlap between "direct investment debt" series and the "BIS loans" series if the loan is from a BIS reporting bank to an offshore non-financial entity in which it has at least a 10% ownership stake. In practice, we expect this to be small.

[28]A few AEs have had some discrepancies between the BOP data and the BIS Bank data, in particular Japan, Switzerland, and the US. These are isolated cases that are well known. We make sure to use BOP data, which is generally well reported for these cases, and other data sources first to avoid these issues.

[29]It is almost always the case that when the total is missing, the underlying instruments are also missing, except for perhaps IMF credit.

[30]In some cases, the flows for other investment debt, by sector or for total, is reported as coming from just one instrument (usually loans) even though in reality it reflects flows from other instruments as well (e.g. trade credit). So, summing these instruments can capture the proper total in some cases (this almost always not necessary since other investment debt itself is reported when the underlying instruments have non-missing data). We thank Gian-Maria Milesi-Ferretti for bringing this to our attention.

[31]An important example is advanced economy government bonds, which are issued domestically and then traded abroad. These flows would not be captured by the BIS debt securities data, which captures bonds that are issued in international markets.

measures often line up very well with reported BOP data and allow us to be more accurate as we fill missing data.

We deflate GDP and all capital flows to 1996 USD and express them in billions.[32] Additionally, we construct accompanying stock measures of external debt by sector. Here, we rely first on the IIP data as the main source. When this is missing after the internal fill, we rely on QEDS data on external debt by sector. We fill any remaining observations with our BIS estimates.

A detailed description of the datasets and our construction of the estimates to fill missing data can be found in the Appendix. Here, we briefly illustrate the validity of our approach. To gauge how well our estimates capture the true inflows, we undertake a counterfactual exercise. We take a sample of countries where BOP data by sector is non-missing over 2006q1-2013q4. Then we compare this data to our estimates done for this period as if the BOP data was missing. Then, for each country group, we plot the aggregate flows for each sector and capital flow type using non-missing BOP data, and our constructed estimates. Figures B.1 and B.2 in Appendix B.4 report these plots for both other investment debt flows and portfolio debt flows for each sector. The match is pretty strong and speaks to the quality of our constructed estimates to fill missing data over the entire sample. The correlation between the two series is over 98 percent. On the whole, our filled series capture most of the volume and variation of inflows for most countries and allow us to extend substantially the coverage of our sample.

[32] Quarterly GDP data is from Datastrem and national sources. We deflate series using US CPI from FRED.

There are few important details to note. We remove exceptional financing flows to banks and corporates, within portfolio debt and other investment debt, and reassign them to the central bank. Exceptional financing captures financial flows made or fostered by the authorities for balance of payments needs. Thus, they can be seen as a substitute for reserves or IMF Credit.[33]

Direct investment contains both debt and equity flows and is split by debt and equity components in the BOP data. However, it is not disaggregated by sector in the BOP data. Nevertheless, debt flows between related enterprises are recorded as direct investment debt only when at least one counterparty is a non-financial firm. Direct investment debt flows between two financial firms (including banks) are instead classified as either portfolio investment debt or other investment debt. If direct investment debt flows from non-financial firms to financial firms are negligible, then we can think all direct investment debt as flows either from financial firms to non-financial firms or flows from non-financial firms to non-financial firms. In either case, the borrowing sector is the non-financial sector and hence direct investment debt inflows can be assigned in full to the debt inflows of the corporate sector. We include direct investment debt in total debt in our regression analysis of inflows, while more particular detail of the contribution of direct investment debt is discussed in Appendix B.6.3.

To complement our extensive dataset on capital inflows, we also construct a dataset of capital outflows. As with the inflows, we primarily use the BOP data. We combine the general government and central bank sectors into a single public

[33]See the 6th Edition BOP Manual, paragraph A1.1.

sector. As before, we do an internal fill on missing sectors if the remaining two sectors and the total are non-missing.[34] The one external fill that we do is for the bank sector. We fill in portfolio debt asset flows and other investment debt asset flows using the BIS LBS by residency data which has data on bank cross-border claims in each instrument. This data only covers banks domiciled in BIS reporting countries, and so is more limited in terms of coverage.

3.2.2 Coverage of the New Dataset

We divide the countries into three groups by level of development: Advanced, Emerging, and Developing.[35] See Appendix B.5 for specific details about the countries. For reference, our primary sample of capital inflows using the annual data consists of the following 89 countries:

Advanced (25): Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States

Emerging (34): Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Czech Republic, Egypt, Estonia, Hungary, India, Indonesia, Jordan, Kazakhstan, Latvia, Lebanon, Lithuania, Macedonia, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, South

[34] Note that combining government and central banks into a single sector makes the internal filling exercise more fruitful, as only bank and corporates needs to be non-missing in order to fill missing data for the public sector.

[35] We rely on the 2000 IMF WEO classification to define the group of advanced economies. Generally, the WEO does not divide emerging and developing countries into separate groups. We use the MSCI and IEO-IMF classifications to guide the definition of our EM group.

Africa, Thailand, Turkey, Ukraine, Uruguay, Venezuela

Developing (30): Albania, Angola, Bangladesh, Belarus, Bolivia, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, El Salvador, Gabon, Ghana, Guatemala, Jamaica, Kenya, Liberia, Mongolia, Montenegro, Morocco, Namibia, Nigeria, Pakistan, Papua New Guinea, Paraguay, Serbia, Sri Lanka, Sudan, Trinidad and Tobago, Tunisia, Vietnam

At the quarterly frequency, our sample drops to 85 countries, leaving off El Salvador, Mongolia, Montenegro, and Serbia. For the regression and correlation analysis below where we use quarterly GDP, our sample is further limited due to unavailability of quarterly GDP for many emerging/developing countries.

The outflow sample consists of 31 countries (15 advanced, 16 emerging) at a quarterly frequencey spanning 2004q1-2014q4. For the annual data, we have 31 countries (13 advanced and 18 emerging) spanning 2002-2014. Details on the sample are in Appendix B.5.

Table 3.1 illustrates the impact of our data filling exercise on sample coverage for inflows. For each capital flow type, sector, and country group, the table shows the percentage of observations in our balanced panel that come from the raw BOP data, from our internal filling procedure, and from our filling from external data sources. Generally speaking, developing countries, central banks, and portfolio debt tend to have less data available in the original BOP. Our internal filling procedure makes a large difference for the coverage of central banks, but otherwise does not provide many more observations for portfolio debt and/or developing countries. Our external filling procedure, on the other hand, makes a large difference, especially for the quarterly data, where 25-40 percent of observations for EM and 75-90 percent of observations for developing countries that were missing under portfolio debt are filled. In the case of other investment debt, only 11 percent of observations are filled for EM, but for developing countries 40-50 percent of observations are filled. A sizeable number of observations are filled by external data also for advanced economies: 20-30 percent for portfolio debt observations, and 15-18 percent of other investment debt.

Our filling exercise has a dramatic impact on the time and country coverage of the data. A balanced sample requires that portfolio debt and other investment debt not be missing for any of the 4 sectors in any period. With 8 components required to be non-missing in each period, the probability that at least one is missing is high. With no adjustments to the BOP data, we have 0 countries in our sample (12 in the annual data). After our internal BOP fill, our sample of countries increases to 10 (16 in the annual data). After incorporating the IIP, BIS, and QEDS data, our balanced sample increases to 85 countries (89 in the annual data). Given the advantages of a balanced country sample for cross-section and panel regression analysis, the impact of our data filling on sample size can be very consequential.

Figure 3.4 compares aggregate inflows as measured by our filled data and from the BOP alone, for total external debt for banks and corporates in our samples of AE and EM. We plot annual flows here for clarity. These graphs show that generally both series tell the same story, but there are periods in which accounting for the missing data makes a significant difference. For advanced economy

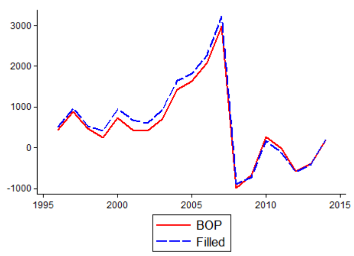
Table 3.1: Data Filling Summary

			Annual			Quarterly		
Flow	Sect.	Group	BOP	Int. Fill	Ext. Fill	BOP	Int. Fill	Ext. Fill
PD	GG	Adv.	80.6	0.0	19.4	79.4	0.0	20.6
PD	GG	Em.	82.4	0.3	17.3	74.2	0.8	25.0
PD	GG	Dev.	40.2	0.7	59.1	25.0	0.1	74.9
PD	CB	Adv.	9.5	58.3	32.2	7.5	60.5	32.0
PD	CB	Em.	23.5	40.6	35.9	19.5	35.6	44.9
PD	CB	Dev.	11.2	8.2	80.5	2.6	4.8	92.7
PD	DC	Adv.	67.6	3.6	28.8	67.7	3.4	28.8
PD	DC	Em.	61.7	4.1	34.3	55.6	3.5	40.9
PD	DC	Dev.	18.6	1.6	79.8	10.3	0.7	89.0
PD	OS	Adv.	75.4	0.0	24.6	74.7	0.0	25.3
PD	OS	Em.	69.8	2.3	28.0	64.4	1.9	33.6
PD	OS	Dev.	29.3	0.5	70.2	13.3	0.3	86.5
OID	GG	Adv.	80.0	2.1	17.9	78.4	3.2	18.4
OID	GG	Em.	93.7	0.8	5.6	88.1	0.9	11.0
OID	GG	Dev.	87.7	0.0	12.3	49.7	0.0	50.3
OID	CB	Adv.	68.2	13.9	17.9	65.8	15.4	18.7
OID	CB	Em.	87.4	6.6	6.0	79.2	9.8	11.0
OID	CB	Dev.	74.6	13.3	12.1	46.0	6.7	47.3
OID	DC	Adv.	81.9	0.0	18.1	81.4	0.0	18.6
OID	DC	Em.	94.0	0.0	6.0	89.0	0.0	11.0
OID	DC	Dev.	77.7	6.1	16.1	48.0	1.8	50.2
OID	OS	Adv.	84.0	0.4	15.6	82.8	0.1	17.2
OID	OS	Em.	94.4	0.0	5.6	89.0	0.0	11.0
OID	OS	Dev.	88.4	1.1	10.5	52.5	0.7	46.8
Balanced Sample			12	16	89	0	10	85

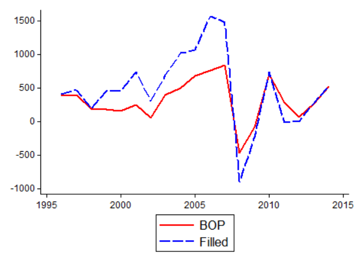
This table displays the percentage of total observations in our final sample of Advanced (Adv.), Emerging (Em.) and Developing (Dev.) countries (89 for annual, 85 for quarterly) that is derived from each step of our data construction. BOP = Percent coverage of sample from raw BOP data; Int. Fill = Percent coverage of sample from Internal Filling exercise; Ext. Fill = Percent coverage of sample from non BOP data sources. OID = other investment debt; PD = portfolio debt; GG = General Government; CB = Central Bank; DC = Banks; OS = Corporates. The last line indicates the number of countries in our balanced sample 1996 to 2014 that we have data for each sector non-missing.

corporates, a significant expansion leading up to the 2008 crisis and a contraction following it is missed. This is due primarily to filling in portfolio debt data for the US and Spain for the 2008 surge, as well as a few other AE for the earlier 2001 peak. For EM, both banks and corporates had much larger flows relative to the BOP measure following the 2008 collapse, driven primarily by filling data for other investment debt inflows for China.

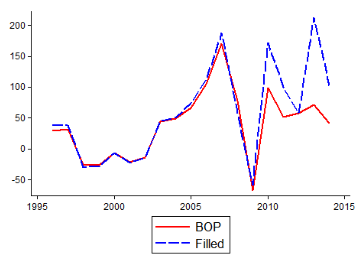
Figure 3.4: Aggregate External Debt Inflows for Banks and Corporates, Billions 1996 USD



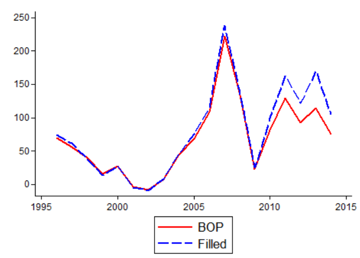
(a) Advanced Bank



(b) Advanced Corporate



(c) Emerging Bank

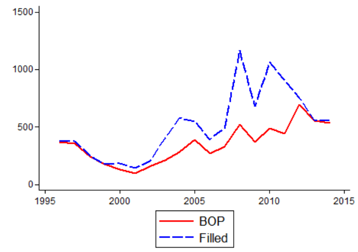


(d) Emerging Corporate

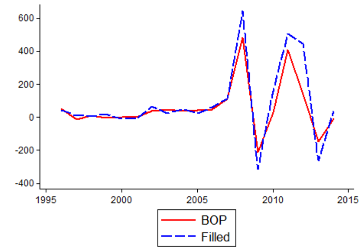
Source: BOP, IIP, QEDS, and BIS, authors' calculations. Debt is portfolio debt + other investment debt. BOP series is only BOP data, Filled is BOP data filled by other data sources when missing.

Figure 3.5 plots total external debt inflows for government and central bank sectors. Missing U.S. government portfolio debt drives the difference for the AE in panel (a). Emerging market governments and advanced central banks are fairly well represented in terms of volume. Note that net inflows can be negative

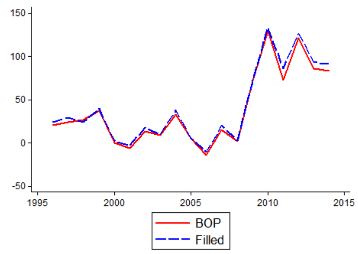
Figure 3.5: Aggregate External Debt Inflows for Governments and Central Banks, Billions 1996 USD



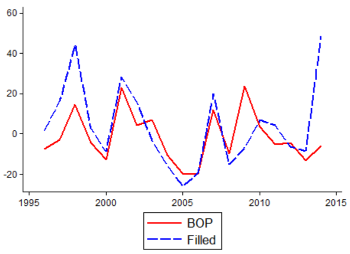
(a) Advanced Government



(b) Advanced Central Bank



(c) Emerging Government



(d) Emerging Central Bank

Source: BOP, IIP, QEDS, and BIS, authors' calculations. Debt is portfolio debt + other investment debt. BOP series is only BOP data, Filled is BOP data filled by other data sources when missing.

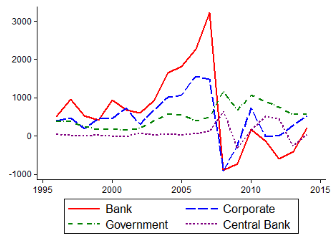
as well as positive, which is the case for emerging market central banks where some missing data consists of negative net inflows, which brings our filled data below the raw BOP total. The surge at the end of the sample for emerging market central banks is driven by China.

Our dataset captures a large volume of capital inflows by sector that may otherwise be missed. Additionally, our data increases the number of both large and small countries with debt inflow data by sector over a long time horizon at the quarterly frequency.

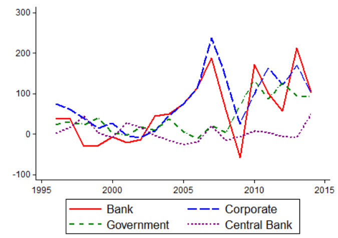
3.3 Descriptive Patterns in the Data

In this section, we present patterns and trends observed in our data over time. We use the annual version of the dataset for clarity in the figures.

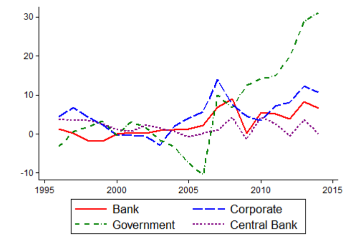
Figure 3.6: Aggregate External Debt Inflows, Billions 1996 USD



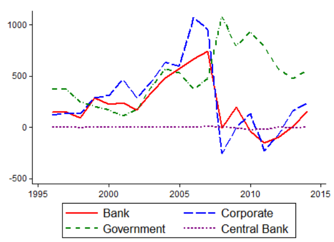
(a) Total Debt, Advanced



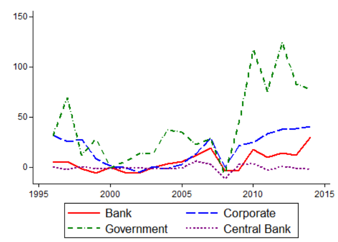
(b) Total Debt, Emerging



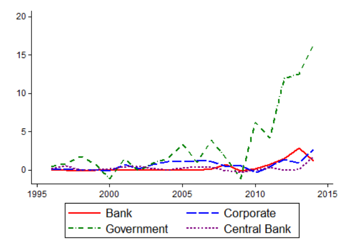
(c) Total Debt, Developing



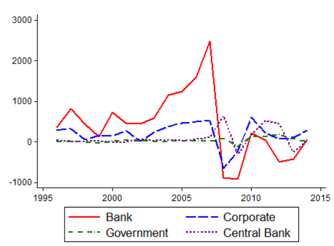
(d) Portfolio Debt, Advanced



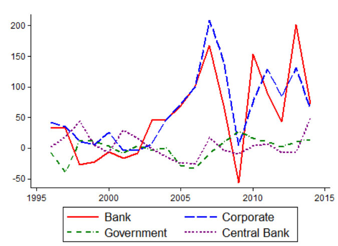
(e) Portfolio Debt, Emerging



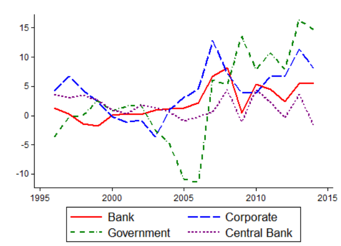
(f) Portfolio Debt, Developing



(g) Other Investment Debt, Advanced



(h) Other Investment Debt, Emerging



(i) Other Investment Debt, Developing

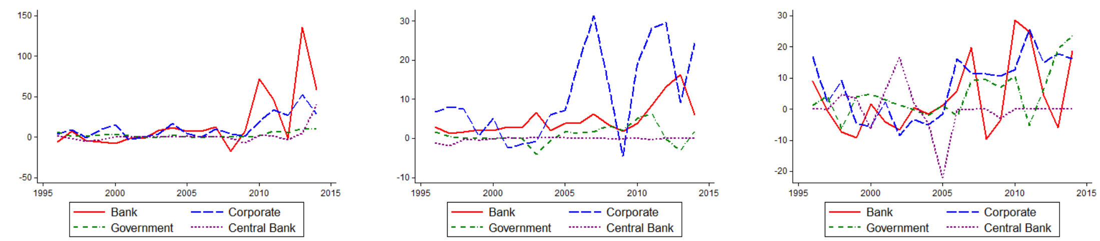
Source: BOP, IIP, QEDS, and BIS, authors' calculations. Total debt is portfolio debt + other investment debt.

Figure 3.6 (a)-(c) plots the aggregate debt inflows by sector for each country group. The buildup and collapse surrounding the 2008 financial crisis (or global financial crisis, GFC) is the most striking feature in all of these figures. An interesting distinction between AE and EM is the response following the crisis. While advanced country flows collapse and remain fairly low, flows to emerging and developing countries rebound and increase across all sectors. An important difference in flows by sector is in the evolution of debt inflows to governments. Across all country groups, governments see an increase in debt inflows precisely when private flows collapse, with an especially large and sustained increase for developing nations relative to their private flows. Advanced-country central banks also see a small increase as private flows collapse.

Panels (d)-(i) plot portfolio debt and other investment debt flows. We see that the increase in inflows for governments comes primarily in the form of bonds, with the exception of developing country governments who also see an increase in other investment debt funding, that is loans. Advanced economy corporates also have a significant amount of their inflows coming from portfolio debt. Although emerging market banks and corporates see an increase in bond flows in the wake of the GFC, the aggregate pattern of their flows is driven primarily by other investment debt. Advanced country banks get the lion's share of capital inflows prior to 2008, the majority of which is in the form of other investment, but they see consistent negative net inflows for several years following the GFC reflecting the deleveraging of these institutions. Developing country banks and corporates are also primarily receiving inflows in the form of other investment debt.

Much of the increase in emerging-market private debt after 2008 is attributable to a few large EM. Foremost among these is China, whose debt inflows are shown

Figure 3.7: Emerging Market External Debt Inflows, Billions 1996 USD



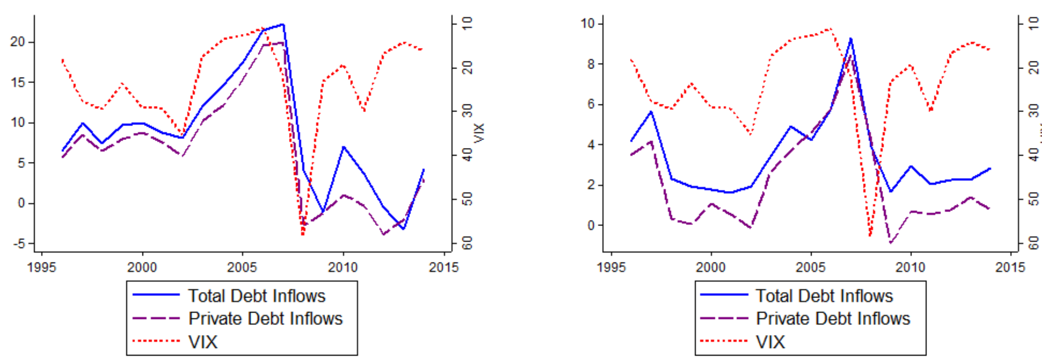
(a) China Debt (b) India Debt (c) Brazil Debt

Source: BOP, IIP, QEDS, and BIS, authors' calculations. Debt is portfolio debt + other investment debt.

in Figure 3.7. China is a large country with poor sector coverage in the BOP data, so much of the measured effect is derived from our data filling series. Both bank and corporate inflows increase substantially, but bank inflows to China have been much larger. In India, the corporate sector has been the dominant recipient of debt flows, though bank flows increased a lot after 2010. Brazil saw a sustained increase in corporate debt inflows, and volatile increases in bank and government flows.

The finding that public sector inflows increase when private inflows are falling is an important pattern that complements existing work on public vs private net flows (Aguiar & Amador, 2011; Alfaro, Kalemli-Özcan, & Volosovych, 2014; Gourinchas & Jeanne, 2013). The public sector is often able to borrow from abroad even as such funding dries up for the private sector. Thus, the public sector acts as a countervailing force to the private sector, smoothing the total debt inflows into the country. Thus far our figures have plotted aggregate flows, but figures showing the dynamic patterns of average flows to GDP are shown in Appendix B.6. Figure 3.8 illustrates the impact of the public sector for an average country using the average of flows to GDP. It plots the cross-country average of total debt flows (portfolio debt + other investment debt) to GDP as compared to flows from just the private sectors (Banks and Corporates) for advanced and emerging countries. The VIX is shown in red (right axis), for reference. For advanced economies, the steep fall in private inflows after the global financial crisis is mitigated by a few years of substantial government borowing from abroad. These public inflows disappear by 2014, where private flows recover. For EM, the story is more pronounced. The crash in total capital flows is much less than that of private capital flows, reflecting increased public sector debt inflows following the crisis. We see a similar pattern, that is more government borrowing when private sector flows had collapsed, during 1998–2002. As private flows recover heading towards 2008, the difference between total and private flows disappears.

Figure 3.8: Total vs Private Average Debt Inflows, Percent of GDP



(a) Advanced (b) Emerging

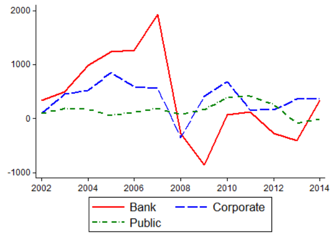
Source: BOP, IIP, QEDS, and BIS, authors' calculations.

Turning to outflows, Figure 3.9 plots the debt asset flows for a subset of 31 countries, defined in Appendix B.5, over 2002-2014. The public sector is the sum of central banks and general government sectors, and total debt asset flows for the public sector include the flow of reserves.

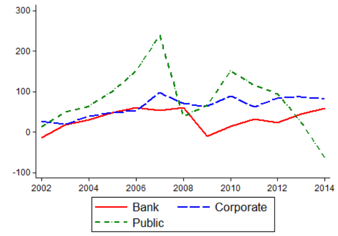
For advanced countries, we see the same pattern for total and other investment debt as we see with inflows, with the landscape of flows dominated by the buildup of private flows in the mid-2000s, led by the banking sector, followed by a sharp contraction at the time of the global financial crisis. The public sector plays a relatively small role for AE outflows. Portfolio debt outflows for AEs show a sharp contraction for banks at the time of the crisis, but there is actually an increase in external portfolio debt investment by the corporate sector, followed by a brief contraction corresponding more closely to the Eurozone crisis.

Emerging market banks and corporates show a contraction in their other investment debt outflows followed by a much stronger rebound than that seen in AEs. However, the decline in corporate other investment debt is offset by an increase in corporate portfolio debt outflows. EM public sector sees a drop in both portfolio and other investment outward investment around the crisis, but portfolio debt recovers robustly in the following years. However, public sector outflows, and total EM debt outflows, are clearly dominated by reserves, as seen in panel (b), with a large buildup and collapse mirroring the private sector inflow and outflows pattern.

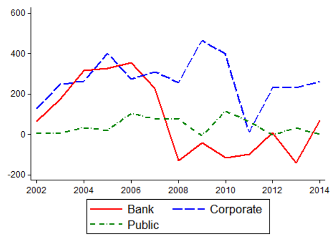
Figure 3.9: Aggregate Asset Flows, AHKS Outflow Sample, Billions USD



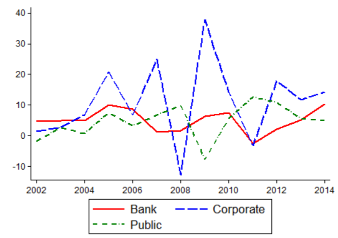
(a) Total Debt Asset Flows, Advanced



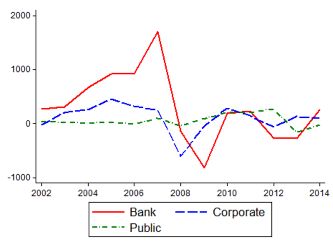
(b) Total Debt Asset Flows, Emerging



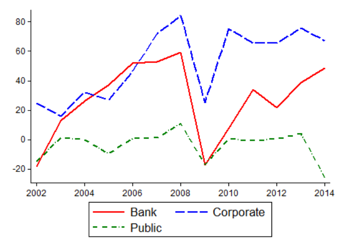
(c) Portfolio Debt Asset Flows, Advanced



(d) Portfolio Debt Asset Flows, Emerging



(e) Other Investment Debt Asset Flows, Advanced



(f) Other Investment Debt Asset Flows, Emerging

Source: BOP and BIS, authors' calculations.

3.4 Empirical Analysis

3.4.1 Comovement of Capital Inflows and Outflows

Table 3.2 presents correlations of inflows and outflows across sectors. These correlations are partial correlations of debt flows/country GDP, conditional on country fixed effects, lagged log of VIX, and lagged GDP growth.[36] The sample is our asset flow sample detailed in Appendix B.5, consisting of 31 countries (15 advanced and 16 emerging) over 2004q1-2014q4. The public sector consists of general government and central bank sectors. Debt is the sum of portfolio and other investment debt, and also reserves in the case of public sector outflows.

The strength of inflow-outflow correlation within the bank sector is striking. Even conditioning on GDP growth and VIX, which can drive capital flow behavior as we show below, banks still show a high degree of matching between their inflows and outflows. This is clearly the case in AEs, but banks are still the strongest positive correlation in EMs though with lower magnitude. Within sector correlations are also relatively high for corporates and banks relative to cross-sector correlations. Interestingly, inflows and outflows are always positively correlated regardless of sector, but the key to understanding the inflow-outflow comovement is the banking sector. All of the negative correlations in this table have to do with the public sector, either public inflows with private inflows or public outflows with private outflows. While small, except in the case of EM public outflow with bank inflow, these patterns reinforce the point that the public sector often behaves differently than the private sector.

Table 3.3 plots these correlations for AE and EM while distinguishing by instrument. The correlations are presented as a heatmap, with blue values indicating positive correlations, red values indicating negative correlations, and darker

[36]Unconditional correlations of aggregated inflows are presented in Appendix B.6, with unconditional aggregate inflow-outflow correlations in Table B.9.

shading indicating stronger correlations. Examining these heatmaps makes it clear to see that the strongest comovement at this disaggregation is among AE banks, particularly within other investment debt flows. Global banks' borrowing and lending patterns within their internal capital market combined with their hedging motives produce a strong correlation between capital inflows and outflows, especially for AE. Corporate other investment debt flows also appear to be highly correlated, while public sector inflows are broadly negatively correlated with other inflows.

Table 3.2: Correlation of Inflows and Outflows

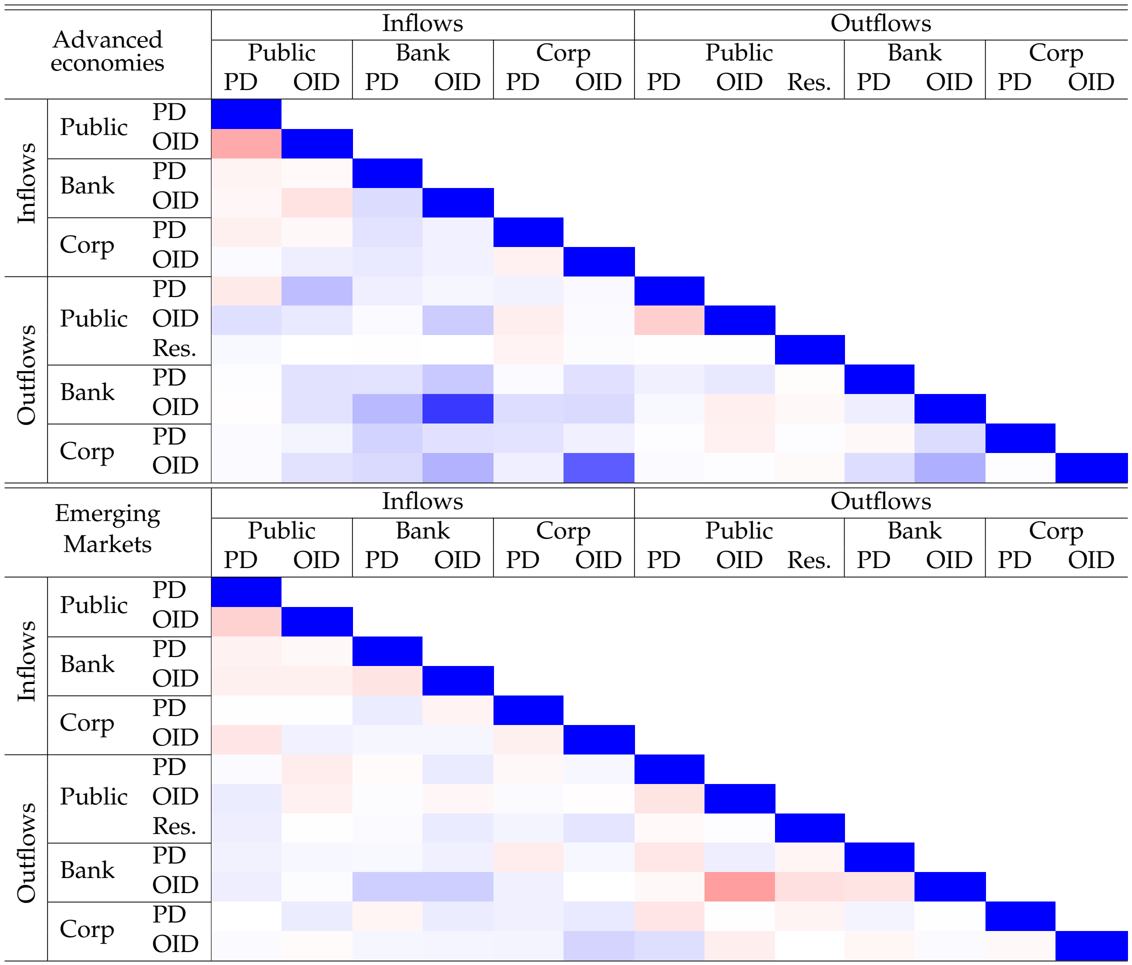
All Countries		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.10	1.00				
	Corp	0.04	0.10	1.00			
Outflows	Public	0.24	0.17	0.03	1.00		
	Bank	0.15	0.77	0.19	-0.08	1.00	
	Corp	0.14	0.33	0.50	-0.03	0.32	1.00

Advanced Economies		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.14	1.00				
	Corp	0.04	0.10	1.00			
Outflows	Public	0.27	0.20	0.01	1.00		
	Bank	0.14	0.81	0.21	-0.03	1.00	
	Corp	0.14	0.35	0.56	-0.02	0.34	1.00

Emerging Markets		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.08	1.00				
	Corp	-0.04	0.04	1.00			
Outflows	Public	0.23	0.18	0.11	1.00		
	Bank	0.08	0.27	0.02	-0.33	1.00	
	Corp	0.03	0.07	0.21	-0.04	0.01	1.00

Sample consists of 31 countries (15 advanced, 16 emerging) over 2004q1-2014q4, and is described in Appendix B.5. N=1408, 660, and 704 respectively for each panel. Correlations are conditional on country fixed effects, lagged log VIX, and lagged GDP growth.

Table 3.3: Correlation of Inflows and Outflows, by Instrument



Sample consists of 31 countries (15 advanced, 16 emerging) over 2004q1-2014q4, and is described in Appendix B.5. Correlations are conditional on country fixed effects, lagged log VIX, and lagged GDP growth. Blue indicates a positive correlation, red indicates a negative correlation, with darker shadings indicating stronger correlations.

EMs don't display correlations as strong as those of AEs at this disaggregation, but it is still easy to see that the strongest positive correlation is that of other investment debt outflows of banks with bank inflows. Corporate other investment debt flows show some correlation as well. An interesting feature of the emerging markets panel is that outflows of public other investment debt have a strong negative correlation with inflows of other investment to banks. This suggests that there is more to understand about the relationship between the banking sector and the sovereign, particularly when it comes to EM capital flows.

3.4.2 Panel Regressions: Capital Inflows by Sector

We next examine the response of capital inflows by sector to global risk apetite measured by the VIX (push factor) in conjunction with the business cycle properties of capital inflows, measured as the response of inflows to GDP growth (pull factor) in a panel regression setup with our quarterly data. We focus on a very simple specification to illustrate our results:

$$\frac{INFLOW_{it}}{GDP_{it}} = \alpha_i + \beta \log(VIX_{t-1}) + \gamma GDPGrowth_{it-1} + \epsilon_{it} \tag{3.1}$$

Our dependent variable is capital flows as a percent of GDP. $INFLOW_{it}$ is a measure of capital inflows for country i in quarter t. We examine inflows by capital flow type as well as by sector.[37] GDP_{it} is quarterly GDP from datastream and national sources. The dependent variables are capital flows expressed as a

[37] Regressions by capital flow type across all types, without splitting by sector, can be found in Table B.10 in the Appendix

percent of GDP. α_i is a country fixed effect. VIX_{t-1} is the implied volatility of S&P 500 index options, measured in logs. The VIX is often used as a measure of global risk aversion, and is a standard push factor for capital inflows, particularly in EM. $GDPGrowth_{it-1}$ is real GDP growth year-on-year for country i in the previous period, which is a standard pull factor attracting foreign capital to a particular country. Our standard errors are clustered at the country level. Using quarterly GDP data significantly restricts our sample along both country and time dimensions. We use a balanced sample, detailed in Appendix B.5 of 55 countries (23 advanced, 28 emerging, 4 developing) over 2002q4-2014q4.

For total debt inflows, we take direct investment debt (DID) and add it to corporate and total debt to obtain a more complete measure of debt inflows.[38] Table 3.4 shows our regressions on total debt inflows. Columns (1)-(4) in each panel are portfolio debt plus other investment debt, while columns (5)-(6) add direct investment debt to that total.[39] The public sector is the sum of government and central bank sector flows.

For the full set of countries in Panel A, total debt inflows respond negatively to increases inthe VIX. This response is driven by the private sector (banks and corporates), and holds (with larger magnitude) when DID is included in columns (5) and (6). The public sector's response to the VIX is positive, reflecting patterns shown in the aggregate data, but the response is not significant. Similarly

[38]Recall that with the assumption that direct investment debt flows from offshore non-financial firms to onshore banks are negligible, we can allocate direct investment debt to the corporate sector.

[39]Observations missing DID data over this time period, 2002q4-2014q4, are dropped in columns (5)-(6). See Appendix B.6 for more discussion of FDI and DID.

Table 3.4: Drivers of Total Debt Inflows, by Sector (Quarterly AHKS data, missing filled from Public Sources)

	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Public	Banks	Corp.	Total w/DI Debt	Corp. w/DI Debt
Panel A: All Countries						
$\log(\text{VIX}_{t-1})$	-4.974***	0.960	-4.362***	-1.572***	-5.744***	-2.003***
	(1.260)	(0.667)	(0.989)	(0.419)	(1.516)	(0.696)
GDP Growth_{it-1}	0.232***	-0.00864	0.190***	0.0501***	0.239***	0.0730***
	(0.0650)	(0.0146)	(0.0490)	(0.0156)	(0.0541)	(0.0164)
Observations	2695	2695	2695	2695	2615	2615
R^2	0.041	0.002	0.045	0.028	0.044	0.028
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Advanced Economies						
$\log(\text{VIX}_{t-1})$	-9.101***	0.813	-7.630***	-2.284**	-10.57***	-3.196
	(2.676)	(1.400)	(2.068)	(0.962)	(3.132)	(1.563)
GDP Growth_{it-1}	0.506***	0.0616	0.363**	0.0819	0.480***	0.101**
	(0.179)	(0.0340)	(0.131)	(0.0466)	(0.141)	(0.0420)
Observations	1127	1127	1127	1127	1109	1109
R^2	0.065	0.002	0.056	0.026	0.065	0.027
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: EM						
$\log(\text{VIX}_{t-1})$	-2.261**	1.077	-2.265***	-1.073***	-2.336**	-1.117***
	(0.829)	(0.652)	(0.706)	(0.253)	(0.922)	(0.374)
GDP Growth_{it-1}	0.116***	-0.0394***	0.118***	0.0381***	0.142***	0.0635***
	(0.0347)	(0.0123)	(0.0346)	(0.00928)	(0.0416)	(0.0161)
Observations	1372	1372	1372	1372	1310	1310
R^2	0.071	0.021	0.116	0.075	0.073	0.053
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

for GDP growth, the total and private sector respond positively to a domestic boom, while the public sector is mildly countercyclical and not significant in its response. This pattern is largely the same in Panel B for the AE countries, but with larger coefficients.

Inflows for EM countries in Panel C also follow a similar pattern. As the VIX rises or as GDP falls, total or private inflows fall. This is in contrast to total debt flows to the public sector, which run counter-cyclical to domestic growth and show a positive (though insignificant) coefficient on the VIX.[40] These results are the gross inflows analog to the results found in Alfaro, Kalemli-Özcan, and Volosovych (2014) for net debt flows. They show, using the DRS data explored in Appendix B.6, that net flows to public sector are counter-cyclical, due primarily to sovereign to sovereign flows, while debt flows to the private sector are procyclical. Our results thus complement theirs and contribute to our understanding of upstream gross capital flows together with net flows.

The global financial crisis (GFC) is a prominent feature in the landscape of capital flows, and it has generated a lot of discussion about how the nature of capital flows may have changed in its wake.[41] Tables B.11 and B.12 in Appendix B.6 show our regressions for total debt for advanced and emerging economies, split

[40]The results for total debt on GDP growth are robust to the inclusion of a time trend and other pull factors, as shown in Tables B.13 and B.14 in Appendix B.6. Results on the VIX are robust to the inclusion of a time trend and the TED spread, but significance drops with the inclusion of other factors capturing US monetary conditions, such as the federal funds rate and the slope of the yield curve. These results are also robust to measuring GDP growth as the differential growth over the advanced economy average growth. We show these results for total debt in Tables B.15 and B.16

[41]For instance, Cerutti, Claessens, and Ratnovski (2016) find using BIS data that the VIX is significantly associated with bank lending flows to the bank and non-bank sectors, and this was especially the case after the GFC. Shin (2013) highlights how bond flows to EM have increased after the GFC.

into pre-GFC (2002q4-2007q4) and post-GFC (2008q1-2014q4) periods. For advanced economies, flows are significantly associated with the VIX before the GFC with the expected negative sign, but after the crisis they are more strongly driven procylically by GDP growth.[42] EM similarly see a stronger connection to the VIX prior to the GFC and stronger connection to GDP growth after it, with the expected signs. Banking flows in EM move opposite to the VIX in both the pre and post GFC periods.

In Tables 3.5-3.6, we separately show regressions for other investment debt and portfolio debt. In Table 3.5, we see the standard results of a negative relationship with the VIX and a positive relationship with GDP growth for other investment debt inflows. However, public inflows have these signs reversed and do not exhibit significant relationships.

Examining advanced and emerging countries separately reveals more detail on these relationships. Looking at just advanced economies, Panel B shows the same results in the first 4 columns as in Panel A, with the exception that the coefficient on GDP growth for flows to the public sector is now positive.

Panel C shows these results for EM, which exhibit some unexpected features. Total other investment debt flows do not show a significant coefficient on the VIX, but this is because different sectors are pulling in opposite directions. While the public sector response to the VIX is not significant for total debt flows, column (2) reveals a positive and significant coefficient on the VIX, opposite the

[42] Avdjiev, Hardy, Kalemli-Özcan, and Servén (2017) similarly find that international bank lending became much less sensitive to global risk conditions following the crisis.

Table 3.5: Drivers of Other Investment Debt Inflows, by Sector (Quarterly AHKS data, missing filled from Public Sources)

Panel A: All Countries				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-3.814***	1.017	-3.645***	-1.186***
	(1.148)	(0.636)	(0.878)	(0.301)
GDP Growth$_{it-1}$	0.202***	-0.00423	0.166***	0.0397***
	(0.0459)	(0.0161)	(0.0380)	(0.00780)
Observations	2695	2695	2695	2695
R^2	0.035	0.002	0.043	0.022
CountryFE	Yes	Yes	Yes	Yes

Panel B: Advanced Economies				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-7.365***	0.287	-6.073***	-1.579**
	(2.380)	(1.269)	(1.817)	(0.672)
GDP Growth$_{it-1}$	0.360***	0.0304	0.294***	0.0353**
	(0.120)	(0.0490)	(0.0938)	(0.0159)
Observations	1127	1127	1127	1127
R^2	0.044	0.001	0.048	0.012
CountryFE	Yes	Yes	Yes	Yes

Panel C: EM				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-1.511	1.500**	-2.130***	-0.880***
	(0.875)	(0.704)	(0.719)	(0.213)
GDP Growth$_{it-1}$	0.140***	-0.0167	0.113***	0.0440***
	(0.0360)	(0.00855)	(0.0330)	(0.00917)
Observations	1372	1372	1372	1372
R^2	0.087	0.018	0.113	0.090
CountryFE	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Other Investment Debt inflow data is constructed by AHKS, as described in Section 3.2. Public inflows are defined as the sum of General Government and Central Bank inflows. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Column (5) of Panel A and Column (3) of Panel C use data solely from BOP, with missing data left unfilled. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

negative response of the private sectors (banks and corporates). Note that while other investment debt is usually not the primary form of financing for the public sector, it can account for an important share at times, including IMF credit and other official flows. Thus at least along some margins, the public sector does indeed respond opposite to the private sector in response to external shocks. For GDP growth, total, banks, and corporates have a positive relationship, but flows to the public sector show a negative and insignificant coefficient.

Table 3.6 examines portfolio debt inflows. For all countries and advanced economies in Panels A and B, there is not much in terms of significant relationships. Total and corporate portfolio debt inflows exhibit a significantly negative relationship to the VIX for the full set of countries, but advanced economies show no systematic relationship of portfolio debt inflows due to either cyclical or global factors

In Panel C for EM, we find our expected negative relationship between the VIX and inflows across all sectors, though the coefficient is again only significant for the total and for the corporate sector. The coefficient on the VIX for public flows is significant only at the 10% level, suggesting that emerging market sovereigns may share the same fate as their corporates in international bond markets, but that may not be uniform for all EM. For GDP growth, we find a negative and significant relationship for public and corporate sectors, but not for banks (who have a positive but insignificant coefficient) or for the total.

This decomposition of results by sector helps highlight a possible reason why Blanchard et al. (2015) find a null result on bond inflows: bank sector port-

Table 3.6: Drivers of Portfolio Debt Inflows, by Sector - (Quarterly AHKS data, missing filled from Public Sources)

Panel A: All Countries				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-1.160**	-0.0572	-0.717	-0.386**
	(0.531)	(0.201)	(0.381)	(0.183)
GDP Growth_{it-1}	0.0297	-0.00441	0.0237	0.0104
	(0.0323)	(0.0135)	(0.0156)	(0.0119)
Observations	2695	2695	2695	2695
R^2	0.006	0.000	0.008	0.005
CountryFE	Yes	Yes	Yes	Yes

Panel B: Advanced Economies				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-1.736	0.526	-1.557	-0.705
	(1.263)	(0.360)	(0.901)	(0.435)
GDP Growth_{it-1}	0.147	0.0311	0.0689	0.0466
	(0.0938)	(0.0363)	(0.0476)	(0.0364)
Observations	1127	1127	1127	1127
R^2	0.025	0.004	0.019	0.018
CountryFE	Yes	Yes	Yes	Yes

Panel C: EM				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-0.750***	-0.423	-0.135	-0.192***
	(0.234)	(0.207)	(0.108)	(0.0567)
GDP Growth_{it-1}	-0.0242	-0.0228**	0.00457	-0.00596***
	(0.0121)	(0.00906)	(0.00625)	(0.00170)
Observations	1372	1372	1372	1372
R^2	0.010	0.010	0.003	0.010
CountryFE	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Portfolio Debt inflow data is constructed by AHKS, as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

folio debt inflows may be acyclical, perhaps weakly procyclical in some cases, while public and corporate inflows follow a much clearer countercyclical pattern. Indeed, our results suggest that different sectors, and even different flow types to the same sector, can move in different directions relative to domestic or international cycles. These contrasting patterns can be obscured without such a decomposition.

3.4.3 Panel Regressions: Capital Outflows by Sector

For debt outflows, we use the same regression setup as the inflow regressions. The sample for outflows is somewhat smaller and shorter, covering 31 countries (15 advanced, 16 emerging) over 2004q1-2014q4, with the sample detailed in Appendix B.5. We focus again on portfolio debt and other investment debt outflows, but we also include flows of official reserves in this analysis.

Table 3.7 shows our regressions for total debt outflows. Columns (1)-(4) include just the sum of portfolio debt and other investment debt, while columns (5) and (6) add in reserve flows to the total. Debt outflows respond negatively to the VIX, reflecting domestic agents retracting their external investments when global risk apetite is low. The response is particularly strong for the banking sector and insignificant for the public sector. As for GDP growth, interestingly when the domestic economy is growing faster, total debt outflows (driven by the domestic banking sector) increases. Thus, domestic banks invest more abroad when the domestic economy is stronger.

Table 3.7: Drivers of Total Debt Outflows, by Sector (Quarterly BOP data, missing Bank data filled from BIS)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Countries						
	Total	Public	Banks	Corp.	Total + Reserves	Public + Reserves
$\log(\text{VIX}_{t-1})$	-6.790***	-0.398	-4.986***	-1.407***	-6.675***	-0.282
	(2.054)	(1.135)	(1.759)	(0.503)	(2.091)	(1.313)
GDP Growth_{it-1}	0.130***	0.0180	0.0978**	0.0145	0.158***	0.0460**
	(0.0431)	(0.0139)	(0.0359)	(0.00982)	(0.0432)	(0.0172)
Observations	1408	1408	1408	1408	1408	1408
R^2	0.047	0.002	0.043	0.015	0.051	0.006
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Advanced Economies						
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Public	Banks	Corp.	Total + Reserves	Public + Reserves
$\log(\text{VIX}_{t-1})$	-11.61***	0.0888	-9.121**	-2.575**	-10.66**	1.040
	(3.772)	(2.400)	(3.233)	(0.966)	(3.965)	(2.606)
GDP Growth_{it-1}	0.339**	0.0553	0.263**	0.0204	0.337**	0.0533
	(0.116)	(0.0361)	(0.0969)	(0.0230)	(0.118)	(0.0401)
Observations	660	660	660	660	660	660
R^2	0.082	0.004	0.087	0.025	0.074	0.004
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: EM						
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Public	Banks	Corp.	Total + Reserves	Public + Reserves
$\log(\text{VIX}_{t-1})$	-2.223***	-0.813	-1.048***	-0.362**	-2.906***	-1.496
	(0.588)	(0.495)	(0.309)	(0.152)	(0.831)	(0.958)
GDP Growth_{it-1}	0.0387	-0.00157	0.0269	0.0135	0.0746***	0.0343**
	(0.0195)	(0.00914)	(0.0154)	(0.00989)	(0.0234)	(0.0159)
Observations	704	704	704	704	704	704
R^2	0.045	0.009	0.017	0.011	0.067	0.020
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes

Sample is from 2004q1-2014q4, countries as listed in Appendix B.5. Total debt is sum of Other Investment Debt and Portfolio Debt, outflow data is primarily from IMF BOP, as described in the text. Public outflows are defined as the sum of General Government and Central Bank outflows. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Advanced economies in Panel B reflect the same patterns as the full sample in Panel A, except the coefficients are much larger. EM in Panel C have the same responses to the VIX as Panel A, with smaller coefficients, but results on GDP growth suggest some different patterns. There is no significance on the relationships for any of the sectors or the total when excluding reserves, but accounting for reserves in the total or in the public sector brings a significant procyclical relationship. This implies possible precautionary saving by the public sector in the form of reserves for EM.

Tables 3.8 and 3.9 show the relationships for other investment debt and portfolio debt outflows separately, with reserve flows included in Table 3.9. Panels A and B of Table 3.8 reflect the same patterns as total debt outflows. One difference, however, is that the response of the corporate sector to the VIX, while negative, is not significant. For EM, the responses are again similar to those in Table 3.7, with the exception that the total and corporate sector responses to GDP growth in columns (1) and (4) are significant and positive. The banking sector does have a larger though insignificant coefficient, but the strong procyclical response of corporate outflows in the form of other investment debt is a bit more surprising.

Table 3.9 shows the response of portfolio debt outflows by sector and reserves. Unlike the other tables, here the full set of countries in Panel A reflects more the behavior of the EM than the advanced economies. The advanced economies in panel A have a negative relationship of total portfolio debt to the VIX, but the response of individual sectors is not strong enough to register significance. EM

Table 3.8: Drivers of Other Investment Debt Outflows, by Sector (Quarterly BOP data, missing Bank data filled from BIS)

	(1) Total	(2) Public	(3) Banks	(4) Corp.
Panel A: All Countries				
$\log(VIX_{t-1})$	-5.321***	0.104	-4.370***	-1.056
	(1.909)	(0.805)	(1.591)	(0.543)
GDP Growth$_{it-1}$	0.126***	0.00452	0.102***	0.0203
	(0.0411)	(0.0152)	(0.0345)	(0.0100)
Observations	1408	1408	1408	1408
R^2	0.041	0.000	0.043	0.016
CountryFE	Yes	Yes	Yes	Yes
Panel B: Advanced Economies				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(VIX_{t-1})$	-9.375**	0.544	-8.129**	-1.791
	(3.614)	(1.748)	(2.948)	(1.084)
GDP Growth$_{it-1}$	0.306**	0.0219	0.256**	0.0275
	(0.111)	(0.0423)	(0.0876)	(0.0277)
Observations	660	660	660	660
R^2	0.071	0.001	0.084	0.020
CountryFE	Yes	Yes	Yes	Yes
Panel C: EM				
	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(VIX_{t-1})$	-1.447***	-0.268	-0.737**	-0.442**
	(0.461)	(0.278)	(0.330)	(0.185)
GDP Growth$_{it-1}$	0.0477**	-0.00515	0.0353	0.0175**
	(0.0187)	(0.00711)	(0.0188)	(0.00805)
Observations	704	704	704	704
R^2	0.040	0.001	0.019	0.022
CountryFE	Yes	Yes	Yes	Yes

Sample is from 2004q1-2014q4, countries as listed in Appendix B.5. Other Investment Debt outflow data is primarily from IMF BOP, as described in the text. Public outflows are defined as the sum of General Government and Central Bank outflows. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Drivers of Portfolio Debt Outflows, by Sector (Quarterly BOP data, missing Bank data filled from BIS)

Panel A: All Countries

	(1) Total	(2) Public	(3) Banks	(4) Corp.	(5) Reserves Only
log(VIX$_{t-1}$)	-1.469***	-0.502	-0.615**	-0.351	0.115
	(0.503)	(0.388)	(0.300)	(0.384)	(0.485)
GDP Growth$_{it-1}$	0.00391	0.0135	-0.00389	-0.00571	0.0280***
	(0.0159)	(0.0100)	(0.00930)	(0.00573)	(0.0100)
Observations	1408	1408	1408	1408	1408
R^2	0.011	0.008	0.005	0.003	0.007
CountryFE	Yes	Yes	Yes	Yes	Yes

Panel B: Advanced Economies

	(1) Total	(2) Public	(3) Banks	(4) Corp.	(5) Reserves Only
log(VIX$_{t-1}$)	-2.232**	-0.455	-0.992	-0.784	0.951
	(0.958)	(0.734)	(0.595)	(0.778)	(0.583)
GDP Growth$_{it-1}$	0.0329	0.0334	0.00661	-0.00711	-0.00203
	(0.0467)	(0.0291)	(0.0276)	(0.0166)	(0.00951)
Observations	660	660	660	660	660
R^2	0.018	0.010	0.008	0.006	0.021
CountryFE	Yes	Yes	Yes	Yes	Yes

Panel C: EM

	(1) Total	(2) Public	(3) Banks	(4) Corp.	(5) Reserves Only
log(VIX$_{t-1}$)	-0.775**	-0.545	-0.310**	0.0796	-0.683
	(0.351)	(0.316)	(0.132)	(0.171)	(0.774)
GDP Growth$_{it-1}$	-0.00891	0.00358	-0.00840	-0.00409	0.0358**
	(0.00879)	(0.00559)	(0.00529)	(0.00392)	(0.0129)
Observations	704	704	704	704	704
R^2	0.014	0.018	0.010	0.003	0.017
CountryFE	Yes	Yes	Yes	Yes	Yes

Sample is from 2004q1-2014q4, countries as listed in Appendix B.5. Portfolio Debt outflow data is primarily from IMF BOP, as described in the text. Public outflows are defined as the sum of General Government and Central Bank outflows. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

on the other hand exhibit a significant negative response to VIX that is driven by the banking sector. Outward portfolio debt investment does not show any significant cyclicality across any of the sectors or country groups, but reserve flows are procyclical for EM. This confirms the relationship observed in Table 3.7 Panel C columns (5) and (6), that reserve flows are an important procyclical capital flow for EM.

3.5 Conclusion

We construct a new data set for gross capital flows during 1996–2014 for a large set of countries at a quarterly frequency. We decompose debt inflows and outflows by borrower and lender type: banks, corporates and sovereigns. We use the standard BOP data from IMF (BMP6) as the starting source and, in order to get a larger, longer, and balanced panel of countries with debt flows split by sector, we proceed with a data filling exercise. When the BOP data by sector is missing, we fill the missing data by using other publicly available data from IMF, WB, and BIS. Our data captures the volume and variation of aggregate flows for most countries and allows us to extend the coverage of the standard samples substantially.

To gauge how well our constructed estimates capture the true flows, we undertake a counterfactual exercise. We take a sample of countries where BOP data by sector is non-missing over 2006q1–2013q4. Then we compare this data to our estimates done for this period as if the BOP data was missing. We match pretty well the aggregate patterns and the correlation between the two series is over 98 percent. At the sector level, our external filling procedure makes a large difference, where 25-40 percent of observations for EM and 75-90 percent of observations for developing countries that are missing in BOP data are filled. A sizeable number of observations for advanced economies – around 15-30 percent, depending on the debt flow type – are filled by external data.

We establish four new stylized facts using our new dataset. First, the well-known positive correlation between capital inflows and outflows is driven by banking flows, mainly by borrowing and lending of global banks in advanced countries. Second, during domestic economic downturns (booms), inflows to domestic banks and corporates decline (increase) in all countries and banks in advanced countries invest less (more) abroad, decreasing (increasing) their outflows, whereas banks and corporates in emerging markets do not change their outflows. Third, private and public inflows respond in opposite directions to domestic business cycles—a fact driven by emerging markets' sovereigns. During a downturn (boom), inflows to private sector decline (increase) but the sovereigns behave in a countercyclical manner by borrowing more (less) from abroad. Fourth, in response to adverse (positive) global credit supply shocks, such as an increase (decrease) in the VIX, inflows to domestic banks and corporates decline (increase), while domestic banks and corporates invest less (more) abroad, decreasing (increasing) their outflows. Sovereigns do not respond to such supply shocks on average. These four facts are inconsistent with the standard models in which all foreign and domestic agents invest or disinvest in the same countries as a response to domestic and global shocks.

Our results highlight the importance of separating capital flows by borrower and lender type to understand better the potential systemic risks that capital flows may pose for the borrowing country and the lending country. They also show the difficulty of establishing stylized facts about the business cycle properties of capital flows and the relation between capital flows and global push factors in a sample that combines EM and AE countries. Our new dataset will be useful for research on capital flows. It will be helpfull to develop models that better fit the facts, as well as to inform policy makers' decisions, not only in terms of systemic risk considerations, but also in terms of monetary policy spillovers from advanced to emerging markets.

Chapter 4: The Global Financial Cycle and Foreign Currency Lending in Emerging Markets

4.1 Introduction

International credit conditions can affect the volume of foreign currency (FX) credit flowing into emerging markets, presenting risks to financial stability. This paper analyzes the role of the domestic banking sector as a transmission point for global liquidity and how the currency composition of bank lending is affected. With a new dataset of the foreign currency loan share of the banking sector, I explore the link between global liquidity and foreign currency lending in emerging markets. I further address the channels of transmission for this relationship using a matched bank-firm dataset from one emerging market, Mexico.

The increase in size and scale of international capital flows and financial linkages has led to important discussions of and concerns about financial cycles at the global level. With such large amounts of funding at play, swings in liquidity and credit can have massive impacts on smaller economies that are financially integrated (Bruno & Shin, 2014a; Cerutti, Claessens, & Ratnovski, 2014; Chung, Lee, Loukoianova, Park, & Shin, 2014; Miranda-Agrippino & Rey, 2014;

Rey, 2013). Much of international funding is in US Dollars or other major currencies, and easier credit conditions make more funding available in these currencies from the international financial market (R. McCauley, McGuire, & Sushko, 2015). Thus, external push factors can drive the flow of credit, usually denominated in foreign currencies, into emerging markets. Such increases in foreign currency credit present risks for financial stability, such as currency mismatch and rollover risk (Acharya et al., 2015; Caballero et al., 2014; Chui et al., 2014).

Domestic banks are an important source of funding and credit for emerging economies and provide a link by which foreign funding can reach domestic firms.[1] Figure 4.1 shows that the average share of total credit to the domestic (private) non-financial sector that comes from the domestic banking sector is well above 60% on average for many emerging markets over 2006q1-2013q4.[2] The exposure of domestic banks to global financial flows can affect bank funding in foreign currencies and thus the currency composition of bank lending, potentially affecting the degree of currency risk in the economy. Given the central role of banks for firm funding, such push factors affecting banks can have an important effect on firm borrowing (and thus firm risk) in foreign currencies.

To address this question, I construct a country-level panel dataset of the foreign currency share of lending by the domestic banking sector of 43 emerg-

[1]The international bond market can also be an important source of foreign currency funding for domestic firms, particularly large ones, and has been examined by Shin (2013); Shin and Zhao (2013); Turner (2014). Domestic bond markets remain largely underdeveloped.

[2]The countries in this figure are: Argentina, Brazil, China, Czech Republic, Hungary, Indonesia, India, Korea, Mexico, Malaysia, Poland, Russia, Thailand, Turkey, and South Africa. This data is drawn from the BIS long series on domestic credit. See Dembiermont, Drehmann, and Muskakunratana (2013) for a discussion of this dataset and its compilation.

ing markets. Using this dataset, I document 2 new facts: First, I document that tighter global liquidity conditions, as measured by the VIX, are associated with a higher share of a country's external debt attributable to the domestic banking sector. It is not obvious why this should be the case, as easier credit conditions in international markets (associated with periods of low VIX) should be associated with a relative increase in foreign currency lending. Second, I find that tighter global monetary conditions lead to a larger share of bank loans in FX. This result goes against the conventional wisdom that foreign currency lending should be more pervasive when funding markets for foreign currencies are more liquid. I analyze these relationship through formal regression analysis and explore the role of country characteristics in that transmission.

In order to identify this relationship, I use a matched firm-bank dataset of loan relationships from a significant emerging market, Mexico, and explore the role of bank characteristics in transmission. This dataset consists of all lending relationships of non-financial firms listed on the Mexican Stock Exchange (BMV). It includes information on the volume of the lending relationship and currency of borrowing (foreign vs domestic). I match this data up to bank balance sheet information from Bankscope. This allows me to examine which bank characteristics matter for the transmission of global liquidity conditions into FX bank lending. While the correlation of FX lending with the VIX may indeed be driven by push factors associated with global liquidity channeled through banks, it could also be driven by demand side factors. The matched nature of the dataset allows me to control for firm demand in each currency by including firm-quarter-currency fixed effects. Thus, I focus on the role of bank characteristics interacted with global liquidity in determining the lending outcomes.

In the country-level panel, I find that global liquidity (as proxied by the VIX) is highly positively correlated with the share of domestic bank loans in foreign currency. This relationship is robust across many specifications. Capital inflows to the banking sector also correlate positively with loans in FX, indicating the role domestic banks may play in transmitting global financing and financial conditions to domestic borrowers. Country characteristics such as capital account openness, fixed exchange rates, and institutional quality don't appear to change these relationships. Banking sector capital does appear to affect the VIX-FX lending relationship, but not in a robust way in the macro data.

In the matched firm-bank panel, I confirm the positive relationship of the VIX with foreign currency lending. Even after adjusting for valuation effects, an increase in the VIX is associated with faster growth in FX credit relative to Peso credit. This result holds after controlling for time-varying firm and bank characteristics. Banks that are better capitalized drive this positive relationship. Indeed, the positive relationship of FX loan growth (relative to Peso loan growth) with the VIX for better capitalized banks gets stronger after controlling for firm-specific demand in foreign and domestic currency. This implies on the other end that poorly capitalized banks lend more in FX when global funding is loose, but restrict their FX lending when times are tight (relative to their domestic currency lending). These results suggest that capitalization of the domestic banking sector may influence how strongly global financial conditions affect FX lending in a country.

What might expain the suprising relationship between low risk periods (loose global funding conditions) with lower shares of lending in FX by banks? A crucial factor at play is the common fact that uncovered interest rate parity (UIP), an arbitrage condition for foreign and local currency borrowing, is often violated in emerging markets such that FX borrowing (specifically US dollar) is attractive (Baskaya, di Giovanni, Kalemli-Özcan, & Ulu, 2017; Salomao & Varela, 2016). Gopinath and Stein (2018) and Gabaix and Maggiori (2015) provide models rationalizing the failure of UIP in models of financial intermediation. Using detailed loan data from one emerging market, Turkey, Baskaya, di Giovanni, Kalemli-Özcan, and Ulu (2017) show that during these low VIX periods, the risk premium associated with UIP failure is compressed, which then leads to an expansion of local currency lending. They call this the "interest rate channel". My results are consistent with this explanation where compressions in UIP deviations are correlated with periods of lower global risk, and I show that these patterns and FX and local currency lending hold in a broad sample of emerging markets.

Coimbra and Rey (2017) build a model where lending by more leveraged (less capitalized) banks are more sensitive to funding costs, suggesting a channel by which banks or banking systems may transmit international credit conditions. In the context of FX lending, this implies that poorly capitalized banks would lend more in FX when FX funding is cheap. Using the same dataset from Turkey as Baskaya, di Giovanni, Kalemli-Özcan, and Ulu (2017), Baskaya, di Giovanni, Peydro, et al. (2017) shows that the increase in lending by banks in response to higher capital inflows is actually driven by well-capitalized banks. I show that poorly capitalized banks lend less in FX relative to local currency when VIX is high, while well capitalized banks (which drive the aggregate) do the opposite and lend relatively more in FX. I find that the gap in the growth rates of FX and Peso lending for these well capitalized banks is smallest when global credit conditions are easy, suggesting that FX credit to banks via capital inflows does expand local currency lending. Thus, this paper provides complementary evidence from loan-level data in a separate emerging market connecting the findings of Baskaya, di Giovanni, Kalemli-Özcan, and Ulu (2017) and Baskaya, di Giovanni, Peydro, et al. (2017).

This paper is related more generally to the expanding literature on global liqudity and the global financial cycle, highlighted by Rey (2013) and Shin (2013). This literature documents the global comovement in credit and asset prices, as well as the implications for spillovers into other countries. Miranda-Agrippino and Rey (2014) shows that looser US monetary policy leads to increased cross border capital flows and increased credit creation. Bruno and Shin (2014a) highlight the role of the international banking system in propogating global liquidity shocks. Their model predicts a connection between local currency appreciation and expansion of banking credit. This paper complements their findings by showing how global liquidity and banking flows affect the currency composition of credit.

This work is also an important contribution to the literature on foreign currency lending. This literature highlights how foreign currency liabilities of banks correlate with foreign currency lending (Arteta, 2005; Basso et al., 2011; Luca & Petrova, 2008; Rosenberg & Tirpák, 2008). Brown, Kirschenmann, and Ongena (2011) use data from a bank in Bulgaria that has information on the requested currency of the loan and the actual currency. Their results suggest that FX borrowing is driven both by firms trying to benefit from lower interest rates and by the bank trying to reduce risk by matching FX liabilities with FX loans. Using a supervisory bank lending dataset from Hungary, Ongena, Schindele, and Vonnak (2018) finds that lending by banks in a given currency increases with looser monetary policy in that currency, thus directly linking monetary policy of global currencies to currency composition of bank lending. I add to this literature by connecting the role of global credit conditions to foreign currency lending across countries, showing that these effects are common across many emerging markets, and identifying the role of bank equity in this transmission.

Lastly, this work is related to the literature on foreign currency risk and corporate risk more generally (Acharya et al., 2015; Chui et al., 2014). Bruno and Shin (2014b) show evidence that firms worldwide have more volatile returns when global financial markets are more liquid, thus synchronizing risk taking across countries. This paper shows that currency risk may also be synchronized across countries with global credit conditions. The increase in FX lending with the VIX potentially increases the currency risk of firms. Thus, this paper also intersects with the extensive literature on firm currency mismatch (Aguiar, 2005; Caballero et al., 2014; Cowan et al., 2005b; Fuentes, 2009; Hardy, 2017; Kalemli-Özcan, Kamil, & Villegas-Sanchez, 2016).

The remainder of this paper is organized as follows: Section 4.2 presents the macroeconomic dataset and analysis; Section 4.3 presents the microeconomic dataset and analysis; and Section 4.4 concludes.

4.2 Macroeconomic Analysis

In this section, I present a new panel database of country level quarterly time-series data on the share of domestic bank loans made in foreign currencies. I then explore the aggregate patterns, and present formal regression analysis.

4.2.1 Macro Data

I construct a quarterly dataset of FX loans for banking sectors in emerging markets from both national and international sources, spanning 1990q1-2014q3. This is an important contribution to the literature on FX lending, as few such existing cross country datasets have a frequency shorter than annual. The only datasets of which I am aware that employ higher frequency data focus on eastern Europe and former Soviet Bloc countries (Basso et al., 2011; Neanidis & Savva, 2009). My dataset expands the scope to include countries from the Americas, Asia, and Africa in the full sample. Also, my data is harmonized with the IMF reported measure for foreign currency loans, providing an extension for analysis using that data.

My primary variable of interest is $FXLoanShare$, defined as the share of loans from the domestic banking sector denominated in foreign currencies:

$$FXLoanShare = \frac{\text{FX loans outstanding}}{\text{total loans outstanding}}$$

This variable is constructed from stock data collected and reported by the IMF in their Financial Soundness Indicators (FSI). These are gross loans to both residents and nonresidents issued by the domestic banking sector. These numbers have been voluntarily reported by many countries, though most only in the last year or two.[3] In order to obtain a larger balanced panel, I collect data from national authorities and construct measures of the share of loans in FX for countries at the quarterly level.[4] Details of this collection can be found in the Appendix. This extends the series for some countries, and adds other previously omitted countries to the sample. For countries that have data both from FSI and national sources, the correlation between the two measures is > 0.99. When both data sources are present, I use that constructed from national sources.

Further details on the construction of the dataset can be found in the Appendix. This dataset ranges from 1990-2014 and covers nearly 70 economies. I focus on 43 emerging and developing economies in the dataset: Afghanistan, Albania, Argentina, Bhutan, Bosnia and Herzegovina, Brazil, Chile, China, Colombia, Costa Rica, Croatia,[5] Czech Republic, Estonia, Georgia, Hungary, India, In-

[3]Reporting of foreign currency composition of balance sheets and portfolios are of increasing concern for stadradized international data reporting. See the IMF's September 2014 report "Advancing the Work on Foreign Currency Exposures".

[4]For many countries, I collect monthly data, which I convert to quarterly by using the end of quarter values.

[5]Croatia's data for FX Loans starts in 2006q2. I fill in the observation for 2006q1 using the trend from the immediately followig data points (2006 q2 and q3), which appears to be the best

donesia, Israel, Latvia, Kazakhstan, Kenya, Korea, Lithuania, Mexico, Moldova, Namibia, Nigeria, Peru, Poland, Romania, Russia, Rwanda, Slovak Republic, South Africa, Sri Lanka, Swaziland, Tajikistan, Tanzania, Turkey, Uganda, Ukraine, and Zambia.[6] I also do some analysis with a smaller, balanced sample of 17 countries over 2006q1-2013q4.[7]

My measure captures the FX share of lending made to any borrower by the domestic banking sector. However, loans to residents, and in particular loans to resident non-financial corporations, are of interest. For a subset of countries, I am able to get measures of the FX share of loans to domestic residents and to the domestic non-financial sector. For these countries[8], I find these measures are strongly correlated with my main variable (about 0.97 and 0.95, respectively). Loans by the domestic banking sector to non-resident counterparties account for 6.5% of the total domestic bank lending for these countries on average, while loans to the private non-financial sector account for 72.2% on average. Thus, using the more widely available measure should still capture behaviors related to domestic lending in foreign currencies.

My primary measure of the global financial cycle is the VIX, a measure of the implied volatility of S&P 500 index options.[9] This measure has been used in

approach given the abrupt change starting in 2006q4.

6 Most of the countries omitted from the sample are developed countries and financial centers, as well as a few countries with too few observations.

7 This sample includes the following countries: Argentina, Brazil, Chile, Colombia, Costa Rica, Croatia, Czech Republic, Hungary, Indonesia, Israel, Latvia, Lithuania, Mexico, Poland, South Africa, Turkey, and Ukraine.

8 Argentina, Chile, Costa Rica, Czech Republic, Latvia, Lithuania, Mexico, Poland. Of these, all have data separately for the domestic non-financial sector except Argentina and Latvia.

9 The implied volatility is the volatility of the S&P 500 index that would yield the current market price for option contracts when put into an options pricing model.

many other studies, and has been shown in Miranda-Agrippino and Rey (2014) to comove with a global factor extracted from global capital flows and prices. I use the logged value of the VIX as my measure, following Rey (2013), Miranda-Agrippino and Rey (2014), and Nier et al. (2014). Note that the VIX is also used as a measure of perceived uncertainty and risk for investors. Additional measures of global financial conditions that I use include the effective federal funds rate (from FRED), the broad dollar index (a trade wieghted measure of US dollar strength), and the growth in global credit to banks (from the BIS global liquidity indicators).

To connect global liqudity directly to the banking sector, I construct measures of external debt of banks for each country. I construct the share of a country's external debt owed by the banking sector from the Quarterly External Debt Statistics (QEDS), published jointly by the IMF and World Bank. That is to say, this measure s defined as banking sector external debt divided by total external debt for each country. I also use gross capital inflows to banks, as a share of GDP, from the dataset of Avdjiev, Hardy, Kalemli-Özcan, and Servèn (2017) to examine specifically the role of capital inflows to domestic banks. From the World Bank, I also use a measure of the capital to assets ratio for the banking system as a whole for each country, as poorly capitalized banks may be more sensitive to external funding conditions.

I also examine the role of other country characteristics. In line with the classic macroeconomic trilemma, the exchange rate arrangement may play an important role for the tranmission of global liquidity shocks into emerging markets.[10]

[10] Rey (2013) suggests that GL may transmit into EM regardless, though it is certainly plausible

I use the classification for pegged exchange rates from Shambaugh (2004), updated through 2014. The institutional development may impact how connected a country is to the global financial system as well as how effectively banks are able to manage risk. As a measure of institutional quality, I construct a variable from International Country Risk Guide data. I use the publically available dataset, which has annual data of subindicator averages from the commercially available dataset.[11] I construct my measure from the average of the Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption subindicators. For a time invariant version of this measure, I use the median value over the sample for each country. I use the Chinn-Ito index (KAOPEN) as a measure of openness to capital flows (Chinn & Ito, 2006).[12,13] Data is annual at the country level, covering up to 2012. I use the version of the variable that varies between 0 and 1, with 1 indicating free capital mobility. For a time invariant measure of openness, I use the country's median value over the sample up to 2012.

4.2.2 Aggregate Patterns

Figure 4.2 shows that the average share (across countries) of credit to the private sector coming from domestic banks loosely follows the VIX, with a notable exception in 2008, though this variation is not very large.

Examining external funding reveals a more striking pattern. Figure 4.3

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that the effect will be stronger for those with more rigid exchange rates. See Shambaugh (2004).

[11] This dataset was downloaded from the World Bank.

[12] This is a *de jure* measure of capital account openness.

[13] Basso, Calvo-Gonzalez, and Jurgilas (2007) find that openness is positively related to loan dollarization to firms, while Arteta (2005) and Barajas and Morales (2003) find a negative relationship.

shows a tight connection between the VIX and the share of external debt outstanding of the country owed by the domestic banking sector.[14] Figure 4.4 shows a similar pattern when considering just banks' share of private external debt. Bank funding seems to be connected to the global financial cycle. Further, a strong positive relationship between the shares of debt flowing to the banking sector and loans in FX is documented in Figure 4.5. Thus, domestic banks could provide an important point of transmission for the global financial cycle to influence currency risk and exposure. It is important to note that since these figures measure the of share of external debt allocated to banks, these results could be influenced from either the banking sector or from other sectors.

Figure 4.6 illustrates this connection directly. We see that with either the full unbalanced panel or the balanced sample, there is a significant positive connection between the VIX and the share of loans in FX. This relationship is opposite from what might first be expected. When global markets are more loose, there is more foreign currency funding available, so banks funding themselves externally would want to make a larger share of their loans in FX to match their FX debt positions. The fact that the share of FX loans moves in the opposite direction is both significant and puzzling.

Figures C.1-C.17 in the appendix illustrate the intertemporal relationships between the VIX and share of loans in FX, share of bank external debt in FX, and banks share of country external debt for individual countries in the balanced

[14] Bruno and Shin (2014a) document a related trend, that bank to bank cross-border liabilities increased in the run up to the 2008 crisis, decreasing afterwards.

sample. Some countries, such as Hungary and Poland, show a very tight linkage between the VIX and FX Loans in panel (a), while others such as Croatia and South Africa are not as responsive. Similarly with the share of external debt allocated to banks in panel (c), Czech Republic and Israel show a tight connection with the VIX, while this pattern isn't evident for Turkey. There is clearly important heterogeneity that causes some countries to follow these patterns more strongly than others, but the general trends with the VIX seem to be present for many countries. Panel (b) displays data, when available, for the foreign currency share of bank external liabilities. Although some interesting variation is present, there is not enough data available to make any general conclusions.

Figure 4.7 shows the long term relationship between changes in FX Loan share and other potentially important factors. The figure plots the change in FX loan share from 2006q1 to 2012q4 (on the y-axis) against the change in exports, GDP growth, Institutional Quality (IQ), and openness (KAOPEN) from 2006 to 2012. An increase in the share of outstanding loans in foreign currencies over time is associated with an increase in exports/GDP, a decrease in IQ, and a slight decrease in openness (there is no apparent relationship with growth, however). The relationship to exports is in line with previous findings and theory. Panel (c) suggests that an improvement in institutional quality is associated with a lower share of loans in FX. The relationship to openness is unexpected, as one would expect more open economies to be more exposed to foreign currencies. Although the focus of this paper is on the high-frequency relationship of FX loans to the global financial cycle, and less on the long term determinants, country characteristics may affect the transmission of global liquidity shocks to FX lending. This is examined in Section 4.2.4.

4.2.3 Empirical Approach

I first seek to establish a relationship between global financial conditions and either external bank capital and FX loans. I consider regressions of the form:

$$Y_{i,q} = \alpha_{i,y} + \beta GL_q + \epsilon_{i,q} \tag{4.1}$$

$Y_{i,q}$ is either the percent of country i's outstanding external debt attributable to the banking sector, external debt inflows to banks as a percent of GDP, or the percent of outstanding domestic bank loans denominated in FX in a given quarter.[15] GL_q is a vector of global liquidity measures in each quarter, primarily the logged value of the VIX, but also potentially the lagged value of log VIX, the federal funds rate, and the growth in international bank credit. Since the data is quarterly, this makes it possible to include country-year fixed effects $\alpha_{i,y}$ to control for slower moving country specific factors that may determine bank borrowing and lending patterns.

To examine how country characteristics affect this relationship, I interact my main measure of global liquidity (the VIX) with a vector of country characteristics CC_i:

[15] So a value of 1 for each of these variables indicates 1%.

$$Y_{i,q} = \alpha_{i,y} + \beta_1 GL_q + \beta_2 GL_q \times CC_i + \epsilon_{i,q} \tag{4.2}$$

Country characteristics that I consider include pegged exchange rate, capital account openness, and institution quality (with variables and sources described in Section 4.2.1). One would expect that global conditions would have a stronger impact on countries that are more open to capital flows and a fixed exchange rate. Better institutions could go either way, as it may indicate better access to foreign funding markets or better development of domestic funding markets. I also consider a dummy variable for having a well capitalized banking system, which I define as having aggregate bank capital to assets greater than 8%.[16] Banking system capitalization my affect how reactive banks are to changes in global funding conditions, with more poorly capitalized banks and banking systems more likely to cut FX lending when the FX funding market tightens.

4.2.4 Results

I first examine the relationship of global liquidity with bank external debt. Table 4.1 presents regressions with the banking sector's share of country external debt or gross capital inflows to banks as a share of GDP as the dependent variables. Columns (1)-(7) show regressions for the bank share of external debt on contemporaneous and lagged VIX and the federal funds rate. The contemporaneous value of the VIX is the most consistent predictor of bank external debt,

[16] 8% is roughly the recommended capital requirement from Basel III for tier 1 and 2 capital relative to risk weighted assets.

but all the measures suggest a significant positive relationship with VIX. That is, as global financial conditions tighten, banks hold a greater share of the country's external debt. Using the results from column (6), an increase in the VIX of 1% results in a 1 percentage point increase in the percent of total external debt made up by banking sector external debt.[17]

Columns (8)-(12) use capital inflows to banks relative to GDP as the dependent variable. These regressions reveal that inflows to banks do decrease as global liquidity tightens, consistent with findings in Avdjiev, Hardy, Kalemli-Özcan, and Servèn (2017). Note however that a higher federal funds rate is associated with an increase in bank inflows. This correlation could be driven by the fact that the federal funds rate was driven to 0 in late 2008, exactly when global banking flows retrenched with the financial crisis. The results of Table 4.1, taken together, imply that while international capital flows to banks fall when global financial conditions tighten, it doesn't fall by as much as flows to the rest of the economy (such that banks end up with a higher share of external debt).

Table 4.2 establishes the second key fact, concerning the relationship of global liquidity with the share of loans in FX. I find that as the VIX increases, so does the share of bank lending done in FX. Using the results from column (3), a 1% increase in the VIX is associated with an increase of almost one percentage point in the share of loans in FX. This relationship is most robust with contemporaneous VIX. The federal funds rate has a negative relationship, whereby loose

[17] Note that this implies a decrease in the country's share of external debt outstanding for the government and/or the non-bank private sector.

monetary policy (associated with the recession and collapse in capital flows) is associated with less FX lending. This is the opposite result as that implied by the VIX, but this is again driven by the fact that loose monetary policy is associated with the recession and aftermath, when global liquidity was quite low.

Columns (1) and (2) of Table 4.3 capital inflows to the banking sector and the index of US dollar strength to the standard regression. In the full sample, the VIX and Federal Funds Rate have the same sign and significance, with slightly smaller magnitudes as compared to column (6) of Table 4.2. As expected, banking inflows are positive and significantly related to share of loans in FX, as funding flowing to banks from abroad is predominantly denominated in foreign currencies. US dollar strength is also positively associated with share of loans in FX, perhaps capturing valuation effects of an appreciated dollar as well as indicating the state of the dollar funding market. Moving to the balanced sample in column (2), only the VIX and Bank Inflows survive in terms of significance. This again suggests the importance of the banking sector as a transmission point for global flows, though perhaps not the only factor in determining lending outcomes by currency.

In columns (3) and (4), I include interactions of the VIX with a capital openness measure (index from 0 to 1, with 1 being more open), fixed exchange rate dummy, and a measure of institutional quality to see how other country characteristics may affect the transmission of global financial conditions to domestic bank loans. Generally, there is no significant or robust relationship with these interactions. The exception is for the balanced sample of countries, more capital openness reverses the relationship of the VIX with FX loan share. Countries that are more open to capital flows see a higher share of loans in foreign currencies when the VIX is low, as compared to countries with more capital controls in place. As this result does not hold in the full sample of countries, however, it cannot be said that the relationship is robust.

Table 4.4 considers the role of bank capitalization. Columns (1) and (2) present results of the full sample, while columns (3) and (4) consider the balanced sample.[18] In columns (1) and (3) including country fixed effects, we see that the positive relationship of VIX with FX loan share is driven by countries with high levels of capital in the banking system. For the balanced panel in column (3), the coefficient on the VIX is negative, though not significant. Though not a significant result, this aligns with the previous literature that finds that poorly capitalized banks are more sensitive to global funding conditions, and so when global funding is loose, poorly capitalized banks increase more their lending in foreign currencies. After controlling for country-year fixed effects in columns (2) and (4), the significance disappears for the interaction with bank capital, and the sign even reverses on the coefficient with the full sample in column (2). Note, however, that unlike the interactions in Table 4.3, the inclusion of the interaction of bank capital with the VIX does appear to affect the direct effect of the VIX. To better examine the role of bank capital in determining sensitivity to global funding conditions along this measure, I turn to microdata in the next section.

[18]Hungary is dropped from the balanced sample due to a lack of data on bank capitalization from the World Bank.

4.3 Microeconomic Analaysis

This section introduces a mcirodataset of matched firm-bank lending data from Mexico. I use this data to analyze and extend the results from Section 4.2.

4.3.1 Mexico Data

I use matched firm-bank data from Mexico. This dataset is described in detail in Hardy (2017). This data consists of all lending relationships of non-financial firms listed on the Mexican stock exchange (BMV). This includes data on the loan volume outstanding, the interest rate, the remaining maturity, the currency of the loan (foreign or domestic). The loan data is matched to firm balance sheets (from quarterly financial reports filed with the BMV) and bank balance sheets from Bankscope. Since this data is collected from firms, it includes lending relationships both from banks resident in Mexico and cross-border banks. For each firm-bank-currency triplet, I aggregate all loans up in each quarter (as many firms have multiple loan products open simultaneously with the same bank). To maintain consistency with the macro data analysis in Section 4.2, I focus on just the lending done by domestic banks. This leaves a dataset of 116 firms borrowing from 92 banks over 27 quarters: 8214 bank-firm-quarter-currency observations. I adjust the FX loans for valuation effects on the assumption that they are all denominated in US dollars.[19]

[19] On average, over 90% of all FX liabilities of the firms in this sample are denominated in USD.

4.3.2 Empirical Approach

I focus on explaining real changes in FX lending (relative to local currency lending) due to global liquidity conditions. Most of the banking relationships in the data do not use both foreign and domestic currency loans at the same time. Hence, defining the dependent variable as the share of loans in FX, as in Section 4.2, may not be appropriate. Thus, the regression analysis is formulated as follows:

$$\Delta \log(loan^{c}_{f,b,q}) = \alpha_{f,q} + \alpha_{b,q} + \alpha_{b,f} + \gamma_0 FX^{c} + \gamma_1 FX^{c} \times GL_q + \mu^{c}_{f,b,q} \tag{4.3}$$

where $loan^{c}_{f,b,q}$ is the loan volume outstanding between firm f and bank b at time q in currency c. Firm-quarter fixed effects $\alpha_{f,q}$ control for firm-specific time-varying factors (observed and unobserved), and similarly bank-quarter fixed effects $\alpha_{b,q}$ remove variation from individual banks over time, to account for bank-level shocks to credit supply. $\alpha_{b,f}$ controls for unobserved characteristics of a given bank-firm pair. I focus on the interaction of the dummy variable for foreign currency loans FX and the measure of globali liquidity. This means the identifying variation is coming from differences in the growth of FX loans relative to peso loans with respect to global financial conditions, having controlled for firm and bank specific factors that may influence such loan growth.

The emphasis in this paper is on bank credit supply of foreign currency loans, and how that supply is influenced by global financial conditions. Controlling for firm-quarter fixed effects helps account changes in loan demand, while bank-quarter fixed effects capture bank specific changes in credit supply. However, changes in global liquidity may differentially affect the demand for FX vs local currency loans. For instance, some firms who previously issued bonds in FV may be unable to do so during periods of global tightening, leading them to increase their demand for FX loans as a substitute. Also, firms may track the VIX as an indicator of global business and may thus demand more or less credit depending on their perception of the global business environment. Thus, I need to control for this differential demand to understand how global liquidity transmits through domestic banks (i.e. the supply side effects). I account for this in the following regression:

$$\Delta \log(loan^{c}_{f,b,q}) = \alpha^{c}_{f,q} + \alpha_{b,q} + \alpha_{b,f} + \gamma_2 FX^{c} \times BC_b + \gamma_3 FX^{c} \times GL_q \times BC_b + \mu^{c}_{f,b,q} \tag{4.4}$$

where $\alpha^{c}_{f,q}$ is a firm-quarter-currency fixed effect, capturing changes in firm loan demand in FX and local currency separately, and BC_b is a time invariant bank characteristic, either average equity/assets, average tier 1 capital ratio, or average size (measured by log assets). The interaction with bank characteristics is necessary as $\alpha^{c}_{f,q}$ absorbs the variation from $FX^{c} \times GL_q$. This specification additionally allows me to explore channels by which global liquidity may influence FX lending of domestic banks by looking at the characteristics of banks who respond more strongly. Bank characteristics are demeaned so that the interpretation of the direct effect $FX^c \times GL_q$, when not absorbed by the fixed effects, is the impact for the average bank.

4.3.3 Results

Table 4.5 presents the main results for the impact of global liquidity on loan growth in foreign vs. domestic currency. In columns (1)-(4), I consider FX loans and Peso loans separately. Controlling for bank and firm characteristics, the growth of lending in both currencies appears to increase with the VIX, with a larger response for FX loans. While it seems at odds with standard reasoning that loan growth would increase as financial conditions tighten, the sample of firms here is listed firms, which tend to be very large. Hence, there may be a time-varying reallocation effect on the supply side towards large firms during tighter periods of global liquidity.

To compare these responses and control for time varying bank and firm specific factors, columns (5)-(8) pool FX and Peso loans together. The main coefficient of interest is then on the interaction between the FX dummy and the VIX, which indicates how the growth of FX debt relative to peso debt changes with the VIX. Consistently, FX loan growth is higher than Peso loan growth when the VIX is high. Thus, the foreign currency share of loans would increase. Hence, in the microdata we see a strong response of non-valuation driven changes in the foreign currency share of loans to changes in global liquidity (as the FX loans have been corrected for valuation effects). These results are robust to controlling for firm-time, bank-time, and firm-bank fixed effects. Using estimates from column (8), a 1% increase in the VIX results in a 0.01% increase in credit growth of FX loans relative to credit growth of peso loans.

While there is a clear correlation between FX lending and the VIX, it is still not clear if this is driven by external push factors affecting foreign currency capital flows through the domestic banking system, or if these global movements change the relative demand for FX vs local currency loans by firms. Table 4.6 address this by controlling for time-varying firm-specific effects in each currency with the inclusion of firm-time-currency fixed effects. Having the time*currency interaction in the fixed effects will absorb the variation in the $FX \times VIX$ coefficient. Thus, the main object of interest become the interaction of $FX \times VIX$ with bank characteristics, to observe more directly the potential role of the banking sector in this transmission.

In columns (1)-(3), we see that the correlation of the VIX with lending in FX is driven by banks with low leverage (high equity). This effect gets stronger once we account for firm specific demand for FX loans in column (3). Columns (4)-(6) illustrate a similar relationship, looking instead at the Tier 1 capital ratio. Banks that were better capitalized increased their FX loan growth (relative to their Peso loans) with the VIX, more so than poorly capitalized banks. Since bank capital to assets is demeaned, the relationship turns negative for banks below the average capital ratio. Larger and better capitalized banks made more loans than less capitalized banks, which explains why the total effect is positive in Table 4.5. This finding helps to confirm the less robust relationship at the country level with bank capital. Poorly capitalized banks lend more in foreign currencies when global funding conditions are loose, but comparatively less when things tighten relative to their domestic currency lending. On the opposite side, a well capitalized banking system may facilitate greater FX lending when global liquidity is tight, especially as a substitute for FX bond debt that firms may not be able to directly access. Columns (7)-(9) examine the relationship with bank size, which does not appear to be a significant determinant of the relationship between FX lending and the VIX.

While the microdata is useful for identifying channels and effects, it does have drawbacks for external validity. This sample of firms and loans may be unique along several dimensions which may affect the resutls. First, the banking system in Mexico is largely dominated by foreign owned banks. Foreign ownership of banks may be an important dimension to consider, but this particular dataset may not be as useful to explore that possibility. Second, this dataset consists of large, publicly traded companies which may not reflect the aggregate dynamics of FX borrowing. For the case of Mexico, this is likely less important as most FX borrowing is anecdotally done by the larger firms, but other countries do have significant FX borrowing by small firms and households which may change the relationships. Third, Mexico's banking system is well capitalized. This is actually largely true of emerging markets generally. From the world bank data, high income countries as a whole have a capital to assets ratio between 6 and 8% over 2008-2014, whereas middle income countries are typically closer to 10.5%.

Mexico's banking system had a capital ratio closer to 16% over this period, which is quite high for its income group. Recognizing these caveats, both the macro- and micro-data suggest a positive relationship of FX lending with the VIX, and bank capital may be an important factor in determining this response.

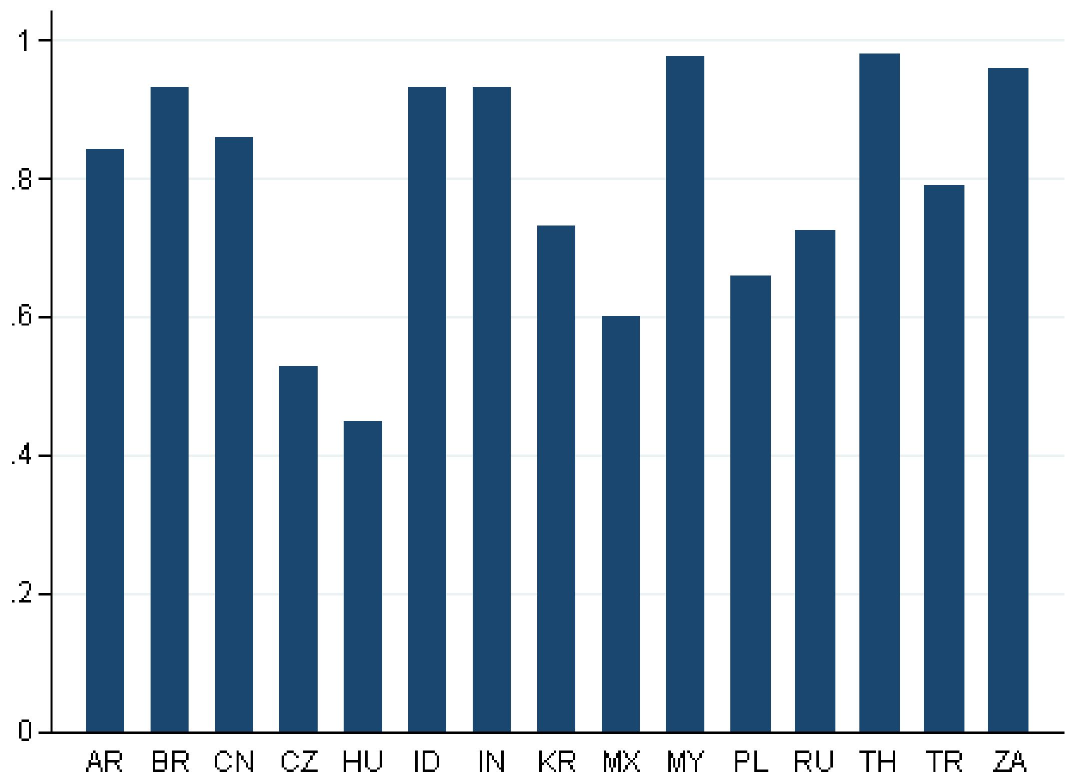
4.4 Conclusion

Global liquidity conditions can drive flows of foreign currency funds into emerging markets. The domestic banking sector is an important source of funds for firms and a transmission point for global flows. This paper examines the relationship of global liquidity with foreign currency lending by domestic banks. I construct a country panel dataset of foreign currency loan shares for the domestic banking sector, and document that these shares move positively with the VIX. I also show that the share of country-level external debt flowing through banks varies positively with the VIX. Capital inflows to banks are positively associated with loans in FX, highlighting the role of domestic banks as a transmission point for global funding conditions to affect foreign currency borrowing by firms.

I use a unique dataset of firm-bank lending relationships in Mexico to further identify the channels for this effect. I find the positive relationship of the VIX with FX lending holds in the microdata. This transmission is driven by well capitalized banks. These results hold after controlling for firm-specific demand for FX and local currency loans and thus focusing on supply side drivers connected to the VIX. Taken together, these results imply that poorly capitalized banks are more likely to lend in FX when times are easy (low VIX) and less likely to lend in FX when times are tight. Well capitalized banks are able provide more foreign currency funding to firms precisely when foreign currency funding begins to dry up. Emerging market banking systems tend to be better capitalized on average than developed economies, which may help explain the positive correlation in the aggregate data for emerging markets. These results are consistent with a compression of deviations from UIP, such that when global financial conditions are loose, UIP deviations compress resulting in relatively cheaper local currency interest rates and a relative expansion of local currency lending.

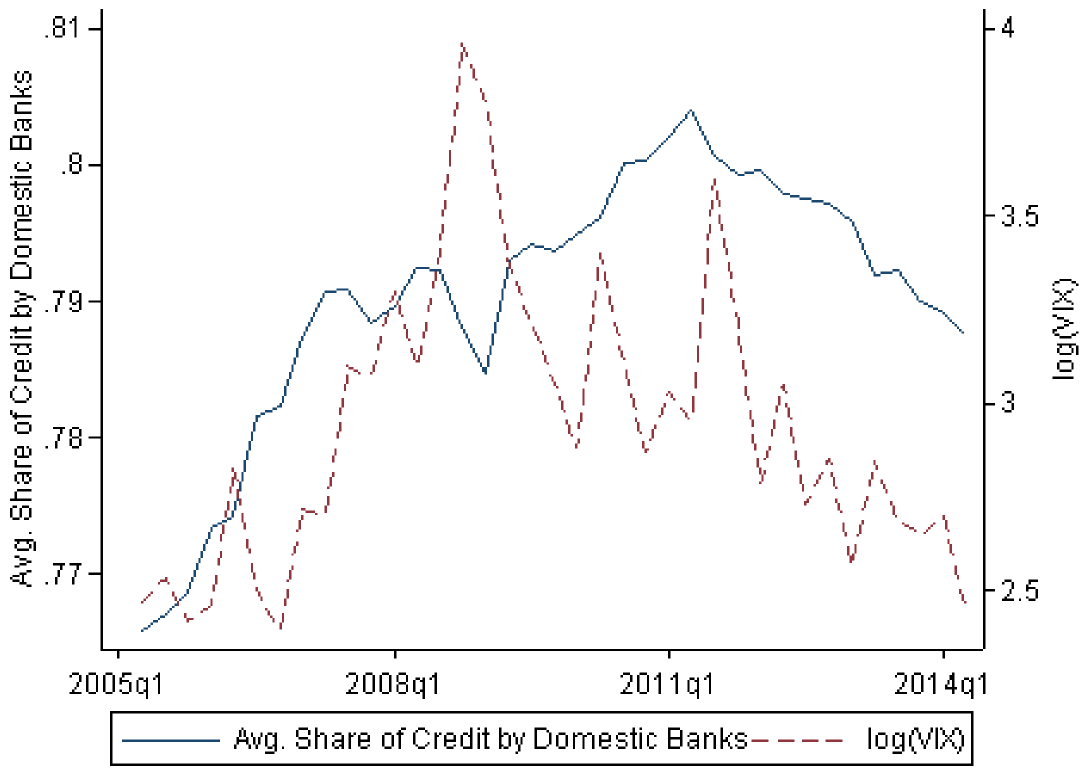
The relationship of global financial conditions, capital inflows, and foreign currency credit is crucial to understand in order to mitigate potential spillover effects of global liquidity and manage currency risk. Future research should continue to examine the role of the domestic banking sector in conjunction with bond markets and other sources of credit to determine the prudence and effectiveness of policies mitigating the tranmission of global liqudity (capital controls, macro prudential policies) and controlling foreign currency exposures.

Figure 4.1: Average Share of Credit from Domestic Banks, 2006-2013



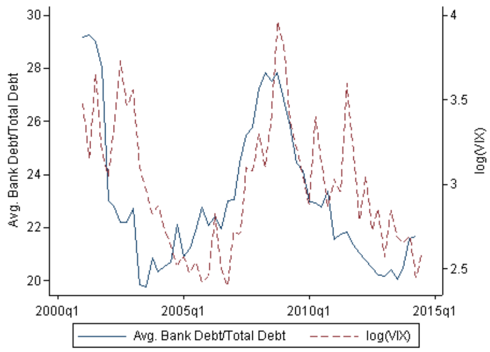
Source: BIS, author's calculations. Variable is the country average of credit to the private non-financial sector from the domestic banking sector relative to total credit received. The countries are: Argentina, Brazil, China, Czech Republic, Hungary, Indonesia, India, Korea, Mexico, Malaysia, Poland, Russia, Thailand, Turkey, and South Africa.

Figure 4.2: Domestic Bank Credit to Total Credit

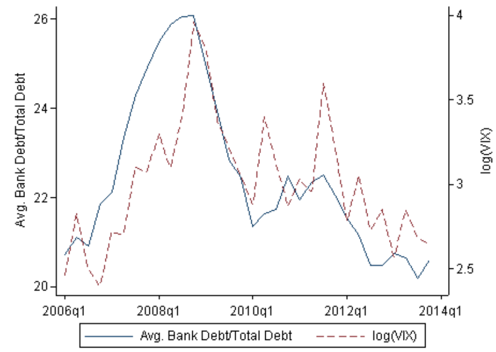


Source: BIS, author's calculations. Solid line is the period average of credit to the private non-financial sector from the domestic banking sector relative to total credit received. A value of .77 indicates 77%. Dashed line is the logged value of the VIX. The countries included are: Argentina, Brazil, China, Czech Republic, Hungary, Indonesia, India, Korea, Mexico, Malaysia, Poland, Russia, Thailand, Turkey, and South Africa.

Figure 4.3: Average Bank External Debt and VIX



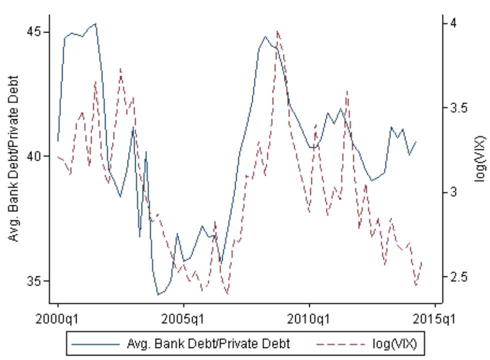
(a) Full EM Sample (unbalanced)



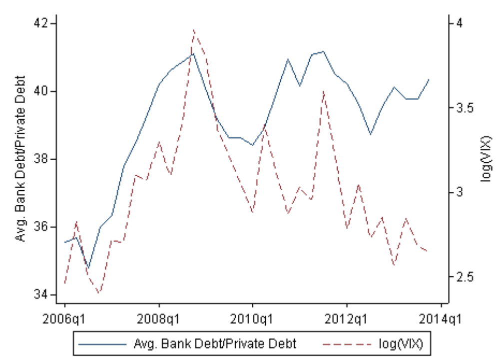
(b) Balanced EM Sample

Source: QEDS, author's calculations; BIS. Solid line is the period average share of external debt outstanding from the domestic banking sector relative to the country total. Dashed line is the logged value of the VIX.

Figure 4.4: Average Bank Debt to Private Debt and VIX



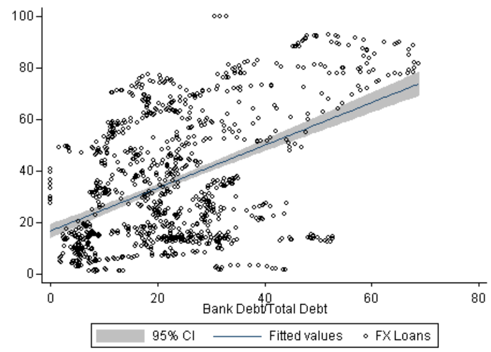
(a) Full EM Sample (unbalanced)



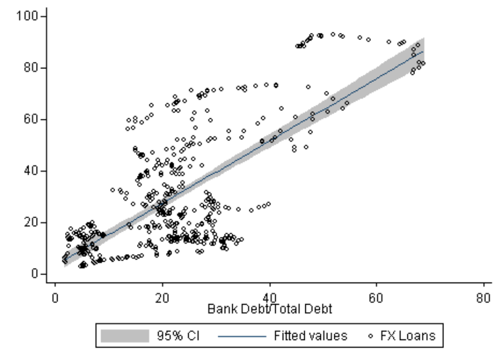
(b) Balanced EM Sample

Source: QEDS, author's calculations; BIS. Solid line is the period average share of external debt outstanding from the domestic banking sector relative to the total debt of both banking and other private sectors. Dashed line is the logged value of the VIX.

Figure 4.5: FX Loans and Bank External Debt



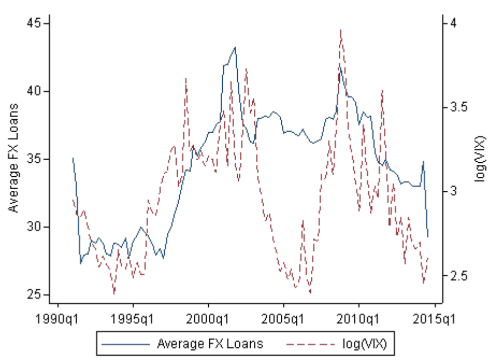
(a) Full EM Sample (unbalanced)



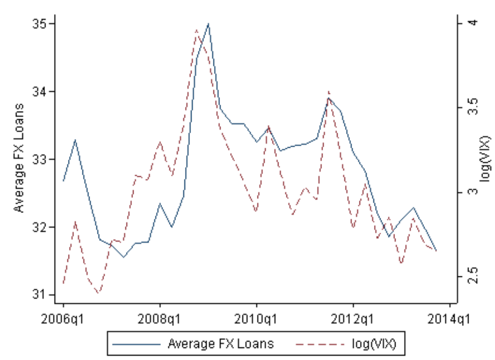
(b) Balanced EM Sample

Source: IMF FSI and National Sources, author's calculations; QEDS. Horizontal axis is the share of external debt attributable to banks. Vertical axis is the share of loans in FX. The line is an OLS line of best fit, with a 95% confidence interval.

Figure 4.6: Average FX Loans and VIX



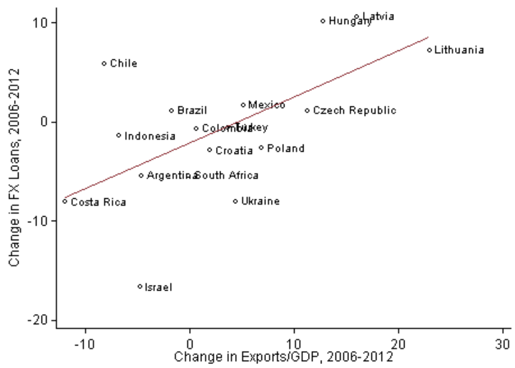
(a) Full EM Sample (unbalanced)



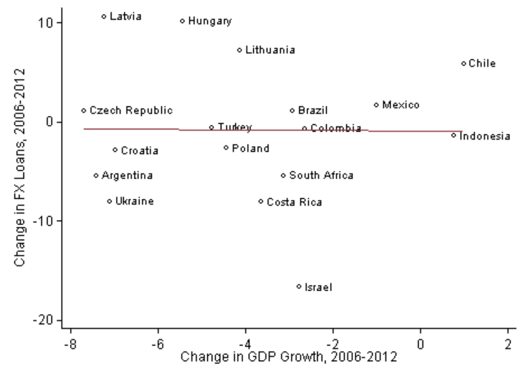
(b) Balanced EM Sample

Source: IMF FSI and National Sources, author's calculations; BIS. Solid line is the period average share of loans outstanding of the domestic banking sector in FX. Dashed line is the logged value of the VIX.

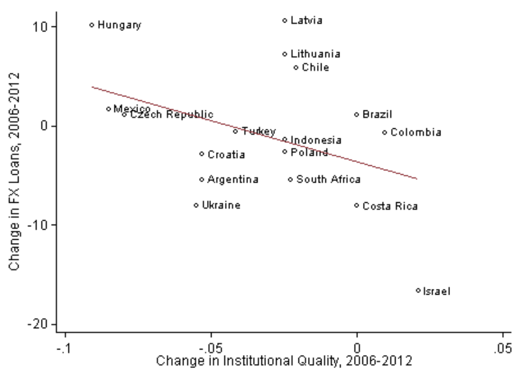
Figure 4.7: Change in FX Loan Share and Other Factors, 2006-2012



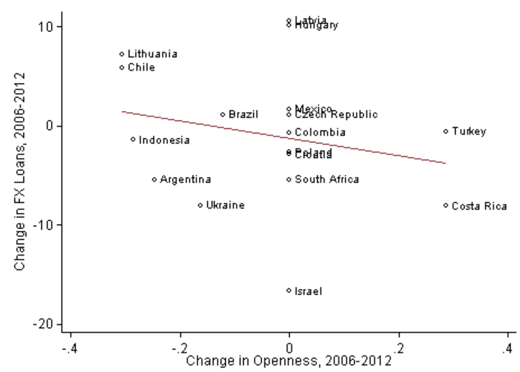
(a) FX Loans and Exports



(b) FX Loans and GDP Growth



(c) FX Loans and Institutional Quality



(d) FX Loans and Openness

Source: IMF FSI and National Sources, author's calculations; World Bank, ICRG, Chinn and Ito (2006). FX Loan difference is from 2006q1 to 2012q4. Exports, GDP Growth, Institutional Quality, and KAOPEN from annual data, difference from 2006 to 2012. Sample is emerging economies from the balanced sample.

Table 4.1: External Bank Debt and Global Liquidity

	Bank Share of External Debt							Inflows to Banks/GDP				
	(1)	(2)	(3)	(4) Bal. Samp.	(5)	(6)	(7) Bal. Samp.	(8)	(9)	(10)	(11)	(12)
VIX$_q$	3.495***	3.362**	0.481	0.955**	3.998**	0.992*	1.238*	-2.048*	-1.776**	-1.537**	-1.765**	-1.503*
	(1.230)	(1.255)	(0.382)	(0.443)	(1.484)	(0.524)	(0.603)	(1.006)	(0.786)	(0.717)	(0.850)	(0.814)
VIX$_{q-1}$		0.190	0.946*	1.318**						-1.250**		
		(0.959)	(0.495)	(0.506)						(0.508)		
FFR$_q$					0.391	0.433	-0.0355				0.521**	0.490
					(0.363)	(0.262)	(0.326)				(0.230)	(0.332)
Observations	1043	1043	1036	512	1043	1036	512	1287	1280	1280	1287	1280
R^2	0.846	0.846	0.992	0.992	0.848	0.992	0.992	0.095	0.592	0.594	0.134	0.593
Countries	30	30	30	16	30	30	16	30	30	30	30	30
Quarters	66	66	66	32	66	66	32	75	75	75	75	75
CountryFE	Yes	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
CountryYearFE	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes

Dependent variable in columns (1)-(7) is the percent of a country's external debt owed by the domestic banking sector. Dependent variable in columns (8)-(12) is capital inflows to the domestic banking sector as a percent of GDP, as constructed in Avdjiev, Hardy, Kalemli-Özcan, and Servèn (2017). VIX is the logged value of the CBOE S&P 500 implied volatility index. FFR is the effective federal funds rate. Bal. Samp. indicates that a balanced sample, as defined in the text, is used. Standard errors are double clustered by country and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2: Foreign Curreny Loans Share and Global Liquidity

	(1)	(2)	(3)	(4) Bal. Samp.	(5)	(6)	(7) Bal. Samp.
VIX_q	3.300**	1.980***	0.964***	1.683***	3.743***	0.886***	1.417**
	(1.257)	(0.725)	(0.316)	(0.448)	(1.385)	(0.294)	(0.491)
VIX_{q-1}		1.864**	0.394	0.380			
		(0.732)	(0.320)	(0.272)			
FFR_q					0.569	-0.268***	-0.421
					(0.967)	(0.0888)	(0.278)
Observations	1769	1769	1752	544	1769	1752	544
R^2	0.808	0.809	0.997	0.998	0.810	0.997	0.998
Countries	44	44	44	17	44	44	17
Quarters	100	100	99	32	100	99	32
CountryFE	Yes	Yes	-	-	Yes	-	-
CountryYearFE	No	No	Yes	Yes	No	Yes	Yes

Dependent variable is the domestic banking sector's percent of loans outstanding in foreign currency. VIX is the logged value of the CBOE S&P 500 implied volatility index. FFR is the effective federal funds rate. Bal. Samp. indicates that a balanced sample, as defined in the text, is used. Standard errors are double clustered by country and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3: Foreign Curreny Loans Share, Global Liquidity, and Country Characteristics

	(1)	(2) Bal. Samp.	(3)	(4) Bal. Samp.
VIX_q	0.686**	1.074**	1.455***	1.268**
	(0.330)	(0.499)	(0.366)	(0.539)
FFR_q	-0.233***	-0.284	-0.236***	-0.421
	(0.0444)	(0.302)	(0.0534)	(0.298)
Banks Inflows/$\text{GDP}_{i,q}$	0.0300***	0.0252**		
	(0.00946)	(0.0109)		
USD Index_q	0.0644**	0.0505		
	(0.0265)	(0.0362)		
$\text{VIX}_q \times \text{KAOPEN}_i$			0.431	-3.177**
			(1.212)	(1.335)
$\text{VIX}_q \times$ Fixed XR_i			-0.821	0.457
			(0.679)	(0.922)
$\text{VIX}_q \times \text{IQ}_i$			1.122	7.063
			(2.205)	(4.346)
Observations	1280	528	1499	544
R^2	0.997	0.998	0.997	0.998
Countries	30	17	35	17
Quarters	75	32	99	32
CountryYearFE	Yes	Yes	Yes	Yes

Dependent variable is the domestic banking sector's percent of loans outstanding in foreign currency. VIX is the logged value of the CBOE S&P 500 implied volatility index. FFR is the effective federal funds rate. Banks Inflows/GDP is capital inflows to the domestic banking sector as a percent of GDP, as constructed in Avdjiev et al. (2017). USD Index is the broad trade weighted value of the US dollar (from FRED). KAOPEN is the median value of the Chinn-Ito capital account openness index for each country, demeaned. Fixed XR is the median value of the exchange rate peg classification as defined in Shambaugh (2004), dummy variable with 1 indicating fixed. IQ is the median value of institutional quality index, derived from ICRG as defined in the text, demeaned. Bal. Samp. indicates that a balanced sample, as defined in the text, is used. Standard errors are double clustered by country and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Foreign Curreny Loans Share, Global Liquidity, and Bank Capitalization

	Full Sample		Balanced Sample	
	(1)	(2)	(3)	(4)
VIX_q	0.0799	0.954***	-1.391	0.925
	(1.905)	(0.335)	(1.025)	(0.645)
FFR_q	1.165	-0.310***	-0.0153	-0.361
	(0.888)	(0.104)	(0.358)	(0.314)
$\text{VIX}_q \times$ High Bank Capital_i	4.358*	-0.187	3.091**	0.288
	(2.406)	(0.530)	(1.194)	(0.751)
Observations	1622	1607	512	512
R^2	0.834	0.997	0.978	0.998
Countries	41	41	16	16
Quarters	99	99	32	32
CountryFE	Yes	-	Yes	-
CountryYearFE	No	Yes	No	Yes

Dependent variable is the domestic banking sector's percent of loans outstanding in foreign currency. VIX is the logged value of the CBOE S&P 500 implied volatility index. FFR is the effective federal funds rate. High Bank Capital is a dummy equal to 1 when the country-level bank capital ratio is above 8%. Balanced sample is defined in the text. Standard errors are double clustered by country and date. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: Global Liquidity and Loan Growth: Mexico Bank-Firm Level

	FX Loans		Peso Loans		All Loans			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VIX_q	0.0742**	0.0866***	0.0402***	0.0753***				
	(0.0327)	(0.0291)	(0.00718)	(0.00185)				
FX					-0.0734***	-0.0801*	-0.134***	-0.0305
					(0.0225)	(0.0426)	(0.00425)	(0.0240)
FX $\times$ VIX_q					0.0264***	0.0301***	0.0487***	0.0133***
					(0.00811)	(0.00204)	(0.00803)	(0.00407)
Observations	2145	2114	6059	6006	7825	7821	7197	7112
R^2	0.068	0.112	0.030	0.091	0.252	0.261	0.353	0.408
Banks	38	38	79	79	92	88	53	49
Firms	79	78	102	102	102	102	100	99
Quarters	26	26	27	27	27	27	26	26
BankFE	Yes	-	Yes	-	No	Yes	-	-
FirmFE	Yes	-	Yes	-	-	-	-	-
BankFirmFE	No	Yes	No	Yes	No	No	No	Yes
BankQuarterFE	No	No	No	No	No	No	Yes	Yes
FirmQuarterFE	No	No	No	No	Yes	Yes	Yes	Yes

Sample is loans from domestic banks to listed non-financial firms over 2008q1-2014q3. Dependent variable is the log difference of loans outstanding in FX or Peso at the Bank-Firm level in each period, winsorized by 1%. VIX is the logged value of the CBOE S&P 500 implied volatility index. FX is a dummy equal to 1 if the loan is denominated in a foreign currency. Regressions are weighted by the lagged value of the log of loan volume. Standard errors are triple clustered at the bank, firm, and date levels. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 4.6: Global Liquidity, Loan Growth, and Bank Characteristics: Mexico Bank-Firm Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FX	-0.0919	0.00607		-0.0764	-0.0337		-0.115**	-0.0375	
	(0.115)	(0.0584)		(0.0600)	(0.0661)		(0.0420)	(0.0735)	
FX × VIX_q	0.0353	0.00294		0.0298*	0.0161		0.0432***	0.0144	
	(0.0356)	(0.0177)		(0.0147)	(0.0223)		(0.00976)	(0.0249)	
FX × $Equity/Assets_b$	-3.758***	-5.818***	-7.485***						
	(0.425)	(1.472)	(2.532)						
FX × VIX_q × $Equity/Assets_b$	1.173***	1.742***	2.420***						
	(0.249)	(0.472)	(0.830)						
FX × Capital $Ratio_b$				-6.190**	-9.694***	-12.90***			
				(2.658)	(2.930)	(4.342)			
FX × VIX_q × Capital $Ratio_b$				1.902*	2.866***	4.056**			
				(0.960)	(0.998)	(1.482)			
FX × Bank $Size_b$							0.00521	0.0309	0.0672
							(0.0190)	(0.0333)	(0.0873)
FX × VIX_q × Bank $Size_b$							-0.00269	-0.00751	-0.0255
							(0.00636)	(0.0109)	(0.0255)
Observations	6959	6876	6167	6477	6401	5765	6959	6876	6167
R^2	0.342	0.397	0.462	0.344	0.395	0.459	0.342	0.396	0.462
Banks	44	40	38	34	33	32	44	40	38
Firms	99	97	91	98	94	89	99	97	91
Quarters	26	26	26	26	26	26	26	26	26
BankFirmFE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmQuarterFE	Yes	Yes	-	Yes	Yes	-	Yes	Yes	-
FirmQuarterCurrencyFE	No	No	Yes	No	No	Yes	No	No	Yes

Sample is loans from domestic banks to listed non-financial firms over 2008q1-2014q3. Dependent variable is the log difference of loans outstanding in FX or Peso at the Bank-Firm level in each period, winsorized by 1%. VIX is the logged value of the CBOE S&P 500 implied volatility index. FX is a dummy equal to 1 if the loan is denominated in a foreign currency. Equity/Assets is the average ratio of the bank's total equity to total assets. Capital Ratio is the bank's average Tier 1 capital ratio. Bank Size is the logged value of the bank's average asset size. Regressions are weighted by the lagged value of the log of loan volume. Standard errors are triple clustered at the bank, firm, and date levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A: Chapter 2 Appendix

A.1 Appendix Tables

Table A.1: Aggregate Representativeness

Year	Share of GDP	Share of NFC Value Added	Share of Total Credit to Private Non-Financial Sector
2006	9.34	14.73	55.75
2007	9.19	14.42	56.05
2008	12.67	19.77	62.02
2009	14.52	24.41	61.13
2010	11.90	19.64	63.06
2011	10.85	17.49	61.47
2012	8.34	13.19	61.98
2013	7.05	11.31	60.40
2014	6.24	9.96	60.28

Source: World Bank WDI, INEGI, BIS, author's calculations. Total credit is loans + bonds. Value added from my sample calculated as sales - cost of goods sold. Credit to non-financial sector series from BIS is to the private non-financial sector, so PEMEX is excluded from those calculations.

Table A.2: Comparability to Other Firms In Mexico

	All Firms	1000 Largest Firms	Listed Firms
Assets	1.62	3930.89	45 588.96
Equipment	0.74	1796.25	29 805.38
Sales	4.09	8846.96	9493.23
Employment	5.44	3344.42	15 807.39
Operating Margin	126.58	135.88	139.17

Source: Mexico 2009 Economic Census, author's calculations. The 1000 largest firms include some financial firms, so those firms are excluded from these numbers resulting in the 921 largest non-financial firms. All firms are similarly adjusted to remove financial firms. All figures are averages. Assets, equipment, and sales are expressed in millions of pesos, employment is expressed in total persons, and operating margin (defined as Operating Income/Sales) is expressed in percent.

Table A.3: Growth in Bank Loans (%), Firm-Bank Level - Difference in Difference Justification

	Pre-Period Differences		Firm Specific Time Trend	
	(1) FX	(2) Peso	(3) FX	(4) Peso
Exposure$_f$ × 2008q3	0.212	0.202		
	(0.327)	(0.560)		
Exposure$_f$ × 2008q4	-0.0298	0.928		
	(0.503)	(0.882)		
2008q3 × Small$_f$		-0.130		
		(0.119)		
2008q4 × Small$_f$		0.0149		
		(0.145)		
Exposure$_f$ × 2008q3 × Small$_f$		-0.583		
		(0.988)		
Exposure$_f$ × 2008q4 × Small$_f$		0.461		
		(2.068)		
Exposure$_f$ × Shock$_t$	-0.521***	1.118**	-0.594***	0.913***
	(0.108)	(0.466)	(0.167)	(0.313)
Shock$_t$ × Small$_f$		0.0661		0.0631
		(0.0481)		(0.0423)
Exposure$_f$ × Shock$_t$ × Small$_f$		-1.177**		-1.003***
		(0.485)		(0.335)
Observations	764	2377	1636	2819
R^2	0.475	0.157	0.815	0.255
Firms	34	47	40	50
FirmFE	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes
FirmTimeTrend	No	No	Yes	Yes
JointTest		0.691		0.509

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Growth in Bank Loans (%), Firm-Bank Level - Exporters

	FX			Peso		
	(1)	(2)	(3)	(4)	(5)	(6)
Shock_t	-0.0155			-0.0365*		
	(0.0240)			(0.0207)		
$\text{Exposure}_f \times \text{Shock}_t$	-0.0273	0.00681	0.0217	0.176	0.347**	0.413*
	(0.0679)	(0.0826)	(0.0888)	(0.144)	(0.169)	(0.243)
$\text{Small}_f \times \text{Shock}_t$			-0.0110			-0.0179
			(0.0975)			(0.104)
$\text{Exposure}_f \times \text{Small}_f \times \text{Shock}_t$			-0.0970			-0.109
			(0.351)			(0.384)
Observations	3853	2271	2271	1485	1162	1162
R^2	0.013	0.387	0.387	0.041	0.261	0.261
Firms	37	36	36	34	34	34
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	No	Yes	Yes	No	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest			0.828			0.351

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Loan Growth(%), Firm-Bank Level, Alternate Specifications

	$\Delta \log(L)$		$\frac{L-L_{-1}}{L_{-1}}$		$\frac{L-L_{-1}}{0.5*(L+L_{-1})}$	
	(1) FX	(2) Peso	(3) FX	(4) Peso	(5) FX	(6) Peso
Short $\text{FXL}_f \times \text{Shock}_t$	-1.848***	1.796**				
	(0.640)	(0.672)				
$\text{Shock}_t \times \text{Small}_f$		0.0761		0.102***		0.0696*
		(0.0480)		(0.0367)		(0.0356)
Short $\text{FXL}_f \times \text{Shock}_t \times \text{Small}_f$		-1.745**				
		(0.735)				
$\text{Exposure}_f \times \text{Shock}_t$			-0.539***	0.941***	-0.417***	0.832***
			(0.128)	(0.257)	(0.116)	(0.260)
$\text{Exposure}_f \times \text{Small}_f \times \text{Shock}_t$				-0.956***		-0.948***
				(0.296)		(0.277)
Observations	764	2458	772	2377	911	2681
R^2	0.483	0.154	0.471	0.162	0.502	0.172
Firms	34	49	34	47	34	48
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.799		0.926		0.303

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1) and (2) is the log difference of loans outstanding at the firm-bank level in each period, winsorized at 1%. Dependent variable in columns (3) and (4) is $(L^c_{f,b,t} - L^c_{f,b,t-1})/L^c_{f,b,t-1}$, winsorized at 3% for outliers. Dependent variable in columns (5) and (6) is $(L^c_{f,b,t} - L^c_{f,b,t-1})/(0.5*(L^c_{f,b,t} + L^c_{f,b,t-1}))$, which admits firm-bank entry and exit, and is bounded by [-2,2]. Short FXL is the firm's average 2008 short term fx liabilities to total assets, with 1 outlier firm winsorized. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Risky is a dummy equal to 1 if the firm is a small firm whose average leverage is above the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Growth in Bank Loans by Remaining Maturity (%), Firm-Bank Level

	FX				Peso			
	(1) Short	(2) Short	(3) Long	(4) Long	(5) Short	(6) Short	(7) Long	(8) Long
$\text{Exposure}_f \times \text{Shock}_t$	-0.811***	-0.768*	-0.00147	0.599	0.154	0.129	0.864**	1.326**
	(0.259)	(0.446)	(0.466)	(0.356)	(0.169)	(0.277)	(0.389)	(0.538)
$\text{Shock}_t \times \text{Small}_f$		-0.366***		0.189		-0.0411		0.0524
		(0.112)		(0.153)		(0.0568)		(0.0712)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$		0.316		-1.038***		0.0962		-1.157*
		(0.490)		(0.362)		(0.372)		(0.626)
Observations	560	560	397	397	2002	2002	1422	1422
R^2	0.448	0.457	0.505	0.513	0.150	0.150	0.206	0.208
Firms	28	28	25	25	47	47	42	42
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.0430		0.284		0.333		0.640

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Risky is a dummy equal to 1 if the firm is a small firm whose average leverage is above the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Growth in Bank Loans (%), Firm-Bank Level, Alternate Samples and Placebos

	FX			Peso		
	(1) Sample: Domestic Banks	(2) Sample: 2009q1-2013q1	(3) Placebo: 2010q3-2011q2	(4) Sample: Domestic Banks	(5) Sample: 2009q1-2013q1	(6) Placebo: 2010q3-2011q2
$\text{Exposure}_f \times \text{Shock}_t$	-0.583***	-0.407***	-0.257	0.896***	1.253**	-0.440
	(0.162)	(0.134)	(0.265)	(0.277)	(0.522)	(0.327)
$\text{Shock}_t \times \text{Small}_f$				0.0723*	0.0945**	-0.0158
				(0.0388)	(0.0454)	(0.0454)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$				-1.012***	-1.340**	0.0847
				(0.297)	(0.539)	(0.380)
Observations	493	634	764	2371	2075	2377
R^2	0.492	0.490	0.469	0.154	0.153	0.150
Firms	30	32	34	47	45	47
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest				0.334	0.554	0.169

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable is the log difference of loans outstanding in FX or Peso at the firm-bank level in each period, winsorized at 1%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Regressions are weighted by the lagged value of log loan. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Growth in Firm Level Outcomes (%)

	Pre-Period Differences		Firm Specific Time Trend	
	(1) Emp	(2) PPE	(3) Emp	(4) PPE
Exposure$_f$ × 2008q3	0.000349	-0.0539		
	(0.178)	(0.0600)		
Exposure$_f$ × 2008q4	0.0990	-0.0347		
	(0.0899)	(0.0726)		
2008q3 × Small$_f$	-0.0488	0.0107		
	(0.0305)	(0.0210)		
2008q4 × Small$_f$	0.00145	-0.0173		
	(0.0291)	(0.0282)		
Exposure$_f$ × 2008q3× Small$_f$	-0.00180	-0.0622		
	(0.227)	(0.197)		
Exposure$_f$× 2008q4 × Small$_f$	-0.308	0.149		
	(0.254)	(0.251)		
Exposure$_f$ × Shock$_t$	0.190	0.109	0.296	0.375*
	(0.115)	(0.0731)	(0.220)	(0.214)
Shock$_t$ × Small$_f$	0.00282	0.0147	0.0168	0.0160
	(0.0146)	(0.0119)	(0.0220)	(0.0154)
Exposure$_f$ × Shock$_t$ × Small$_f$	-0.300**	-0.229**	-0.284	-0.593**
	(0.129)	(0.0890)	(0.244)	(0.223)
Observations	768	790	545	567
R^2	0.173	0.208	0.250	0.312
Firms	51	52	47	48
FirmFE	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes
FirmTimeTrend	No	No	Yes	Yes
JointTest	0.0829	0.0237	0.927	0.00927

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1) and (3) is the log difference of employment at the firm level in each period, winsorized at 2%. Dependent variable in columns (2) and (4) is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Growth in Firm Level Outcomes (%) - Exporters

	Bank Debt		Employment		PPE	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Exposure}_f \times \text{Shock}_t$	0.390**	0.207	0.0205	0.0253	0.0166	0.0303
	(0.156)	(0.163)	(0.0248)	(0.0319)	(0.0244)	(0.0237)
$\text{Shock}_t \times \text{Small}_f$		-0.0750		0.00793		0.0136
		(0.0940)		(0.0160)		(0.0173)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$		0.621*		-0.0215		-0.0550
		(0.352)		(0.0527)		(0.0597)
Observations	641	641	599	599	601	601
R^2	0.159	0.164	0.179	0.179	0.329	0.331
Firms	38	38	38	38	38	38
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.0160		0.929		0.664

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1) and (2) is the log difference of bank credit outstanding at the firm level in each period, winsorized at 1%. Dependent variable in columns (3) and (4) is the log difference of employment at the firm level in each period, winsorized at 2%. Dependent variable in columns (5) and (6) is the log difference of physical capital outstanding, measured as property, plant, and equipment, at the firm level in each period, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Growth in Firm Level Outcomes (%), Alternate Specifications

	$\Delta\log(E)$		$\frac{E-E_{-1}}{E_{-1}}$		$\Delta\log(PPE)$		$\frac{PPE-PPE_{-1}}{PPE_{-1}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short $\text{FXL}_f \times \text{Shock}_t$	-0.0907	0.173			-0.00186	0.351^{**}		
	(0.0931)	(0.258)			(0.0634)	(0.146)		
$\text{Shock}_t \times \text{Small}_f$		0.00999		0.00406		0.0169		0.0183
		(0.0206)		(0.0146)		(0.0118)		(0.0122)
Short $\text{FXL}_f \times \text{Shock}_t \times \text{Small}_f$		-0.324				-0.436^{***}		
		(0.279)				(0.161)		
$\text{Exposure}_f \times \text{Shock}_t$			0.0747	0.155^{*}			0.0345	0.139^{*}
			(0.0456)	(0.0777)			(0.0634)	(0.0701)
$\text{Exposure}_f \times \text{Shock}_t \times \text{Small}_f$				-0.203^{*}				-0.272^{***}
				(0.105)				(0.0893)
Observations	797	797	749	749	819	819	787	787
R^2	0.166	0.168	0.151	0.156	0.191	0.195	0.192	0.201
Firms	53	53	51	51	54	54	52	52
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankShock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
JointTest		0.176		0.525		0.268		0.0232

Sample spans 2008q1-2013q1, Firms reports the number of firms in each regression. Dependent variable in columns (1) and (2) is the log difference of employment at the firm level in each period, winsorized at 2%; in columns (3) and (4) is employment growth $(E - E_{-1})/E_{-1}$ at the firm level in each period, winsorized at 2%; in columns (5) and (6) is the log difference of physical capital outstanding, measured as property, plant, and equipment (PPE), at the firm level in each period, winsorized at 2%.; and in columns (7) and (8) is $(PPE - PPE_{-1})/PPE_{-1}$, winsorized at 2%. Exposure is the firm's average 2008 net FX position to assets, with 2 outlier firms winsorized. Short FXL is the firm's average 2008 short term fx liabilities to total assets, with 1 outlier firm winsorized. Small is a dummy equal to one if the firm's average size (measured by log assets) is below the sample median. Shock is a dummy variable taking a value of 1 in 2009 and 2010 and 0 otherwise. Bank shock is a control for credit supply shocks to each firm, as constructed in the text, lagged one period. Firm Controls include one quarter lags of firm size (log assets), cash to assets ratio winsorized at 1%, total liabilities to assets ratio winsorized at 2%, bond credit to assets, share of sales to foreigners (including exports and sales by foreign subsidiaries), sales to assets ratio, and net derivatives position to total liabilities winsorized at 3%. Errors are clustered at the firm level. JointTest reports the p-value of the F-test that the sum of the coefficients of Exposure*Shock and Exposure*Shock*Small is equal to 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Equivalence of using demeaned estimates of bank shocks

Proof of Proposition 2.6.1. Rewrite the estimated effect as

$$\hat{\alpha}_{b,t} = \hat{\alpha}^*_{b,t} - \hat{\alpha}^*_{ref,t} \tag{A.1}$$

Note that the time average of $\hat{\alpha}^*_{ref,t}$ is $\hat{\alpha}^*_{ref,t}$. Thus $\hat{\alpha}_{b,t} - \overline{\hat{\alpha}_t} = \hat{\alpha}^*_{b,t} - \overline{\hat{\alpha}^*_t}$, where $\overline{\hat{\alpha}_t}$ is the time average of $\hat{\alpha}_{b,t}$. By the same logic, $\hat{\alpha}_{f,t} - \overline{\hat{\alpha}^f_t} = \hat{\alpha}^*_{f,t} - \overline{\hat{\alpha}^{f*}_t}$ where $\overline{\hat{\alpha}^f_t}$ is the time average of $\hat{\alpha}_{f,t}$.

Define $L_{f,t-1} = \sum_{b \in B_{f,t}} L_{f,b,t-1}$. Then, by time demeaning $\widehat{BS}_{f,t}$ and substituting in equation A.1, we obtain

$$\begin{aligned}
\widehat{BS}_{f,t} - \overline{\widehat{BS}_t} &= \frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times \hat{\alpha}_{b,t}) - \frac{1}{F_t} \sum_{f; \in F_t} \left(\frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times \hat{\alpha}_{b,t}) \right) \\
&= \frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times (\hat{\alpha}^*_{b,t} - \hat{\alpha}^*_{ref,t})) \\
&\quad - \frac{1}{F_t} \sum_{f \in F_t} \left(\frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times (\hat{\alpha}^*_{b,t} - \hat{\alpha}^*_{ref,t})) \right) \\
&= \frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times \hat{\alpha}^*_{b,t}) - \frac{\hat{\alpha}^*_{ref,t} \sum_{b \in B_{f,t}} L_{f,b,t-1}}{L_{f,t-1}} \\
&\quad - \frac{1}{F_t} \sum_{f \in F_t} \left(\frac{1}{L_{f,t-1}} \sum_{b \in B_{f,t}} (L_{f,b,t-1} \times \hat{\alpha}^*_{b,t}) - \frac{\hat{\alpha}^*_{ref,t} \sum_{b \in B_{f,t}} L_{f,b,t-1}}{L_{f,t-1}} \right) \\
&= \widehat{BS}^*_{f,t} - \hat{\alpha}^*_{ref,t} - \frac{1}{F_t} \sum_{f \in F_t} \left(\widehat{BS}^*_{f,t} - \hat{\alpha}^*_{ref,t} \right) \\
&= \widehat{BS}^*_{f,t} - \hat{\alpha}^*_{ref,t} - (\overline{\widehat{BS}}^*_t - \hat{\alpha}^*_{ref,t}) \\
&= \widehat{BS}^*_{f,t} - \overline{\widehat{BS}}^*_t
\end{aligned}$$

$\blacksquare$

A.3 Model Solution

Solution for Firm's Problem

Recall that $E[1+\phi] = \frac{1+r}{1+r^*}\frac{1}{\gamma}$. Let the CDF of the random variable $1+\phi$ be given by $G(\cdot)$.

The t=1 decision breaks into 6 cases (denoted by cutoffs W_0 to W_4), whose probability depend on w_1 and z_2:

Case 0: $w_1 \leq 0 = W_0$

$Pr(Case0) = 1 - G(\frac{z_1 k_1^\alpha - (1+r)d_1}{(1+r^*)d_1^*})$

$k_2 = 0, d_2^* = 0, d_2 = 0$

$\Pi_2 = 0$

Case 1: $0 < w_1 \leq \frac{\left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_0} = W_1$

$Pr(Case1) = G(\frac{z_1 k_1^\alpha - (1+r)d_1}{(1+r^*)d_1^*}) - G(\frac{z_1 k_1^\alpha - (1+r)d_1 - W_1}{(1+r^*)d_1^*})$

$k_2 = (1+\kappa_0)w_1, d_2^* = \kappa_1 w_1, d_2 = (\kappa_0 - \kappa_1)w_1$

$\Pi_2 = z_2((1+\kappa_0)w_1)^\alpha - (1+r)(\kappa_0 - \kappa_1)w_1 - (1+r^*)(1+\phi_2)\kappa_1 w_1$

Case 2: $\frac{\left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_0} \leq w_1 < \frac{\left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_0} = W_2$

$Pr(Case2) = G(\frac{z_1 k_1^\alpha - (1+r)d_1 - W_1}{(1+r^*)d_1^*}) - G(\frac{z_1 k_1^\alpha - (1+r)d_1 - W_2}{(1+r^*)d_1^*})$

$k_2 = \left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}}, d_2^* = \kappa_1 w_1, d_2 = \left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}} - (1+\kappa_1)w_1$

$\Pi_2 = z_2\left(\frac{z_2\alpha}{1+r}\right)^{\frac{\alpha}{1-\alpha}} - (1+r)\left(\left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}} - (1+\kappa_1)w_1\right) - (1+r^*)(1+\phi_2)\kappa_1 w_1$

Case 3: $\frac{\left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_0} \leq w_1 < \frac{\left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_1} = W_3$

$Pr(Case3) = G(\frac{z_1 k_1^\alpha - (1+r)d_1 - W_2}{(1+r^*)d_1^*}) - G(\frac{z_1 k_1^\alpha - (1+r)d_1 - W_3}{(1+r^*)d_1^*})$

$k_2 = (1+\kappa_1)w_1, d_2^* = \kappa^* w_1, d_2 = 0$

$\Pi_2 = z_2((1+\kappa_1)w_1)^\alpha - (1+r^*)(1+\phi_2)\kappa_1 w_1$

Case 4: $\frac{\left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}}}{1+\kappa_1} \leq w_1 < \left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}} = W_4$

$Pr(Case4) = G(\frac{z_1k_1^\alpha-(1+r)d_1-W_3}{(1+r^*)d_1^*}) - G(\frac{z_1k_1^\alpha-(1+r)d_1-W_4}{(1+r^*)d_1^*})$

$k_2 = \left(\frac{z_2\alpha\gamma}{1+r}\right)^{\frac{1}{1-\alpha}}, d_2^* = \left(\frac{z_2\alpha\gamma}{1+r}\right)^{\frac{1}{1-\alpha}} - w_1, d_2 = 0$

$\Pi_2 = z_2\left(\frac{z_2\alpha\gamma}{1+r}\right)^{\frac{\alpha}{1-\alpha}} - (1+r^*)(1+\phi_2)\left(\left(\frac{z_2\alpha\gamma}{1+r}\right)^{\frac{1}{1-\alpha}} - w_1\right)$

Case 5: $\left(\frac{z_2\alpha\gamma}{(1+r)}\right)^{\frac{1}{1-\alpha}} \leq w_1$

$Pr(Case5) = G(\frac{z_1k_1^\alpha-(1+r)d_1-W_4}{(1+r^*)d_1^*})$

$k_2 = w_1, d_2^* = 0, d_2 = 0$

$\Pi_2 = z_2w_1^\alpha$

Using the probabilities of being in these cases and the expected profit from each, we can express the period 0 decision as maximizing the expected period 2 profit, given w_0, and subject to the budget constraint and borrowing constraints.

$$\max_{d_1,d_1^*}\sum_{i=0}^{5} Pr(Case_i|z_2) * \Pi_2^i(w_1,z_2) \tag{A.2}$$

s.t.

$$w_1 = z_1k_1^\alpha - (1+r)d_1 - (1+r^*)E[1+\phi_1]d_1^* \tag{A.3}$$

$$k_1 = w_0 + d_1 + d_1^* \tag{A.4}$$

$$d_1 + d_1^* \leq \kappa_0 w_0 \tag{A.5}$$

$$d_1^* \leq \kappa_1 w_0 \tag{A.6}$$

Proofs

Proof of Proposition 2.7.1. If $0 < w_1 \leq W_1$, the constrained optimal debt and investment choices are $d_2^* = \kappa_1 w_1$, $d_2 = (\kappa_0 - \kappa_1)w_1$, and $k_2 = (1+\kappa_0)w_1$. It follows that $\frac{\partial d_2^*}{\partial w_1} = \kappa_1 > 0$, $\frac{\partial d_2}{\partial w_1} = (\kappa_0 - \kappa_1) > 0$, and $\frac{\partial k_2}{\partial w_1} = 1 + \kappa_0 > 0$. Hence, a negative shock to w_1 leads to lower FX debt, peso debt, and investment.

If $W_1 < w_1 \leq W_2$, the semi-constrained optimal debt and investment choices are $d_2^* = \kappa_1 w_1$, $d_2 = \left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}} - (1+\kappa_1)w_1$, $d_2 + d_2^* = \left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}} - w_1$, and $k_2 = \left(\frac{z_2\alpha}{1+r}\right)^{\frac{1}{1-\alpha}}$. It then follows that $\frac{\partial d_2^*}{\partial w_1} = \kappa_1 > 0$, $\frac{\partial d_2}{\partial w_1} = -(1+\kappa_1) < 0$, $\frac{\partial (d_2 + d_2^*)}{\partial w_1} = -1 < 0$, and $\frac{\partial k_2}{\partial w_1} = 0$. Hence, a negative shock to w_1 which leaves $w_1 > W_1$, results in lower FX debt, higher peso debt, higher total debt, and unchanged investment. ■

Proof of Proposition 2.7.2. The proof proceeds in several steps: First, I show that $E_1[Pi_2]$ is strictly increasing in w_1, $\forall\, w_1 > 0$:

Case 1: $\frac{\partial E_1[\Pi_2]}{\partial w_1} = \alpha z_2((1+\kappa_0)w_1)^{\alpha-1}(1+\kappa_0) - (1+r)(\kappa_0 - \kappa_1\frac{\gamma-1}{\gamma}) > 0\ \forall\ w_1 \in (0, W_1)$

Case 2: $\frac{\partial E_1[\Pi_2]}{\partial w_1} = (1+r)(1+\kappa_1\frac{\gamma-1}{\gamma}) > 0$

Case 3: $\frac{\partial E_1[\Pi_2]}{\partial w_1} = \alpha z_2((1+\kappa_1)w_1)^{\alpha-1}(1+\kappa_1) - \kappa_1\frac{1+r}{\gamma} > 0\ \forall\ w_1 \in (W_2, W_3)$

Case 4: $\frac{\partial E_1[\Pi_2]}{\partial w_1} = \frac{1+r}{\gamma} > 0$

Case 5: $\frac{\partial E_1[\Pi_2]}{\partial w_1} = \alpha z_2 w_1^{\alpha-1} > 0$

Thus, maximizing $E_1[\Pi_2]$ requires maximizing $E_0[w_1]$, accounting for the probability of default.

Next, I show that $E_0[w_1]$ is increasing in FX debt, holding k_1 (and thus $d_1 +$

d_1^*) constant and thresholds W_i constant:

$\frac{\partial E_0[w_1]}{\partial d_1^*}|_{W_i=\bar{W}_i,(k_1=\bar{k})} = (1+r)\frac{\gamma-1}{\gamma} > 0$

Next, I show that the default probability is increasing in d_1^*, again holding investment constant:

$\frac{\partial Pr(w_1<W_0)}{\partial d_1^*}|_{k_1=\bar{k}} = G'(\cdot)\frac{z_1 k_1^\alpha-(1+r)(k_1-w_0)}{(1+r^*)(d_1^*)^2} > 0$ for all values of debt $d_1+d_1^*$ such that the firm does not default with probability 1 (prevented by borrowing constraint).

Lastly, I show that the default probability is increasing in z_1:

$\frac{\partial Pr(w_1<W_0)}{\partial z_1} = \frac{k_1^\alpha}{(1+r^*)d_1^*} > 0$

This implies that with a higher z_1, the firm could increase their share of FX debt while maintaining their original default probability and thus have higher expected wealth w_1 and then higher expected period 2 profits Π_2. So, $\frac{\partial d_1^*}{\partial z_1} > 0$

■

Proof of Proposition 2.7.3. From Proposition 2.7.2, we know that the probability of default in period 1 does not depend on z_2 and is decreasing in z_1. For the remaining thresholds, it is sufficient to find conditions for W_4 such that $Pr(w_1 < W_4|z_1,z_2) < Pr(w_1 < W_4|\bar{z})$:

$$\frac{\bar{z}k_1^\alpha-(1+r)d_1-W_4(\bar{z})}{(1+r^*)d_1^*} < \frac{z_1k_1^\alpha-(1+r)d_1-W_4(z_2)}{(1+r^*)d_1^*}$$

$$W_4(z_2)-W_4(\bar{z}) < k_1^\alpha(z_1-\bar{z})$$

$$\left(z_2^{\frac{1}{1-\alpha}}-\bar{z}^{\frac{1}{1-\alpha}}\right)\left(\frac{\alpha\gamma}{1+r}\right)^{\frac{1}{1-\alpha}} < k_1^\alpha(z_1-\bar{z})$$

$$\frac{z_2^{\frac{1}{1-\alpha}} - \bar{z}^{\frac{1}{1-\alpha}}}{z_1 - \bar{z}} < X_1 k_1^{\alpha}$$

where $X_4 = \left(\frac{1+r}{\alpha\gamma}\right)^{\frac{1}{1-\alpha}}$. Note that for the other thresholds, the constant is, $X_1 = (1+\kappa_0)\left(\frac{1+r}{\alpha}\right)^{\frac{1}{1-\alpha}}$ $X_2 = (1+\kappa_0)\left(\frac{1+r}{\alpha\gamma}\right)^{\frac{1}{1-\alpha}}$, and $X_3 = (1+\kappa_1)\left(\frac{1+r}{\alpha\gamma}\right)^{\frac{1}{1-\alpha}}$, so $X_4 < X_3 < X_2 < X_1$.

Assuming this condition holds, then $Pr(w_1 < W_i|z_1, z_2) < Pr(w_1 < W_i|\bar{z})\ \forall\ i \in \{1, 2, 3, 4\}$. From the logic in the proof to Proposition 2.7.2, this implies that $d_1^*(w_0, z_1, z_2) > d_1^*(w_0, \bar{z}, \bar{z})$.

■

Appendix B: Chapter 3 Appendix

B.1 Capital Flow Data

Some of the presentations and definitions of international capital flow data can be ambiguous or inconsistent across data sources. In order to be clear about what we are doing, we briefly highlight some basic concepts regarding capital flow data generally.

B.1.1 Net Flows vs Gross Flows

In the literature and in the data, there is some ambiguity of terms when referring to net and gross flows. Essentially, there are three distinctions:

Gross Flows: Strictly speaking, gross inflows and outflows refer to one-way flows without netting out any capital flowing in the opposite direction. This definition of gross flows is generally what comes to mind when the term is used. Nevertheless, data that actually matches this definition are quite scarce.

Net Inflows and Outflows: What is commonly called "gross flows" in the literature is actually more accurately described as "net inflows" and "net outflows". There are no comprehensive datasets on flows that are truly gross. Instead, researchers tend to use net inflows and net outflows, which can be obtained from the IMF's BOP dataset. Net inflows are gross liability flows, net of repayments. Net outflows are gross asset flows, net of disinvestment. Thus, although these measures are often called "gross", they can be positive or negative. The separation of flows into asset and liability flows allows interpreting liability flows as net inflows from foreign agents, and asset flows as net outflows by domestic agents. This is the primary working definition of capital flows, which we use across all data sources for consistency.

Net Flows: This relates to the net movement of capital into and out of a country. This is the equivalent of the negative of the current account, that is, the difference between Net Inflows and Net Outflows (or equivalently the difference between Gross Inflows and Gross Outflows).

Stock/Position Data: In general, there is no standard definition of "net" stocks, as some countries report outstanding debt net of some financial assets (Arslanalp & Tsuda, 2014b), while others do not. A more widely-agreed view is that the net stock of external wealth should be equivalent to the Net International Investment Position, which is the difference between outstanding external stock of assets and outstanding external stock of liabilities. Gross positions then refer to the outstanding stocks of assets and liabilities separately.

B.1.2 External Borrowing of Sectors

The focus of this paper is on the differentiation of capital flows by sector in the domestic economy. The term "sector" is used here to refer to institutional sectors: general government, central banks, depository corporations except the central bank ("banks"), and other sectors ("corporates").[1] There are other ways to define the sectors of the economy, but this breakdown is the most common in the data.[2]

These broad sectors can sometimes be decomposed into various institutional subsectors (for example, other sectors are sometimes split into other non-bank financial and other non-financial sectors in the BOP data). Thus, sectors can also be defined differently depending on the dataset or measure. For instance, several datasets such as the WB DRS produce statistics on public and publicly guaranteed (PPG) debt. In this case, public refers to general government, central banks, and the public sector portions of banks and corporates. Publicly guaranteed private sector debt is defined precisely as its name suggests and is the complement to PPG. Otherwise, most datasets using a sectoral breakdown conform to the standard definition of the main institutional sectors and subsectors given above. We will use the standard 4 sector split for most of our analysis, but we separately consider PPG vs. PNG debt in Appendix B.6.4.

[1] It should be noted that the BoP category "other sectors" is broader than what is captured than the term "corporates". Nevertheless, in most cases, there is fairly broad overlap between the two categories. That is why, in the rest of this paper, we use the two terms interchangeably for presentational convenience.

[2] See Chapter 4 Section D of the 6th Edition Balance of Payments Manual for an overview of Systems of National Accounts sectoral breakdowns, and the sectoral breakdowns used in the BOP (and often other) data sources.

B.1.3 Sign of Flows

There remains some confusion about the sign of capital inflows and outflows in the data. This is primarily due to a change in sign conventions that occurred when the BOP data switched from the BPM5 to the BPM6 version. In BPM5, a negative sign indicated that capital was leaving the country on net, regardless of whether it was an asset or liability flow. In the current version of the BOP data (BPM6), a positive asset flow represents capital leaving the country on net by domestic residents, while a positive liability flow represents capital entering the country on net by foreigners. We use the updated convention, where a positive sign indicates an increase in either assets or liabilities, and adjust our interpretation accordingly.

B.2 Balance of Payments Data

The IMF's Balance of Payments (BOP) data is the most comprehensive dataset available on international capital flows. It comprises two main accounts – the Current Account and the Financial Account.[3] The current account records transactions from the real side, capturing imports and exports, factor income, and transfer payments. The financial account records transaction from the financial side, capturing the acquisition of financial assets and the incurrence of financial

[3] A third account, the Capital Account, is generally much smaller than these two. Since the BOP uses double entry bookkeeping, the sum of the accounts should be zero, so a Balancing Account called "Net errors and omissions" is defined to satisfy the identity: current account + financial account + capital account + net errors and omissions = 0. Errors and omissions are usually interpreted as unrecorded private capital flows (see Forbes and Warnock (2012)).

liabilities. We focus on the Financial Account portion of the BOP data.

There are several presentations of the BOP data.[4] The standard presentation disaggregates the data by flow type and instrument. The analytic presentation, which is the one available within the IMF's International Financial Statistics (IFS), reports exceptional financing (used to meet balance-of-payments financing needs) separately from the standard presentation.[5] The analytic presentation can be useful to separate some public flows from private flows, because exceptional financing can be viewed as an alternative instrument to the use of reserve assets or IMF credit to help deal with balance of payments shortfalls.[6] We use the sectoral presentation, which breaks down the standard presentation by domestic institutional sector, but we also use measures of exceptional financing from the analytic presentation to allocate all exceptional financing flows to the public sector.

In theory, the structure of the BOP dataset should allow separating the flows by institutional sector, but the requisite data is sometimes missing. It is difficult to determine if missing data is truly missing, or if it is zero. Data on outflows are generally more sparse than data on inflows. Further, the time coverage of the data varies greatly across countries. Especially for variables with sectoral breakdown, the coverage is weighted heavily towards recent years.

[4]See Chapter 14 Section C of the 6th edition BOP manual for a description of the various presentations.

[5]Exceptional Financing is usually classified under the other investment category.

[6]See the 6th edition BOP manual Appendix 1 for a description of Exceptional Financing. See Alfaro, Şebnem Kalemli-Özcan, and Volosovych (2014) for discussion and use of IFS data to divide net flows into public and private components.

B.2.1 Types of Flows

Capital flows in the Financial Account of the BOP are disaggregated first by type of flow. The main types are direct investment, portfolio equity, portfolio debt, other investment, financial derivatives, and reserves. For each of these flow types, the BOP reports asset flows and liability flows. We describe each type of flow and how it can be broken down into the various institutional sectors.[7]

Direct Investment: Direct investment, commonly called FDI, captures investment involving at least 10% ownership. It is meant to reflect investment relationships based on control and influence. In addition to equity investment, it also captures other investments under a controlling relationship, including debt and reverse investment.

Direct investment is not broken down by sector. Unlike the BPM5 version of the data, the BPM6 data does have splits according to liability and asset flows for direct investment (consistent with other BOP flows).[8] The debt portion of direct investment can be allocated with some assumptions. Debt flow between affiliated parties are only recorded as direct investment debt if at least one party is a non-financial firm. Thus for inflows, we can attribute all direct investment debt to the Corporate sector if we assume that such lending from offshore non-financial firms to onshore banks is negligible.

Portfolio Equity: Portfolio equity captures investment in equity securities

[7]See Appendix 9 of the Balance of Payments Manual for a list of all the components of the Financial Account with their structure in the BOP data.

[8]This is one of the main differences between the BPM5 and BPM6 versions of the data.

not included in direct investment.[9] It is broken down by institutional sector and, in principle, asset and liability flows are defined for all sectors. Note, however, that liability flows for central banks and general government should equal zero regardless of data reporting.[10]

Portfolio Debt: Portfolio debt consists of all debt securities not captured under direct investment. It is separated into asset and liability flows, and then disaggregated by institutional sector.

Financial Derivatives: Financial derivatives tend to be a quantitatively small category of gross flows, covering derivatives and employee stock options. Financial derivatives that are associated with reserve asset management are excluded. Both asset and liability flows offer breakdowns by institutional sector.[11] Due to its small size and sparse data, we ignore this component in our analysis.

Other Investment: Other investment captures all other investments not included in the previous categories. It is first broken into other investment equity[12] and other investment debt. Other investment debt is then disaggregated as follows: currency and deposits, loans (including use of IMF credit and loans), insurance and pensions,[13]trade credit and advances, other accounts payable/receivable,

[9] Equity not in the form of securities is not captured here.

[10] Some countries report positive equity liability flows for the government or central bank, but we believe this is equity from state-owned or quasi-public enterprises (banks or corporates) that was mis-recorded.

[11] Some countries may report financial derivatives on a net basis only. See 6th edition BOP manual paragraphs 6.60 and 8.34.

[12] This is equity investment that is not direct investment or reserve assets, and is not in the form of securities. Equity securities are captured under portfolio equity. This category, introduced with the BPM6 version of the BOP data, is sparsely reported.

[13] This includes non-life insurance technical reserves, life insurance and annuities entitlements, pension entitlements, and provisions for calls under standardized guarantees. This component is likely also small, and very sparsely reported.

and SDR allocations.[14]

Other investment debt as a whole, and each of its component instruments, is broken down into asset and liability flows, and then further broken down by institutional sector. However, there is no sectoral breakdown of Other Investment Equity.

Reserves: Reserve Assets are external assets held by the Central Bank or Monetary Authority that are readily available for use to meet Balance of Payments financing needs. These include foreign currency, convertible gold, SDRs, and other reserve assets. Thus, this component is an asset flow of the public sector only.

While in principle the structure of the BOP data contains all the ingredients required to compute each type of flow for each sector, in practice there are some countries which do not exhaustively provide these breakdowns, especially for earlier years.[15] Table B.1 in the appendix highlights the coverage by flow type and sector in the quarterly BOP data.[16] For each component, the table displays the number of countries reporting data, the number of quarters with at least one

[14]SDR holdings (as opposed to SDR allocations) are included in reserve assets. A one time increase in SDR allocations occurred in the 3rd quarter of 2009 for all IMF member countries, so those flows are removed.

[15]Table B.3 lists the BOP variables required to compute each type of capital flow by sector. Variable names are as they are found in the bulk public download of the BP6 version BOP data, as of May 2016. The Balance of Payments data also includes International Investment Position (IIP) data, which is the stock equivalent of the BOP flow measures. Variable names for IIP construction by sector are also included, for reference.

[16]Some items in the BOP data are available back to 1948, but this applies to very few of them. For this table, we consider data only from 1980 onwards. The annual BOP data does have somewhat better coverage. For instance, when shifting from quarterly to annual frequency, the number of countries with full coverage of portfolio debt liability flows over 1996-2014 goes from (1,21,13,19) to (4,32,18,27) for central banks, general government, banks, and other sectors, respectively.

country reporting data, the number of country-quarter observations with non-missing data, and the number of countries that have data for that component in every period over the 1996q1-2014q4 period. Next to each of these numbers, in brackets we report the implied coverage as percentage of the theoretical maximum, given by 190 countries, 144 quarters, and 27360 total observations. The direct investment and reserves lines give us an idea of the coverage of the more standard items that are not disaggregated by sector. Generally, we see that for most sectors and flow types, most countries and periods show some data. However, the data is skewed towards recent years, and few countries show coverage over the full 1996q1-2014q4 period.

Table B.2 shows the coverage breakdown for Other investment Debt by instrument, with each instrument listed separately under Asset and Liability by sector. The table illustrates how more detailed breakdowns tend to result in poorer coverage, as not all countries provide such detail to the IMF. Generally, if other investment debt by sector is missing, then all of the underlying instruments (with the exception of IMF credit) are also missing. When data for instruments is reported, it can be the case that all of other investment debt is recorded under a single instrument (usually loans), despite the number representing other instruments as well (such as trade credit, etc.).[17]

[17] We thank Gian-Maria Milesi-Ferretti for pointing this out.

Table B.1: BOP Data Coverage by Sector

Flow Type	A/L	Sector	Country	Quarter	Country-Quarter	Panel
Direct Investment	Assets	All	133 (70%)	143 (99%)	8495 (31%)	35 (18%)
	Liabilities	All	146 (77%)	143 (99%)	10920 (40%)	63 (33%)
Portfolio Equity	Assets	Central Banks	23 (12%)	60 (42%)	309 (1%)	0 (0%)
		General Gov	58 (31%)	91 (63%)	1480 (5%)	0 (0%)
		Banks	84 (44%)	127 (88%)	3611 (13%)	8 (4%)
		Corporates	107 (56%)	143 (99%)	5045 (18%)	13 (7%)
	Liabilities	Central Banks	1 (0.5%)	18 (13%)	18 (0.0%)	0 (0%)
		General Gov	8 (4%)	73 (51%)	98 (0.0%)	0 (0%)
		Banks	71 (37%)	143 (99%)	3283 (12%)	11 (6%)
		Corporates	102 (59%)	143 (99%)	5338 (20%)	27 (14%)

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Table B.1 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**Country**	**Quarter**	**Country-Quarter**	**Panel**
Portfolio Debt	Assets	Central Banks	44 (23%)	86 (60%)	1154 (4%)	0 (0%)
		General Gov	60 (32%)	104 (72%)	1990 (7%)	3 (2%)
		Banks	100 (53%)	134 (93%)	5097 (17%)	18 (9%)
		Corporates	101 (53%)	143 (99%)	5090 (19%)	18 (9%)
	Liabilities	Central Banks	38 (20%)	143 (99%)	981 (4%)	1 (0.5%)
		General Gov	104 (55%)	143 (99%)	6243 (23%)	21 (11%)
		Banks	91 (48%)	143 (99%)	4037 (15%)	13 (7%)
		Corporates	93 (49%)	143 (99%)	5217 (19%)	19 (10%)
Other Investment Debt	Assets	Central Banks	92 (48%)	143 (99%)	3734 (14%)	2 (1%)
		General Gov	104 (55%)	143 (99%)	5653 (21%)	12 (6%)
		Banks	138 (73%)	143 (99%)	9793 (36%)	53 (28%)
		Corporates	135 (71%)	143 (99%)	9209 (34%)	45 (24%)

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Table B.1 – *Continued from previous page*

Flow Type	A/L	Sector	Country	Quarter	Country-Quarter	Panel
	Liabilities	Central Banks	130 (68%)	143 (99%)	8768 (32%)	29 (15%)
		General Gov	138 (73%)	143 (99%)	10292 (38%)	47 (25%)
		Banks	137 (72%)	143 (99%)	10372 (38%)	54 (28%)
		Corporates	139 (73%)	143 (99%)	10307 (38%)	56 (29%)
Other Equity	Assets	All	(%)	(%)	(%)	(%)
	Liabilities	All	(%)	(%)	(%)	(%)
Financial Derivatives	Assets	Central Banks	14 (7%)	95 (66%)	225 (1%)	0 (0%)
		General Gov	25 (13%)	86 (60%)	578 (2%)	0 (0%)
		Banks	58 (31%)	103 (72%)	1906 (7%)	3 (2%)
		Corporates	53 (28%)	111 (77%)	1620 (6%)	4 (2%)
	Liabilities	Central Banks	9 (5%)	85 (59%)	136 (0.5%)	0 (0%)
		General Gov	17 (9%)	95 (66%)	346 (1%)	0 (0%)

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Table B.1 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**Country**	**Quarter**	**Country-Quarter**	**Panel**
		Banks	52 (27%)	103 (72%)	1603 (6%)	2 (1%)
		Corporates	49 (26%)	113 (78%)	1400 (5%)	2 (1%)
Reserves	Assets	Central Bank	146 (77%)	143 (99%)	11387 (42%)	65 (34%)

The dataset covers 190 Countries over 1980q1-2015q4 (144 Quarters), yielding 27360 Country-Quarter observations. The first number in each cell is the total number of countries, quarters, observations, and countries (respectively) with non-missing data, while the second number is the percent of total countries, quarters, observations, and countries, respectively. The Panel column is the number (and percent) of countries with non-missing observations over 1996q1-2014q4. Note that, at the time of donwload, most 2015q4 variables have not yet been reported.

Table B.2: Other Investment Debt Instrument Coverage by Sector

Instrument	A/L	Sector	Country	Quarter	Country-Quarter	Panel
Currency and Deposits	Assets	Central Banks	60 (32%)	137 (95%)	2212 (8%)	0 (0%)
		General Gov	80 (42%)	143 (99%)	2913 (11%)	4 (2%)
		Banks	140 (74%)	143 (99%)	9377 (34%)	49 (22%)
		Corporates	130 (68%)	143 (99%)	7531 (28%)	30 (16%)
	Liabilities	Central Banks	97 (51%)	143 (99%)	4779 (17%)	9 (5%)
		General Gov	21 (11%)	143 (99%)	627 (2%)	1 (0.5%)
		Banks	137 (72%)	143 (99%)	9413 (34%)	41 (22%)
		Corporates	51 (27%)	143 (99%)	1496 (5%)	2 (1%)
Loans	Assets	Central Banks	37 (19%)	134 (93%)	840 (3%)	0 (0%)
		General Gov	62 (33%)	143 (99%)	2910 (11%)	7 (4%)
		Banks	110 (58%)	143 (99%)	6287 (23%)	24 (13%)

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Table B.2 – *Continued from previous page*

Instrument	**A/L**	**Sector**	**Country**	**Quarter**	**Country-Quarter**	**Panel**
		Corporates	98 (52%)	143 (99%)	5377 (20%)	19 (10%)
	Liabilities	Central Banks	107 (56%)	143 (99%)	5521 (20%)	5 (3%)
		General Gov	140 (74%)	143 (99%)	9918 (36%)	44 (23%)
		Banks	117 (62%)	143 (99%)	6477 (24%)	23 (12%)
		Corporates	136 (72%)	143 (99%)	9835 (36%)	48 (25%)
Trade Credit and Advances	Assets	Central Banks	3 (2%)	55 (38%)	113 (0.4%)	0 (0%)
		General Gov	38 (20%)	143 (99%)	1376 (5%)	2 (1%)
		Banks	16 (8%)	107 (74%)	438 (2%)	2 (1%)
		Corporates	108 (57%)	143 (99%)	6423 (23%)	26 (14%)
	Liabilities	Central Banks	5 (3%)	83 (58%)	127 (0.4%)	0 (0%)
		General Gov	39 (21%)	143 (99%)	1177 (4%)	0 (0%)
		Banks	20 (11%)	105 (73%)	456 (2%)	0 (0%)

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Table B.2 – *Continued from previous page*

Instrument	**A/L**	**Sector**	**Country**	**Quarter**	**Country-Quarter**	**Panel**
		Corporates	121 (64%)	143 (99%)	7431 (27%)	34 (18%)
Other Accounts Payable/Receivable	Assets	Central Banks	61 (3%)	143 (99%)	1722 (6%)	1 (0.5%)
		General Gov	82 (43%)	143 (99%)	3235 (12%)	5 (3%)
		Banks	92 (48%)	143 (99%)	4280 (16%)	12 (6%)
		Corporates	105 (55%)	143 (99%)	5256 (19%)	9 (5%)
	Liabilities	Central Banks	81 (43%)	143 (99%)	3305 (12%)	2 (1%)
		General Gov	90 (47%)	143 (99%)	3348 (12%)	7 (4%)
		Banks	95 (50%)	143 (99%)	4257 (16%)	8 (4%)
		Corporates	110 (58%)	143 (99%)	6067 (22%)	13 (7%)

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Table B.2 – *Continued from previous page*

Instrument	**A/L**	**Sector**	**Country**	**Quarter**	**Country-Quarter**	**Panel**
Insurance and Pensions	Assets	Central Banks	n/a	n/a	n/a	n/a
		General Gov	n/a	n/a	n/a	n/a
		Banks	1 (0.5%)	4 (3%)	4 (0.0%)	0 (0%)
		Corporates	29 (15%)	107 (74%)	891 (3%)	3 (2%)
	Liabilities	Central Banks	n/a	n/a	n/a	n/a
		General Gov	n/a	n/a	n/a	n/a
		Banks	n/a	n/a	n/a	n/a
		Corporates	34 (18%)	107 (74%)	1030 (4%)	2 (1%)

The dataset covers 190 countries over 1980q1-2015q4 (144 quarters), yielding 27360 country-quarter observations. The first number in each cell is the total number of countries, quarters, observations, and countries (respectively) with non-missing data, while the second number is the percent of total countries, quarters, observations, and countries, respectively. The Panel column is the number (and percent) of countries with non-missing observations over 1996q1-2014q4. Note that, at the time of download, most 2015q4 variables have not yet been reported.

Table B.3: BOP Variables by Sector

Flow Type	**A/L**	**Sector**	**New BP6**	**New IIP**
Direct Investment	Assets	All	BFDA_BP6_USD	IAD_BP6_USD
	Liabilities	All	BFDL_BP6_USD	ILD_BP6_USD
Portfolio Equity	Assets	Central Banks	(BFPAECB_BP6_USD + BFPAEMA_BP6_USD)	(IAPECB_BP6_USD + IAPEMA_BP6_USD)
		General Government	BFPAEG_BP6_USD	IAPEG_BP6_USD
		Banks	BFPAEDC_BP6_USD	IAPEDC_BP6_USD
		Corporates	BFPAEO_BP6_USD	IAPEO_BP6_USD
	Liabilities	Central Banks	BFPLECB_BP6_USD	ILPECB_BP6_USD

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Table B.3 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**New BP6**	**New IIP**
		General Government	BFPLEG_BP6_USD	ILPEG_BP6_USD
		Banks	BFPLEDC_BP6_USD	ILPEDC_BP6_USD
		Corporates	BFPLEO_BP6_USD	ILPEO_BP6_USD

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Table B.3 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**New BP6**	**New IIP**
Portfolio Debt	Assets	Central Banks	(BFPADCB_BP6_USD + BFPADMA_BP6_USD)	(IAPDCB_BP6_USD + IAPDMA_BP6_USD)
		General Government	BFPADG_BP6_USD	IAPDG_BP6_USD
		Banks	BFPADC_BP6_USD	IAPDDC_BP6_USD
		Corporates	BFPADO_BP6_USD	IAPDO_BP6_USD
	Liabilities	Central Banks	(BFPLDCB_BP6_USD + BFPLDMA_BP6_USD)	ILPDCB_BP6_USD
		General Government	BFPLDG_BP6_USD	ILPDG_BP6_USD
		Banks	BFPLDDC_BP6_USD	ILPDDC_BP6_USD

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Table B.3 – *Continued from previous page*

Flow Type	A/L	Sector	New BP6	New IIP
		Corporates	BFPLDO_BP6_USD	ILPDO_BP6_USD
Other Investment Debt	Assets	Central Banks	BFOADCB_BP6_USD	IAODCB_BP6_USD
		General Government	BFOADG_BP6_USD	IAODG_BP6_USD
		Banks	BFOADDC_BP6_USD	IAODDC_BP6_USD
		Corporates	BFOADO_BP6_USD	IAODO_BP6_USD
	Liabilities	Central Banks	BFOLOCBFR_BP6_USD	ILOOCBFR_BP6_USD
		General Government	BFOLOGFR_BP6_USD	ILOOGFR_BP6_USD
		Banks	BFOLODC_BP6_USD	ILOODC_BP6_USD

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Table B.3 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**New BP6**	**New IIP**
		Corporates	BFOLOO_BP6_USD	ILOOO_BP6_USD
Financial Derivatives	Assets	Central Banks	BFFACB_BP6_USD + BFFAMA_BP6_USD	IADFCB_BP6_USD + IADFMA_BP6_USD
		General Government	BFFAG_BP6_USD	IADFG_BP6_USD
		Banks	BFFADC_BP6_USD	IADFDC_BP6_USD
		Corporates	BFFAO_BP6_USD	IADFO_BP6_USD
	Liabilities	Central Banks	BFFLCB_BP6_USD	ILFCB_BP6_USD
		General Government	BFFLG_BP6_USD	ILFG_BP6_USD
		Banks	BFFLDC_BP6_USD	ILFDC_BP6_USD

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Table B.3 – *Continued from previous page*

Flow Type	**A/L**	**Sector**	**New BP6**	**New IIP**
		Corporates	BFFLO_BP6_USD	ILFO_BP6_USD
Reserves	Assets	Central Bank	BFRA_BP6_USD	IAR_BP6_USD

B.3 BIS Data

B.3.1 International Debt Securities

The Bank for International Settlements (BIS) produces datasets on international bond issuance and bonds outstanding, by sector and by residence or nationality of the issuer. International debt securities (IDS) are defined as those issued in a market other than that of the country where the borrower resides (Gruić & Wooldridge, 2012). This does not necessarily imply that the securities are held by foreigners, but can be taken as an approximation for external holdings of debt securities.[18] Since the IDS data are compiled on a security-by-security basis, granular sectoral splits are easy to obtain, unlike the data on debt from international bank creditors which requires some construction to obtain the split.

The IDS data are important for our exercise. While the BOP data relies on reporting by national statistical offices (which can result in incomplete coverage of portfolio debt securities by sector), the IDS data are compiled directly on a security-by-security basis, which can result in much better coverage. The IDS data can also be presented on a residency basis or by the nationality of the issuing institution. See Avdjiev, Chui, and Shin (2014) and Shin (2013) for a more detailed discussion of this issue.

[18] While this is a reasonable assumption for most borrowing sectors and countries in the world, there are some exceptions. Most notably, the gap between the set of IDS and the set of externally-held debt securities tends to considerable in the case of government bonds issued by reserve currency countries, since these countries often issue large amounts of government debt in domestic markets, which are then traded abroad. Lately, this has also been the case for the government bonds of several large EMEs (e.g. Brazil, Mexico, and Poland), albeit to a lesser degree than for government bonds issued by reserve currency countries. For most of these cases, BOP data is available and used. Otherwise, we rely on other data sources first to avoid this issue.

There are several options for how we allocate international debt securities to each sector. As noted earlier, bonds can be classified based on the residence of the issuer or the nationality of the issuer. Further, the BIS classifies IDS according to sector with several subsectors which can be aggregated up to our public, bank, and corporate sectors: Public banks, private banks, central banks, public other financial corporations, private other financial corporations, public non-financial corporations, private non-financial corporations, and general government sectors.

We keep general government and central bank sectors as they are found. Public and private banks are allocated to the bank sector. Public and private other financial and public and private non-financial corporations are allocated to the corporate sector. This aligns the bonds up with the standard institutional sector definitions in the BOP data. However, the role of public banks and corporations can be quite important in some countries.

B.3.2 BIS External Bank Credit Data

The BIS compiles two sets of statistics on international banking activity. The Locational Banking Statistics (LBS) capture outstanding claims and liabilities of internationally active banks located in 44 reporting countries against counterparties residing in more than 200 countries. Banks record their positions on an unconsolidated basis, including intragroup positions between offices of the same banking group. The data are compiled based on the residency principle (as done for BOP or QEDS). The LBS capture the overwhelming majority of cross-border banking activity.[19] The historical LBS data breaks down counterparties in each country into banks (banks and central bank sectors) and non-banks (corporate and government sectors).[20] The LBS reports outstanding stocks, and based on them BIS calculates exchange rate- and break-adjusted flows.[21]

The second set of banking data is the Consolidated Banking Statistics (CBS). This differs from the LBS in that the positions of banks reporting to the BIS are aggregated by the nationality (rather than by the residence) of the reporting bank.[22] Currently, banking groups from 31 countries report to the CBS. We use the CBS on an immediate counterparty basis (CBS/IC).[23] The CBS data does provide a borrower breakdown of the Non-Bank Sector into Public and Private. Since there is no currency breakdown available for the CBS, the BIS does not calculate adjusted

[19]Due to the fact that not all counties in the world report data to the LBS, these statistics do not capture the entire global stock of outstanding external bank credit. Most countries which host large internationally active banks have reported to the LBS for several decades (the full list of LBS reporting countries is available at: http://www.bis.org/statistics/rep_countries.htm). Nevertheless, there are a small number of notable exceptions, such as China and Russia (the LBS series for both of which starts only as recently as Q4/2015). That said, the LBS capture around 95% of all global cross-border interbank business (BIS, 2015). While there is no similar estimate for the share of cross-border bank lending to non-banks captured by the LBS, it is reasonable to assume that it is also above 90%.

[20]Data on total cross border claims by BIS reporting banks separated by bank and non-bank counterparties are available going back to 1978. The recent enhancements to the BIS LBS data have provided more granular counterparty sector splits. Most importantly in the context of our study, in the enhanced LBS data the non-bank sector has been divided into the non-bank private sector and the public sector (Avdjiev, McGuire, & Wooldridge, 2015).

[21]Breaks may arise from changes in reporting practices, methodology, population of reporting institutions, etc. Other valuation adjustments besides exchange rates are less concerning, as loans are generally not traded in secondary markets.

[22]For example, the positions of a French bank's subsidiary located in New York - which in the LBS are included in the positions of banks in the United States - are consolidated in the CBS with those of its parent and included in the positions of French banks.

[23]The CBS are compiled in two different ways: by immediate counterparty and by ultimate risk. The immediate counterparty is the entity with whom the bank contracts to lend or borrow. Ultimate risk takes account of credit risk mitigants, such as collateral, guarantees and credit protection bought, which transfer the bank's credit exposure from one counterparty to another. (BIS, 2015)

flows.

B.3.3 Obtaining Borrowing Sector Splits for Bank Creditor Data

In this section, we describe our methodology for constructing gross capital inflows and debt outstanding from BIS sources. Our goal is to obtain the stocks and flows measured based on residency (consistent with the LBS data), but we also employ the CBS to obtain certain (non-bank) borrowing sector splits. We deviate from residency in some cases to gain a more complete picture of flows.

The bank loan data is from the LBSR. For observations prior to 2013, the LBS only provide the breakdown between bank and non-bank debtors (where non-bank captures both the non-bank private and the public sector).[24] We focus on cross-border bank lending in the LBS in the form of loans, for which we have data starting in 1996. However, our methodology described below can also be applied to total cross-border bank claims (in all instruments).[25]

Next, we describe how we use the sectoral split information contained in the CBS/IC data in order to divide the Non-Bank sector in the LBS data into Non-Bank Public sector and Non-Bank Private sector. This is described next. First, we go over our methodology for constructing the split for the outstanding stocks of LBS cross-border bank loans. Then, we describe our methodology for con-

[24]The enhanced BIS data, available from 2013 on, splits the non-bank sector into public and private sub-sectors. Note that the LBS include central banks with banks instead of public, but central banks tend to compose a very small portion of cross-border bank claims in the BIS data.

[25]Starting in 1984, we have data for total bank cross-border credit (in all instruments). We don't use this in our initial analysis in order to avoid double counting external bond flows. In practice, the difference between total bank credit and bank credit in just the loan and deposit instruments tends to be small.

structing the split for exchange rate adjusted changes, which relies on currency composition information available in the LBS.

B.3.3.1 Borrowing Sector Splits for Outstanding Stocks

For outstanding stocks, we use the share of international bank debt for each sector from the CBS to estimate the split of the Non-Bank LBS data into Public and Private components.[26] We calculate that as follows:

$$\widehat{XBS}_{nbp,j,t} = XBC_{nb,j,t} \frac{INTC_{nbp,j,t}}{INTC_{nbp,j,t} + INTC_{pub,j,t}} \tag{B.1}$$

$$\widehat{XBS}_{pub,j,t} = XBC_{nb,j,t} \frac{INTC_{pub,j,t}}{INTC_{nbp,j,t} + INTC_{pub,j,t}} \tag{B.2}$$

where npb indicates Non-Bank Private, nb indicates Non-Bank, pub indicates Public, j denotes the borrowing country, and t denotes the time period. $\widehat{XBS}$ is our estimated cross border bank debt, XBC denotes the cross border claims (from the LBS) of BIS reporting banks, and $INTC$ is international claims (from the CBS on immediate counterparty basis). The CBS international claims are defined as the sum of XBC and the local claims by foreign affiliates that are denominated in foreign currencies (LCFC).

This construction of the split of bank debt makes the following assumptions: First, the sectoral shares for $INTC$ are the same as the sectoral shares for XBC. This is reasonable since for most countries, LCFC tends to be small relative to

[26]This estimation is also used in Arslanalp and Tsuda (2014a) and Arslanalp and Tsuda (2014b).

XBC.[27] Second, the sectoral shares for the set of banks that report LBS data (44 countries) are the same as the sectoral shares for the set of banks that report CBS data (31 countries). The 31 CBS reporting countries account for about 90% of the XBC in the LBS, and the CBS captures the activities of the subsidiaries of banks from these 31 countries worldwide. As a result, the CBS data are sufficiently representative to make the above assumption a reasonable one. Third, data for the CBS that allows us to estimate the split of Non-Bank into Public and Private is not available for advanced economies before 2000, and is only available on a semiannual basis for EM for the period before 2000. We linearly extrapolate the semiannual shares to Public and Private into a quarterly series for EM. For advanced economies, we assume constant shares from 2000 backwards.[28]

Having made these assumptions and constructed the external debt to bank creditors, we can then estimate total external debt by sector by adding $\widehat{XBS}$ to IDS for each sector. This will produce a longer series of external debt estimates by sector than the Quarterly External Debt Statistics (QEDS)[29], and cover more countries.

Recently, the BIS has released its enhanced banking data, starting in 2013. This data contain more granular borrowing sector splits - Bank, Public, and Non-Bank Private. We use this short, recent series to judge the quality of our decompo-

[27]While for most countries, LCFC tends to be small relative to XBC, there are a small number of exceptions. For example, this is not the case in dollarized economies (e.g. Ecuador) and some emerging European economies (e.g. Hungary and Poland), where lending denominated in euro and in Swiss francs has been non-negligible.

[28]The assumption of constant shares for advanced economies before 2000 is not too concerning when we are only extending back 4 years.

[29]The QEDS data starts in 2004, and provides data on stocks of external debt by institutional sector for a wide range of countries.

sition. Our methodology for estimating borrowing sector splits for the non-bank borrowing sector and the public sector generates estimates that are very close to the actual (reported) underlying figures.[30]

B.3.3.2 Borrowing Sector Splits for Outstanding Flows

Obtaining exchange rate-adjusted flows to all sectors and to banks is straightforward since they are reported in the LBS data. However, as discussed above, the historical LBS data do not have a split of the non-banks sector into its public and private components. Thus, in order to get estimates for exchange rate-adjusted flows to the non-bank private sector and to the public sector, we rely on the estimated stocks for those sectors obtained in the previous section.[31] We assume that the currency compositions of claims on these sectors are the same as the currency composition of claims on the non-bank sector as a whole.

Using the above assumption, we can obtain estimates of the stock of bank lending to the non-bank private Sector denominated in currency j as follows:

$$\widehat{XBS}_{i,t}^{j,nbp} = \widehat{XBS}_{i,t}^{all,nbp} \left(\frac{XBS_{i,t}^{j,nb}}{XBS_{i,t}^{all,nb}} \right) \tag{B.3}$$

where $\widehat{XBS}_{i,t}^{j,nbp}$ is the *estimated* stock of claims denominated in currency j on the non-bank private Sector in country i at the end of period t; $\widehat{XBS}_{i,t}^{all,nbp}$ is the *es-*

[30]Since not all LBS reporting countries have started providing the enhanced borrowing sector splits, these comparisons are based on the set of LBS reporting countries which had started reporting enhanced LBS data as of March 2016.

[31]Note that since most bank credit is not traded in secondary markets (e.g. loans), fluctuations in market valuations should be negligible.

timated stock of claims denominated in *all* currencies on the Non-Bank Private Sector in country i at the end of period t; $XBS_{i,t}^{j,nb}$ is the *reported* stock of claims denominated in currency j on the Non-Bank Private Sector in country i at the end of period t; and $XBS_{i,t}^{all,nb}$ is the *reported* stock of claims denominated in *all* currencies on the Non-Bank Private Sector in country i at the end of period t.

We then estimate the flow of bank lending to the Non-Bank Private Sector in each currency by converting the USD values of the estimated stocks into their corresponding values in the currency in which they are denominated using the same period USD exchange rate, differencing them, and then converting back into USD using the average exchange rate:

$$\widehat{XBF}_{i,t}^{j,nbp} = \frac{\widehat{XBS}_{i,t}^{j,nbp} FX_t^{j,usd} - \widehat{XBS}_{i,t-1}^{j,nbp} FX_{t-1}^{j,usd}}{\widetilde{FX}_t^{j,usd}} \tag{B.4}$$

where $\widehat{XBF}_{i,t}^{j,nbp}$ is the *estimated* flow of claims denominated in currency j on the Non-Bank Private Sector in country i during period t; $FX_t^{j,usd}$ is the end-of-period t exchange rate between currency j and USD; and $\widetilde{FX}_t^{j,usd}$ is the average exchange rate during period t between currency j and USD.

Now that we have the estimated flow for each currency, we sum these individual flows to obtain the total estimated flow:

$$\widehat{XBF}_{i,t}^{all,nbp} = \sum_j \widehat{XBF}_{i,t}^{j,nbp} \tag{B.5}$$

where nbp denotes the Non-Bank Private Sector.

Estimates of flows to the Public Sector can be obtained in an analogous fashion:

$$\widehat{XBS}_{i,t}^{j,pub} = \widehat{XBS}_{i,t}^{all,pub}\left(\frac{XBS_{i,t}^{j,nb}}{XBS_{i,t}^{all,nb}}\right) \tag{B.6}$$

$$\widehat{XBF}_{i,t}^{j,pub} = \frac{\widehat{XBS}_{i,t}^{j,pub}FX_{t}^{j,usd} - \widehat{XBS}_{i,t-1}^{j,pub}FX_{t-1}^{j,usd}}{\widetilde{FX}_{t}^{j,usd}} \tag{B.7}$$

$$\widehat{XBF}_{i,t}^{all,pub} = \sum_{j}\widehat{XBF}_{i,t}^{j,pub} \tag{B.8}$$

where *pub* denotes the Public Sector.

B.4 Filling Missing Data

We draw on 3 separate sources for data to construct measures of capital flows that can be used when the BOP data is missing. The first is BIS data, which is described in detail in Appendix B.3. We also draw on the International Investment Position (IIP) data that accompanies the BOP data, and the Quarterly External Debt Statistics (QEDS) data which is produced jointly by the World Bank and IMF. Both of these are stock measures, and have the same sector and capital flow type classifications as the BOP data. The QEDS data is quarterly, the IIP data comes either quarterly or annually.

The dataset with the most broad coverage by sector and capital flow type is derived from BIS data. While this data in many cases captures much of the international financial flows we are trying to measure, it is not always an appropriate fill. Specifically, bond inflows are measured in the BIS data as net issuance of debt securities in international markets. While this measure is appropriate for many countries, countries that have many foreigners buying domestically issued bonds or domestics buying international issued bonds will introduce error. An important example of this is government debt issued by advanced economies. The US has a substantial amount of sovereign debt that is traded abroad, but nearly all of the debt is issued domestically, making the BIS measure an inappropriate way to fill the missing series.[32] Thus to increase the accuracy of our filling process, we turn to the IIP and QEDS data. To approximate flows, we first difference the stocks with a simple correction for exchange rate valuation effects.[33] When both IIP and QEDS data are available, we use the IIP measures for consistency with the BOP data. We use these stock measures to fill both portfolio debt and other investment debt for the government and central bank sectors. We also use these measures to fill Corporate portfolio debt in AE.

For the remaining missing data, we use our BIS constructed measures. Table B.1 summarizes the process of constructing matching series using the BIS data.

[32]The only national data that we include is for the United States, which has subtantial capital flows that won't be captured by the BIS data, but also a gap between the availability of QEDS and IIP data and the coverage of the BOP data. Specifically, we fill in the stock IIP measure of government portfolio debt for the US using the TIC data from the US Treasury, Securities data (B) Tables A.2.d and A.2.a, for the period 1999q1-2003q2, and then take the first difference.

[33]Data on currency composition of external debt, split by capital flow type and sector, is scarce. We assume the external debt is denominated in domestic currency. While this is not always the case, changing the assumption to denominated in USD does not appreciably change our filling accuracy.

Table B.1: BIS Data Alignment with BOP

<table>
<tr><td rowspan="2">Capital Flow Type</td><td rowspan="2"></td><td colspan="4">Sector</td></tr>
<tr><td>Banks</td><td>Corporates</td><td>Government</td><td>Central Bank</td></tr>
<tr><td rowspan="2">Bonds</td><td>BOP</td><td>PD to DC</td><td>PD to OS</td><td>PD to GG</td><td>PD to CB</td></tr>
<tr><td>BIS</td><td>NI by Banks</td><td>NI by Corporates</td><td>NI by Government</td><td>NI by Central Bank</td></tr>
<tr><td rowspan="2">Loans</td><td>BOP</td><td>CD to DC</td><td>LN to OS</td><td>LN to GG</td><td>CD to CB</td></tr>
<tr><td>BIS</td><td>Loans to Banks</td><td>Loans to Corporates</td><td>Loans to Government + IMF Credit to GG (BOP)</td><td>Loans to CB + IMF Credit to CB (BOP)</td></tr>
<tr><td rowspan="2">Other Investment Debt</td><td>BOP</td><td>OID to DC</td><td>OID to OS</td><td>OID to GG</td><td>OID to CB</td></tr>
<tr><td>BIS</td><td colspan="4">BIS Filled Loans plus any other non-missing other investment debt instruments from BOP, by sector</td></tr>
</table>

DC = Depository Corproations, except the Central Bank; OS = Other Sectors; GG = General Government; CB = Central Bank; CD = Currency & Deposits; LN = Loans; PD = portfolio debt; OID = other investment debt; NI = Net Issues in International Markets by Residency

For the BIS data, we construct our measure of portfolio debt flows from the BIS IDS data. It captures net issuance of debt securities (bonds) in a market other than that of the country where the borrower resides (Gruić & Wooldridge, 2012). This does not necessarily imply that the securities are held by foreigners, but can be taken as an approximation for external financing flows through debt securities.[34] Since the IDS data are compiled on a security-by-security basis, granular sectoral splits are easy to obtain; we thus construct these net issuances by sector using the same sector definitions as the BOP data.

For other investment debt, we construct our series from our BIS estimates as follows: First, we examine the underlying components of other investment debt. The primary instruments are loans (for corporates and governments) and currency and deposits (for banks and central banks). If loans are missing for corporates or government, or currency and deposits is missing for banks or central

[34] As discussed above, the assumption does not hold well for sovereign debt, particularly in advanced economies, but is otherwise appropriate for many economies.

banks, we rely on the BIS Locational Banking Statistics (LBS) to fill in the data.[35] The BIS data captures cross-border lending from banks in BIS reporting countries.[36,37] This lending can be broken by instrument into loans, debt securities holdings, and other instruments. We use just the loan instrument in our measure, and so avoid capturing any bond holdings or equity investment made by banks. Since the BIS data will not capture official lending, we add IMF Credit to these series to capture that component of loans.[38] The Locational Banking Statistics by Residence (LBSR) historically only break the counterparty sector for Bank lending into banks and non-banks, though recent data includes additional sector splits. We employ the BIS Consolidated Banking Statistics (CBS) and the Locational Banking Statistics by Nationality (LBSN), both of which have further counterparty breakdowns, in order to construct estimates for Bank lending flows for all 4 sectors for the entire period, as described in Appendix B.3.

After augmenting the Loans (or Currency and Deposits) with the BIS data, we sum them with any remaining non-missing instruments within other investment debt. This sum becomes our estimate for other investment debt from BIS data.[39]

[35]Interbank loan flows are automatically classified as deposits in the BOP data. Thus, all loans from BIS reporting banks to bank counterparties, including the central bank, would be captured in the currency and deposits instrument in the BOP.

[36]This captures about 95% of all cross-border interbank business (BIS, 2015).

[37]There have been some discrepancies noted in the past between the BOP ad BIS data due for a few specific cases, such as trustee accounts in Japan and custodial accounts in Switzerland. We give priority to the BOP data, which is well reported for these series.

[38]IMF Credit is a subcomponent of the Loans instrument in other investment debt for general government and central banks. This figure is known by the IMF even if the actual loans by sector are not reported by the country. For central banks, since we fill the currency and deposits instrument with BIS loans, we add IMF Credit to the central bank back in only if the Loans instrument is missing.

[39]In general, when other investment debt is missing, most data on the underlying instruments

Our corresponding stock measures are similarly constructed. We rely first on IIP data, with an internal fill. We next fill any missing data with QEDS measures. And finally any remaining missing observations are filled with our BIS stock estimates derived above.[40]

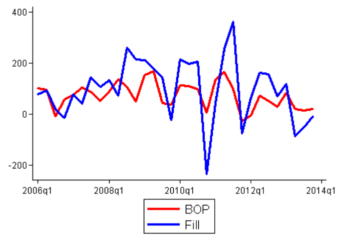
B.4.1 Comparison with BOP data

Having thus constructed our filling series, we compare the result with the available BOP data. Figures B.1 and B.2 illustrates this match by plotting the aggregate flows for each series by sector, capital flow type, and country group. For each sector and capital flow type, we keep only countries that had non-missing BOP data over 2006q1-2013q4.

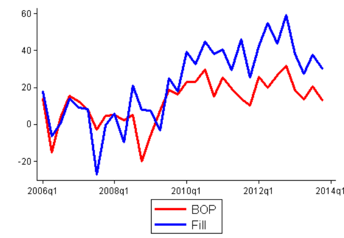
are also missing. A few countries are exceptions to this, and only for a very few periods: Eritrea and Equatorial Guinea in the annual data, and Eritrea and Kosovo in the quarterly data. None of these countries are included in our analysis with this data.

[40]Even though the sector data may be missing in the BOP, the total for portfolio debt or other investment debt inflows often is not. We do not constrain our filled series by sector to match the total of the flow type as reported in the BOP. However, the two series correlate highly (.98) and exhibit similar patterns.

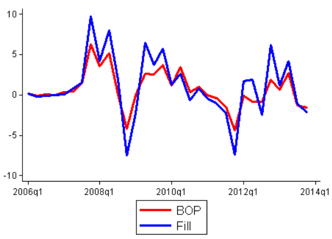
Figure B.1: Aggregate Portfolio Debt, Billions USD



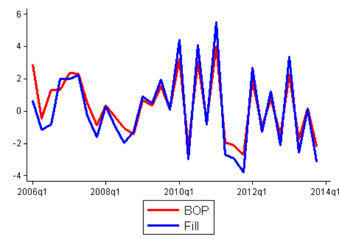
(a) Advanced Government



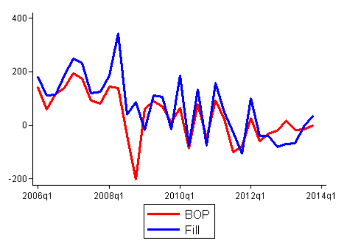
(b) Emerging Government



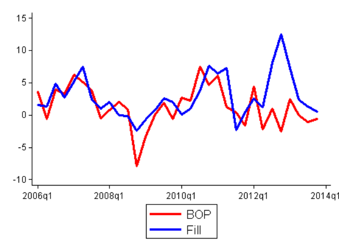
(c) Advanced Central Bank



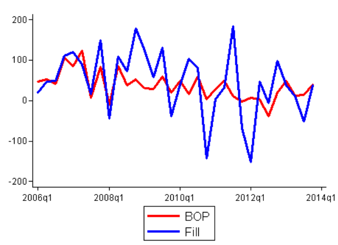
(d) Emerging Central Bank



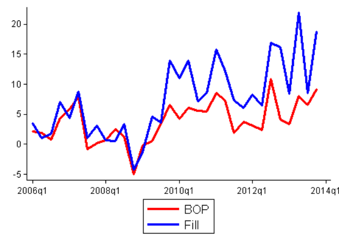
(e) Advanced Banks



(f) Emerging Banks

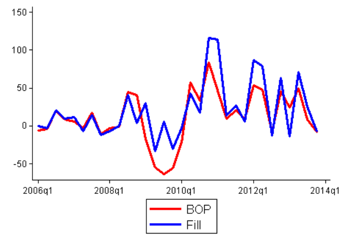


(g) Advanced Corporates

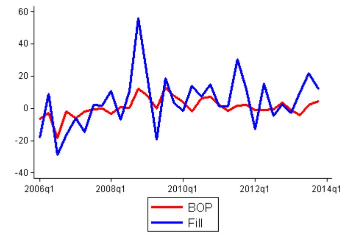


(h) Emerging Corporates

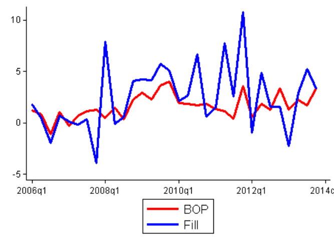
Figure B.2: Aggregate Other Investment Debt , Billions USD



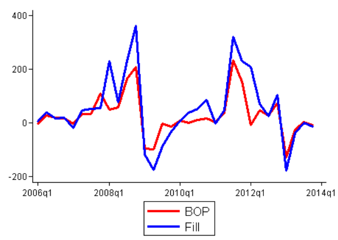
(a) Advanced Government



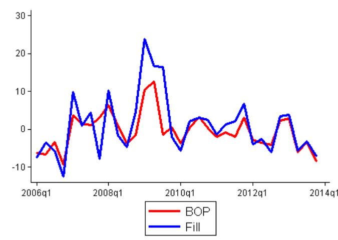
(b) Emerging Government



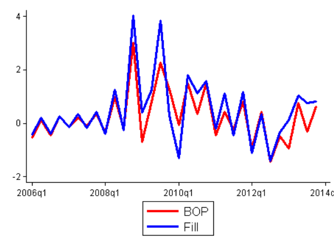
(c) Developing Government



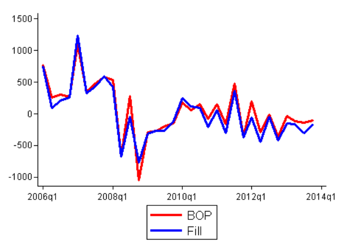
(d) Advanced Central Bank



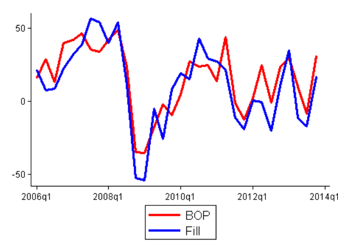
(e) Emerging Central Bank



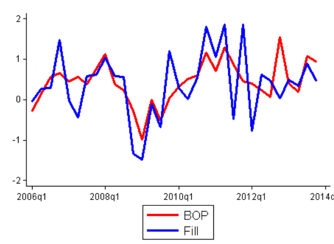
(f) Developing Central Bank



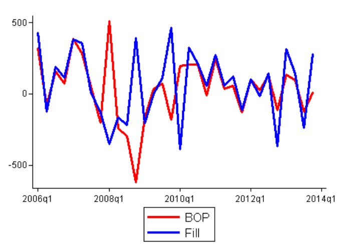
(g) Advanced Banks



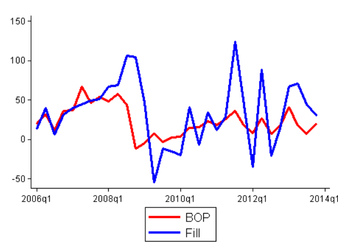
(h) Emerging Banks



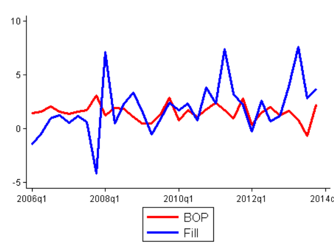
(i) Developing Banks



(j) Advanced Corporates



(k) Emerging Corporates



(l) Developing Corporates

B.5 Samples

B.5.1 Inflow Figures

There are 89 countries in our annual data sample of capital inflows:[41]

Advanced (25): Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States

Emerging (34): Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Czech Republic, Egypt, Estonia, Hungary, India, Indonesia, Jordan, Kazakhstan, Latvia, Lebanon, Lithuania, Macedonia, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, South Africa, Thailand, Turkey, Ukraine, Uruguay, Venezuela

Developing (30): Albania, Angola, Bangladesh, Belarus, Bolivia, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, El Salvador, Gabon, Ghana, Guatemala, Jamaica, Kenya, Liberia, Mongolia, Montenegro, Morocco, Namibia, Nigeria, Pakistan, Papua New Guinea, Paraguay, Serbia, Sri Lanka, Sudan, Trinidad and Tobago, Tunisia, Vietnam

Countries dropped for the Direct Investment figures (22): Angola, Austria, Belgium, Cote d'Ivoire, El Salvador, Gabon, Greece, India, Ireland, Jamaica, Jordan, Lebanon, Liberia, Malaysia, Montenegro, Morocco, New Zealand, Serbia,

[41] If we use quarterly data for these figures our sample drops to 85, leaving off El Salvador, Mongolia, Montenegro, and Serbia.

Trinidad and Tobago, Ukraine, Venezuela, Vietnam

B.5.2 Inflow Regressions

Sample was selected from countries that had data for debt flows for all 4 sectors and for GDP over 2001q3-2014q4.

Advanced (23): Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States

Emerging (28): Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Czech Republic, Egypt, Estonia, Hungary, India, Indonesia, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, South Africa, Thailand, Turkey

Developing (4): Bolivia, Costa Rica, Ecuador, Guatemala

Note that we drop Cyprus and Iceland due to their large debt flows relative to individual GDP.[42]

[42] Samples by region (for appendix correlation tables): **NorthAmerica (2):** Canada, United States; **Latin America (10):** Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Guatemala, Mexico, Peru; **Central and Eastern Europe (13):** Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russian Federation, Slovak Republic, Slovenia, Turkey; **Western Europe (16):** Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom; **Emerging Asia (7):** China, India, Indonesia, Kazakhstan, Malaysia, Philippines, Thailand; **Asia (4):** Australia, Japan, Korea, New Zealand; **Middle East and Africa (7):** Egypt, Israel, South Africa

B.5.3 Outflow Sample

Our outflow sample consists of 31 countries:[43]

Advanced (15): Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Israel, Italy, Japan, Korea, Netherlands, Norway, United Kingdom

Emerging (16): Brazil, Bulgaria, Chile, Colombia, Croatia, Czech Republic, Estonia, Hungary, Kazakhstan, Lithuania, Mexico, Philippines, Russian Federation, South Africa, Thailand, Turkey

B.5.4 DRS Debt Data

The DRS data is annual and does not cover advanced economies. It does, however, extend much further back for many of the countries. Our sample consists of 74 countries over 1981-2014 is as follows:

Emerging (14): Brazil, Bulgaria, China, Colombia, Egypt, India, Indonesia, Jordan, Malaysia, Mexico, Peru, Philippines, Thailand, Turkey

Developing (60): Algeria, Bangladesh, Belize, Benin, Bhutan, Bolivia, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Republic of Congo, Costa Rica, Cote d'Ivoire, Dominica, Dominican Republic, Ecuador, El Salvador, Ethipia, Fiji, Gabon, Ghana, Grenada, Guatemala, Guinea-Bissau, Guyana, Honduras, Jamaica, Kenya, Lesotho, Liberia, Madagas-

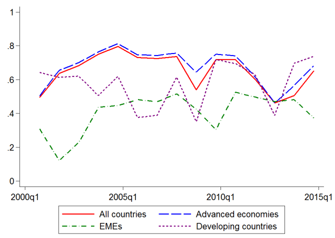
[43] For the outflow figures using the annual data, we extend the sample back to 2002 by dropping Korea and Netherlands from the advanced group, though we are able to add Poland and Uruguay to the EM group. The trends in the figures are the same if we use our main sample and start in 2004.

car, Malawi, Maldives, Mali, Mauritania, Morocco, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Papua New Guinea, Paraguay, Rwanda, Senegal, Sierra Leone, Solomon Islands, Sri Lanka, Sudan, Swaziland, Togo, Tunisia, Uganda, Vanuatu, Zambia, Zimbabwe

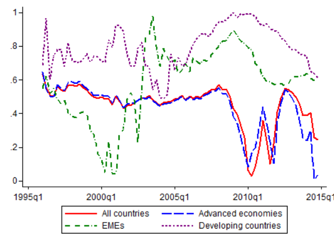
B.6 Additional Results

B.6.1 Flow Shares by Sector

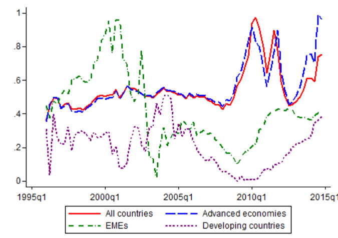
Figure B.1: Composition of External Debt Inflows: Share by Sector



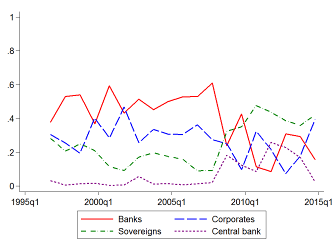
(a) Share of Debt in Total Stocks



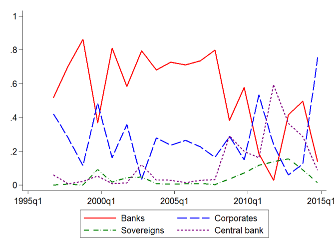
(b) Share of Other Investment in Total Debt Stocks



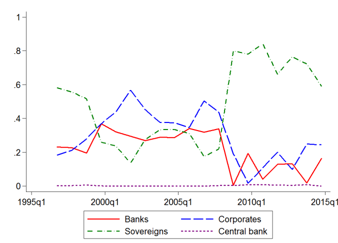
(c) Share of Portfolio Debt in Total Debt Stocks



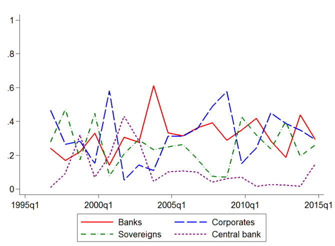
(d) Share of Sectors in Total Debt - Advanced



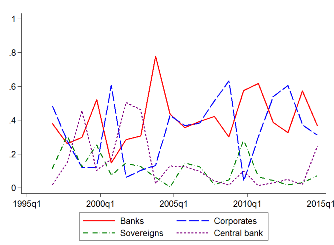
(e) Share of Sectors in Other Investment Debt - Advanced



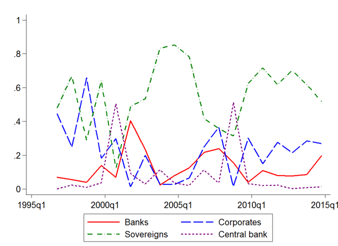
(f) Share of Sectors in Portfolio Debt - Advanced



(g) Share of Sectors in Total Debt - Emerging



(h) Share of Sectors in Other Investment Debt - Emerging

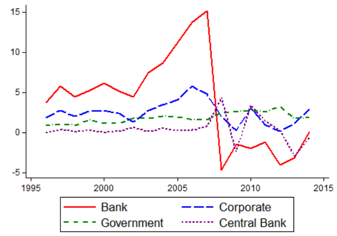


(i) Share of Sectors in Portfolio Debt - Emerging

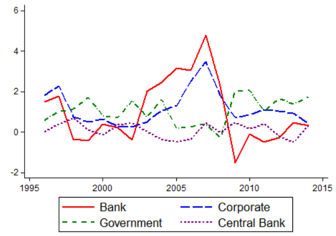
Source: BOP, IIP, QEDS, and BIS, authors' calculations. Panel (a) uses annual data after 2001 in order to get a balanced sample.

B.6.2 Average Debt Flows to GDP

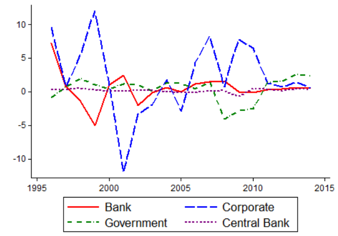
Figure B.2: Average External Debt Inflows, Percent of GDP



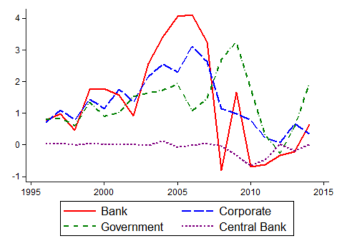
(a) Total Debt, Advanced



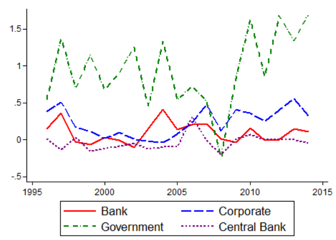
(b) Total Debt, Emerging



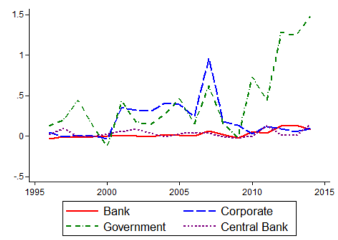
(c) Total Debt, Developing



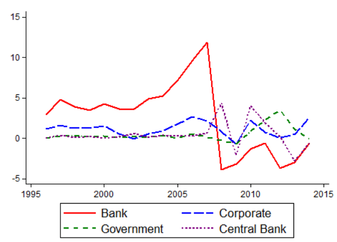
(d) Portfolio Debt, Advanced



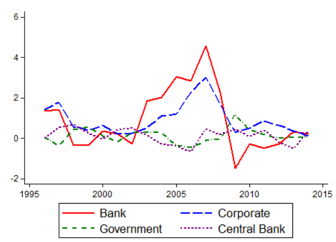
(e) Portfolio Debt, Emerging



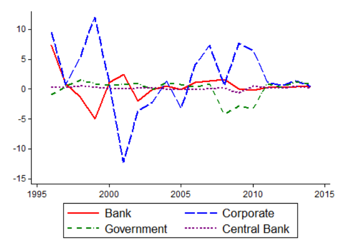
(f) Portfolio Debt, Developing



(g) Other Investment Debt, Advanced



(h) Other Investment Debt, Emerging



(i) Other Investment Debt, Developing

Source: BOP, IIP, QEDS, and BIS, authors' calculations. Total debt is portfolio debt + other investment debt.

Since aggregate figures can be driven by some of the large players in each group, we normalize flows by GDP and examine the evolution of the average. Figure B.2 (a)-(c) plots this for each country group by sector. For both advanced and emerging economies, we see a collective sudden stop in banking inflows at the time of the 2008 crisis. Unlike the aggregate figures, we do not see the dramatic increase in debt inflows to emerging market banks and corporates following the GFC for the average country. Emerging market corporate borrowing similarly dropped at the time of the crisis, but the drop was not as large as for banks. The pattern of government debt inflows surging at the crisis survives for the average emerging market country.

Splitting debt again into portfolio and other investment debt in panels (d)-(f) and (g)-(i), we can see the magnitude of the collapse and the ensuing sustained decrease in other investment debt flows to banks relative to GDP for the average advanced economy. For emerging market corporates, the factor that mitigates the collapse in other investment debt flows is the sustained increase in bond inflows relative to GDP. Bond inflows to governments still tend to be quite large relative to other sectors, particularly after the GFC and generally for EM.

B.6.3 Direct Investment Debt

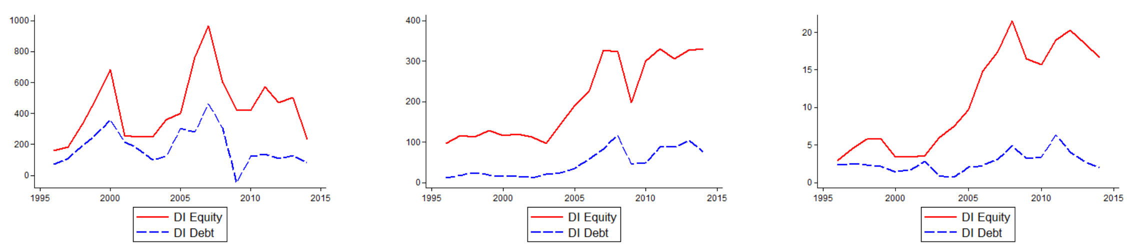
The direct investment debt (DID) component of the data is not as extensively reported as our augmented data for portfolio debt and other investment inflows, so we limit our sample for this analysis.[44] The balanced DID sample is a subsample of 67 countries, of which there are 20 advanced, 28 emerging, and 19 developing. Details of the 22 countries that are dropped can be found in Appendix B.5.

Direct investment debt is an important part of direct investment flows, as

[44] When DID is missing, we fill it by subtracting direct investment equity (DIE) from total direct investment, as with our other data series.

shown in Figure B.3 where we plot it against direct investment equity, in aggregate terms. The figure shows that they share the same pattern over time. However, with the rise in offshore issuance much of direct investment debt may really be more like portfolio debt flows and hence less stable than its equity counterpart (Avdjiev et al., 2014). Direct investment debt makes up a larger share of direct investment for AE, but less so for EM and especially developing countries. It is interesting to note that, for both debt and equity, direct investment has decreased substantially in advanced economies following the global financial crisis, but has leveled off somewhat in emerging and developing economies. Thus, while direct investment debt plays a larger role in the advanced world prior to the crisis, its influence will be felt relatively more in other economies.

Figure B.3: Aggregate Direct Investment Inflows, Billions 1996 USD



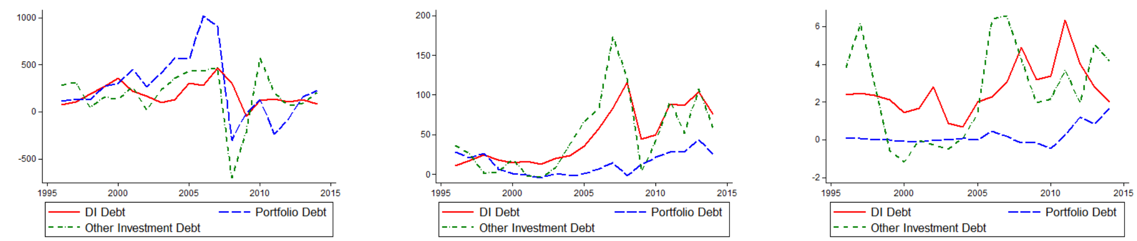
(a) Advanced (b) Emerging (c) Developing

Source: BOP data and authors' calculations.

Direct investment debt is only recorded in the BOP if one of the (related) counterparties involved is a non-financial entity. Debt flows between related financial enterprises (including banks) are captured in either portfolio debt or other investment debt. We make the assumption that direct investment debt flows from offshore non-financial firms to onshore financial firms (or banks) are negligible.

With this assumption, we can allocate direct investment debt to the corporate sector. We compare direct investment debt, portfolio debt, and other investment debt for the corporate sector in Figure B.4.[45]

Figure B.4: Aggregate Corporate Debt Inflows, Billions 1996 USD



(a) Advanced (b) Emerging (c) Developing

Source: BOP data and authors' calculations.

We see that direct investment debt can be significant in size, relative to other capital flow types. It tends to follow the same trends as other forms of debt in the aggregate, but can have some influence on the evolution of total debt. In fact, it is larger than the other debt components in some periods.

B.6.4 PPG vs PNG Debt Inflows

We have focused on the sectoral split of inflows by government, central bank, banks, and corporates, and found important differences between public and private flows. Another way to examine the roles of the public and private sector is to split the data by Public and Publicly-Guaranteed Debt (PPG) vs Private Non-Guaranteed Debt (PNG). This allows us to capture flows nominally al-

[45]When comparing direct investment with our other series that have been filled using BIS data, we need to assume that direct investment debt flows from banks to non-financial firms are negligible (else they would be double counted). This assumption applies to less than 3% of observations in our direct investment debt sample, as most observations with non-zero direct investment debt are not mising the other investment debt for coprorates series in the BOP.

located to the private sector which should actually be considered liabilities of the public sector, such as borrowing by public and quasi-public corporations common in many EM.[46] We can do this for EM and developing economies using the World Bank's Debtor Reporting System (DRS) data found within the World Bank International Debt Statistics (WB-IDS). This data is annual going back to 1970 for many countries, but we use a balanced sample of 14 EM and 60 developing countries over 1981-2014.[47]

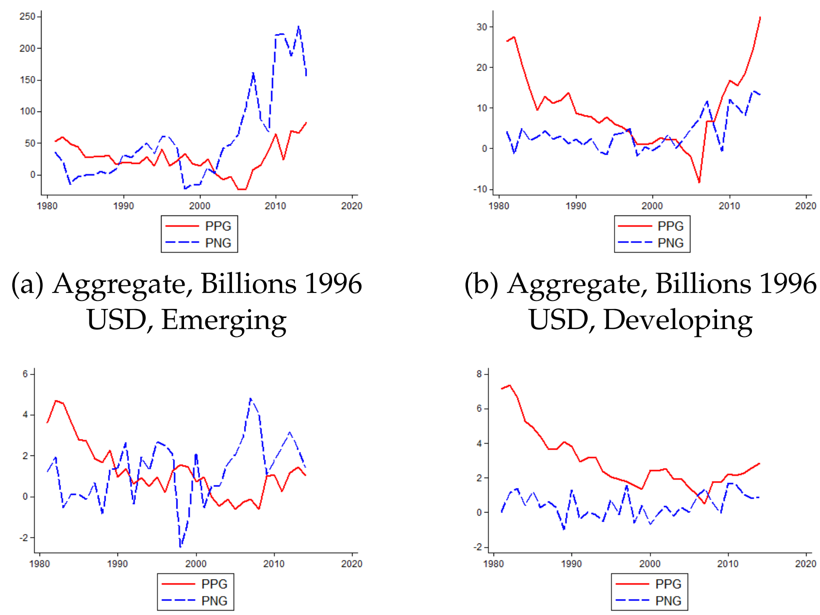
Figure B.5 (a)-(b) plots aggregate debt inflows from the DRS data, with flows split by PPG and PNG debt. Panels (c)-(d) plot the average of PPG and PNG debt to GDP ratio for each group of countries. According to these measures, PNG debt in EM soared leading up to the GFC, as most measures of debt inflows did. Following a brief collapse, PNG debt rebounded significantly in the aggregate, but this rebound is muted if we examine flows relative to GDP for the average country. This is consistent with what we see in Figures 3.6 and B.2, where much of the post-2008 increase in aggregate flows is driven by large and quickly growing EM such as China.[48]

[46]The usual definitions allocate flows to the sector of the immediate borrower, not the sector who is ultimately owes the debt, which may result in effectively misattributing the debt to the wrong sector. Also, note that all of our measures are based on the residency principle, however the recent increase in offshore bond issuance can also be a source of mismeasurement of capital flows. Offshore bond issuance has received significant recent attention in Shin (2013), Avdjiev et al. (2014), Avdjiev, McCauley, and Shin (2016), and others, so we refer the interested reader to those sources for a more complete discussion of the issue.

[47]See Section B.5 in the appendix for details on the sample. The DRS data is first split into short term, long term, and IMF credits. The long term data can be further subdivided by PNG debt and PPG debt. The PPG debt can further be split by creditor. We assume that the portion of PPG debt that is short term is negligible, and so attribute all Short Term Debt to PNG. We further combine IMF credit into PPG debt to get our split of total external debt into public and private components. This is analgous to the decomposition done in Alfaro, Kalemli-Özcan, and Volosovych (2014), who do their analysis in the context of net flows.

[48]These figures will not be exactly comparable in terms of magnitude with our previous dataset

Figure B.5: PPG vs. PNG Debt Inflows



(a) Aggregate, Billions 1996 USD, Emerging

(b) Aggregate, Billions 1996 USD, Developing

(c) Average, Percent GDP, Emerging

(d) Average, Percent GDP, Developing

Source: World Bank DRS data and authors' calculations.

In both emerging and developing economies, and in both the aggregate and average GDP figures, we see a steady decline in PPG debt until the GFC, after which it rebounds, and significantly so in the case of developing economies. This is similar to what we observe in Figures 3.6 and B.2, but in those figures the decrease leading up to 2008 is not as pronounced as when you take the longer time horizon.

These figures also highlight how private and public capital flows can move opposite each other, consistent with our previous results. This is particularly noticeable for EM around the 2008 crisis, where we see PNG flows fall dramatically while PPG flows rise, thus smoothing out the total debt inflows.

in Figure 3.6, as the underlying sample of countries is somewhat different.

B.6.5 Correlations with the VIX

Recent work by Rey (2013), Bruno and Shin (2015), and others highlights how capital flows tend to move together and correlate strongly with the VIX, a common proxy for global liquidity or global risk aversion. We use our dataset to perform this analysis while distinguishing flows by sector. We use the quarterly version of our dataset and restrict our sample to countries where we have quarterly GDP data for the period, 2001q3-2014q4.[49] This reduces our sample to 23 advanced, 28 emerging, and 4 developing countries, 55 in total. The sample is detailed in Appendix B.5. We split our countries into groups, aggregate their flows, and normalize those flows by their aggregate GDP.

Table B.1: Correlation of Aggregate Inflows with VIX, by Capital Flow Type

Regions	DI	PE	PD	OID	DID	DIE
World	-0.17	-0.52	-0.46	-0.47	-0.16	-0.12
N. America	-0.19	-0.12	-0.38	-0.43	-0.47	0.06
Lat. America	0.01	-0.34	-0.43	-0.20	-0.15	0.11
Cent./East. Europe	0.01	-0.39	-0.51	-0.32	-0.01	0.02
West. Europe	-0.12	-0.44	-0.27	-0.42	-0.02	-0.44
Em. Asia	-0.24	-0.50	-0.51	-0.52	-0.24	-0.22
Adv. Asia	0.07	-0.40	-0.41	-0.07	0.04	0.05
ME/Africa	-0.25	-0.37	-0.46	-0.35	-0.27	-0.09

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. DI = direct investment; PE = portfolio equity; PD = portfolio debt; OID = other investment debt; DID = direct investment debt; DIE = direct investment equity. We allow portfolio equity and direct investment to be zero if missing when computing the aggregate figures, but correlations are comparable if we restrict to a balanced sample where equity flows are non-missing. Inflows are aggregated by group and normalized by group aggregate GDP.

Table B.1 is akin to correlations in Rey (2013), with flows split by capital flow type and borrower region. In addition to the 4 main components of flows, we dis-

[49] Availability of quarterly GDP data constrains the size and length of our sample.

play correlations for the debt and equity portions of direct investment separately. Like her results, we see the familiar pattern of capital flows that are negatively correlated with the VIX across all capital flow types. The exception to this is direct investment flows, which Rey finds to be always positively correlated with the VIX. Our results show negative correlations instead, including at the world level, although strictly speaking they are not statistically significant.[50] This is driven by the sample window: Rey's window is 1990q1-2012q4, but direct investment begins to move more opposite of the VIX in more recent years (our sample window is 2001q3-2014q4).

Table B.2: Correlation of Aggregate Debt Inflows with VIX, by Geography and Sector

Regions	Gov	CB	Bank	Corp	All
World	0.24	0.31	-0.52	-0.59	-0.52
N. America	0.34	0.04	-0.11	-0.62	-0.48
Lat. America	-0.27	0.42	-0.47	-0.38	-0.38
Cent./East. Europe	-0.10	0.27	-0.56	-0.37	-0.47
West. Europe	0.11	0.30	-0.49	-0.36	-0.44
Em. Asia	-0.25	-0.13	-0.46	-0.52	-0.57
Adv. Asia	-0.15	0.15	-0.06	-0.37	-0.30
ME/Africa	-0.19	-0.20	-0.25	-0.45	-0.52

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Debt inflows are inflows of portfolio and other investment debt. Inflows are aggregated by group and normalized by group aggregate GDP.

Analysis by capital flow type may obscure important trends and relationships in flows by sector (see Alfaro, Kalemli-Özcan, and Volosovych (2014) for an emphasis on this point for the case of net flows). In Table B.2, we take the debt inflows (portfolio debt + other investment debt) and split them by sector

[50]The approximate standard error of each correlation in the table is 0.13.

Table B.3: Correlation of Aggregate Portfolio Debt Inflows with VIX, by Geography and Sector

Region	Gov	CB	Bank	Corp	All
World	0.23	-0.25	-0.54	-0.50	-0.46
N. America	0.32	-0.02	-0.59	-0.52	-0.38
Lat. America	-0.36	-0.38	-0.45	-0.30	-0.43
Cent./East. Europe	-0.4	-0.02	-0.63	-0.43	-0.51
West. Europe	0.16	-0.09	-0.46	-0.21	-0.27
Em. Asia	-0.34	-0.24	-0.42	-0.38	-0.51
Adv. Asia	-0.22	-0.11	-0.47	-0.41	-0.41
ME/Africa	-0.33	-0.14	-0.13	-0.29	-0.46

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Inflows are aggregated by group and normalized by group aggregate GDP.

Table B.4: Correlation of Aggregate Other Investment Debt Inflows with VIX, by Geography and Sector

Region	Gov	CB	Bank	Corp	All
World	0.11	0.31	-0.49	-0.52	-0.46
N. America	0.28	0.04	0.00	-0.58	-0.43
Lat. America	0.17	0.44	-0.42	-0.29	-0.20
Cent./East. Europe	0.26	0.28	-0.52	-0.33	-0.32
West. Europe	-0.11	0.30	-0.47	-0.30	-0.42
Em. Asia	-0.04	-0.03	-0.42	-0.51	-0.52
Adv. Asia	0.16	0.15	0.10	-0.31	-0.07
ME/Africa	0.23	-0.14	-0.24	-0.39	-0.35

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Inflows are aggregated by group and normalized by group aggregate GDP.

and then examine the correlation with the VIX. The last column is the total flow of all 4 sectors combined. The most striking feature of Table B.2 is that inflows to the banks and corporates (the private sectors) are all negatively correlated with the VIX as usual, but inflows to governments and central banks (the public sectors) are often positively correlated, particularly for more developed regions like North America and Western Europe. The positive correlation of government debt with the VIX at the World level is driven by these large, AE. Tables B.3 and B.4 in Appendix B.6 present these correlations by region with debt split into portfolio debt and other investment debt.

Table B.5: Correlation of Aggregate Debt Inflows with VIX, by Development, Sector, and Capital Flow Type

	Portfolio Debt				Other Investment Debt			
Group	Gov	CB	Bank	Corp	Gov	CB	Bank	Corp
Advanced	0.28	-0.16	-0.53	-0.49	0.02	0.29	-0.44	-0.48
Emerging	-0.49	-0.26	-0.65	-0.48	0.30	0.33	-0.61	-0.51
Developing	-0.19	-0.07	-0.11	-0.14	0.10	0.24	-0.29	-0.15

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Inflows are aggregated by group and normalized by group aggregate GDP.

Table B.5 shows the correlations, but with debt split into portfolio debt and other investment debt and countries grouped by development. Here we see clearly the delineation between public and private sectors. Advanced economy government portfolio debt correlates positively with the VIX. This is consistent with a flight to safe assets during crisis times, or may reflect advanced economy governments borrowing more in response to a crisis. Emerging market sovereigns face the same fate as their private sector, with portfolio debt inflows falling as the VIX rises. Other investment debt to the public sectors is positively correlated across each group, though the correlation is strongest for EM and for advanced central banks. Thus, while emerging market sovereigns may not be able to obtain bond financing from international financial markets during a global crisis, they are able to obtain other forms of credit, perhaps from public sector lenders such as the IMF. Other developing nations have quantitatively the weakest connection of their flows to the VIX, but follow the same qualitative patterns as emerging market countries.

B.6.6 Correlations Between Flows

We also examine the correlation of capital flows across sectors and flow types. Rey (2013) shows that capital flows tend to move together across asset classes and regions. We explore this relationship by sectors in stages. Table B.6 presents these correlations over the whole sample. Consistent with our previous results, public and private flows tend to move in opposite directions.

Table B.6: Correlation of Aggregate Inflows by Sector

	GG DB	CB DB	DC DB	OS DB
GG DB	1.00			
CB DB	0.21	1.00		
DC DB	-0.12	-0.20	1.00	
OS DB	-0.20	-0.30	0.80	1.00

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Aggregate inflows are normalized by aggregate GDP. GG = Government; CB = Central Bank; DC = Banks; OS = Corporates; DB = Debt, which is the sum of portfolio debt and other investment debt.

We disaggregate the flows by type in Table B.7. Here, we see a bit more contrast. Some public flows do not move together, such as central bank portfolio debt, which moves opposite that of central bank and government other investment debt, but co-moves with bank and corporate portfolio debt. Also, government portfolio debt has a weakly positive correlation with corporate other investment debt. Corporate and bank other investment debt tend to move together, and equally strong is the correlation between corporate and bank portfolio debt. The cross correlations of these also tend to be large, with the correlation between other and portfolio debt for corporates being the lowest.

Table B.7: Correlation of Aggregate Inflows by Sector and Capital Flow Type

	GG PD	CB PD	DC PD	OS PD	GG OID	CB OID	DC OID	OS OID
GG PD	1.00							
CB PD	-0.05	1.00						
DC PD	-0.13	0.54	1.00					
OS PD	-0.28	0.43	0.77	1.00				
GG OID	0.05	-0.33	-0.48	-0.34	1.00			
CB OID	0.08	-0.32	-0.45	-0.33	0.46	1.00		
DC OID	-0.01	0.36	0.70	0.55	-0.20	-0.14	1.00	
OS OID	0.01	0.38	0.62	0.46	-0.18	-0.23	0.71	1.00

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Aggregate inflows are normalized by aggregate GDP. GG = Government; CB = Central Bank; DC = Banks; OS = Corporates; PD = portfolio debt; OID = other investment debt

Table B.8 in shows the correlation of flows by sector, capital flow type, and country group for advanced and emerging countries. Similar patterns remain, but additional detail on these relationships is uncovered. For instance, while advanced economy government debt tends to move opposite that of their banks, emerging market government portfolio debt inflows tend to move with either advanced or emerging bank inflows.

When flows are split by sector, the common finding that most flows tend to move together no longer holds. Rather, there is an interesting interplay between flows to the public and private sectors of the economy, and the relationship seems to be different for advanced than for emerging economies.

Table B.8: Correlation of Aggregate Inflows by Country Group, Sector, and Capital Flow Type

	Advanced								Emerging							
	Gov.		Cent. Bank		Bank		Corp.		Gov.		Cent. Bank		Bank		Corp.	
Variables	PD	OID	PD	OID	PD	OID	PD	OID	PD	OID	PD	OID	PD	OID	PD	OID
AE GG PD	1.00															
AE GG OID	0.02	1.00														
AE CB PD	-0.08	-0.23	1.00													
AE CB OID	0.11	0.45	-0.23	1.00												
AE DC PD	-0.21	-0.39	0.43	-0.46	1.00											
AE DC OID	-0.08	-0.11	0.24	-0.11	0.67	1.00										
AE OS PD	-0.32	-0.25	0.29	-0.32	0.76	0.53	1.00									
AE OS OID	-0.06	-0.10	0.09	-0.24	0.58	0.67	0.43	1.00								
EM GG PD	0.10	0.01	-0.02	-0.17	0.23	0.29	0.09	0.55	1.00							
EM GG OID	0.18	-0.09	-0.13	0.03	-0.42	-0.42	-0.43	-0.32	0.08	1.00						
EM CB PD	-0.07	-0.21	0.15	-0.30	0.42	0.33	0.43	0.61	0.37	-0.10	1.00					
EM CB OID	-0.04	0.03	0.08	-0.00	-0.15	-0.12	-0.19	-0.06	-0.25	-0.05	-0.01	1.00				
EM DC PD	-0.01	0.06	0.06	-0.16	0.37	0.38	0.33	0.53	0.53	-0.10	0.35	-0.12	1.00			
EM DC OID	0.02	0.16	0.05	-0.15	0.49	0.49	0.35	0.56	0.37	-0.25	0.27	-0.24	0.47	1.00		
EM OS PD	0.05	-0.02	-0.09	-0.13	0.15	0.15	0.12	0.33	0.61	0.18	0.35	-0.22	0.62	0.39	1.00	
EM OS OID	0.00	0.09	0.17	0.09	0.44	0.38	0.38	0.28	0.11	-0.25	0.19	-0.24	0.46	0.71	0.35	1.00

Sample consists of 55 countries over 2001q3-2014q4, and is described in Appendix B.5. Inflows are aggregated by group and normalized by group aggregate GDP. AE = Advanced Economies; EM = EM; GG = Government; CB = Central Bank; DC = Banks; OS = Corporates; PD = portfolio debt; OID = other investment debt

Table B.9 presents unconditional correlations of aggregate debt inflows and outflows. There are high correlations between all private inflows and outflows, but the largest correlation is for bank inflows with bank outflows (which is the largest sector in terms of outflow and inflow volume). This result is driven by advanced economy banks.

Table B.9: Correlation of Inflows and Outflows

All Countries		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.06	1.00				
	Corp	0.02	0.64	1.00			
Outflows	Public	0.22	0.37	0.28	1.00		
	Bank	0.06	0.97	0.67	0.28	1.00	
	Corp	-0.23	0.79	0.84	0.22	0.74	1.00
Advanced Economies		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.07	1.00				
	Corp	-0.02	0.59	1.00			
Outflows	Public	0.28	0.12	0.09	1.00		
	Bank	0.06	0.96	0.62	0.03	1.00	
	Corp	-0.26	0.78	0.84	-0.00	0.73	1.00
Emerging Markets		Inflows			Outflows		
		Public	Bank	Corp	Public	Bank	Corp
Inflows	Public	1.00					
	Bank	-0.01	1.00				
	Corp	-0.17	0.73	1.00			
Outflows	Public	0.03	0.77	0.70	1.00		
	Bank	-0.29	0.31	0.20	-0.05	1.00	
	Corp	0.16	0.38	0.57	0.52	-0.06	1.00

Sample consists of 31 countries (15 advanced, 16 emerging) over 2004q1-2014q4, and is described in Appendix B.5. Debt is the sum of portfolio debt and other investment debt (and reserves in the case of public outflows). Flows are aggregated to the country group level and normalized by group aggregate GDP.

B.6.7 Inflow Regressions

Table B.10 presents regressions by capital flow type rather than by sector, using the BOP data as is and filling missing data with zero, as typically done in the literature. As expected, we see that capital inflows are negatively associated with the VIX across all capital flow types, with high significance on total flows and other investment debt flows. GDP growth is likewise positively associated with capital inflows, with high significance for total and other investment flows. Portfolio equity is negatively correlated with GDP growth, though this relationship is not significant.

Panel B restricts the sample to just advanced economies. The same results hold generally, but with larger coefficients. Portfolio debt inflows are not significantly related to the VIX, however, and the (insignificant) coefficient on direct investment flows is negative.

Examining the results for EM reveals important differences. Panel C shows these regressions. We similarly see that total flows and other investment debt are negatively related to the VIX and positively related to GDP growth. However, we see that both portfolio debt as well as direct investment are significantly related to the VIX. Direct investment also has a significant positive coefficient on GDP growth.

The fact that the VIX has a negative and statistically significant impact also on FDI in EMs is important because it is a flow category that is generally thought of as less volatile. The negative response is consistent with what has been found

Table B.10: Drivers of Capital Inflows, by Instrument (Quarterly BOP data, missing filled with Zero)

Panel A: All Countries					
	(1)	(2)	(3)	(4)	(5)
	Total	Direct Investment	Portfolio Equity	Portfolio Debt	Other Investment Debt
log(VIX$_{t-1}$)	-7.986***	-1.166	-1.087	-1.252	-4.481***
	(2.654)	(0.626)	(0.809)	(0.670)	(1.347)
GDP Growth$_{it-1}$	0.218***	0.0366	-0.0245	0.0104	0.196***
	(0.0472)	(0.0199)	(0.0178)	(0.0190)	(0.0473)
Observations	2695	2695	2695	2695	2695
R^2	0.041	0.008	0.006	0.005	0.037
CountryFE	Yes	Yes	Yes	Yes	Yes

Panel B: Advanced Economies					
	(1)	(2)	(3)	(4)	(5)
	Total	Direct Investment	Portfolio Equity	Portfolio Debt	Other Investment Debt
log(VIX$_{t-1}$)	-14.87**	-1.801	-2.286	-1.961	-8.823***
	(5.998)	(1.444)	(1.874)	(1.575)	(2.897)
GDP Growth$_{it-1}$	0.370***	-0.00381	-0.0651	0.0883	0.350**
	(0.100)	(0.0342)	(0.0500)	(0.0501)	(0.128)
Observations	1127	1127	1127	1127	1127
R^2	0.055	0.005	0.012	0.015	0.049
CountryFE	Yes	Yes	Yes	Yes	Yes

Panel C: EM					
	(1)	(2)	(3)	(4)	(5)
	Total	Direct Investment	Portfolio Equity	Portfolio Debt	Other Investment Debt
log(VIX$_{t-1}$)	-3.344***	-0.788***	-0.204	-0.734***	-1.618**
	(0.831)	(0.251)	(0.115)	(0.238)	(0.787)
GDP Growth$_{it-1}$	0.165***	0.0552**	-0.00324	-0.0246	0.138***
	(0.0518)	(0.0239)	(0.00233)	(0.0120)	(0.0365)
Observations	1372	1372	1372	1372	1372
R^2	0.074	0.020	0.003	0.010	0.094
CountryFE	Yes	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, samples as listed in Appendix B.5. Capital inflow data is from Balance of Payments, with any missing data replaced with zeros. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

in Lane and Milesi-Ferretti (2016), who argue that FDI flows capture a lot of investment flows by financial entities and booking at financial and offshore centers, and Blanchard and Acalin (2016), who find that FDI inflows and outflows at the quarterly frequency are highly correlated, and emerging market FDI flows respond to the US monetary policy rate. These papers suggest that a lot of measured FDI is in fact transitional flows between financial centers.[51]

Interestingly, portfolio debt has a negative coefficient on GDP growth (significant at the 10% level), which is at odds with the majority of flows.

[51] See Kalemli-Özcan, Sorensen, Volosovych, and Villegas-Sanchez (2016) who decomposes FDI between European countries into industrial and financial FDI separating direct and ultimate investors using micro data on foreign ownership. They find that FDI based on ultimate investment is much lower, less volatile and in fact mostly done by US ultimate investors, but transitions through European financial centers as captured by direct foreign ownership.

Table B.11: Drivers of Total Debt Inflows Before and After the Global Financial Crisis, by Sector - Advanced Economies (Quarterly AHKS data, missing filled from Public Sources)

	Pre-GFC: 2002q4-2007q4						Post-GFC: 2008q1-2014q4					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total	Public	Banks	Corp.	Total w/DI Debt	Corp. w/DI Debt	Total	Public	Banks	Corp.	Total w/DI Debt	Corp. w/DI Debt
log(VIX$_{t-1}$)	-10.47***	-0.405	-7.224***	-2.843**	-10.49***	-3.170***	1.879	2.081	-0.255	0.0529	1.258	-0.568
	(2.308)	(0.817)	(1.805)	(1.143)	(2.189)	(1.087)	(3.714)	(2.351)	(1.938)	(0.647)	(3.339)	(1.374)
GDP Growth$_{it-1}$	0.00662	0.0293	0.00464	-0.0273	0.0568	0.00888	0.441***	0.153***	0.196**	0.0919	0.456***	0.107**
	(0.0741)	(0.0309)	(0.0576)	(0.0429)	(0.0952)	(0.0495)	(0.145)	(0.0462)	(0.0830)	(0.0478)	(0.134)	(0.0383)
Observations	483	483	483	483	465	465	644	644	644	644	644	644
R^2	0.042	0.001	0.025	0.039	0.035	0.028	0.030	0.008	0.011	0.013	0.031	0.011
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Public inflows are defined as the sum of General Government and Central Bank inflows. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table B.12: Drivers of Total Debt Inflows Before and After the Global Financial Crisis, by Sector - Emerging Markets (Quarterly AHKS data, missing filled from Public Sources)

	Pre-GFC: 2002q4-2007q4						Post-GFC: 2008q1-2014q4					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total	Public	Banks	Corp.	Total w/DI Debt	Corp. w/DI Debt	Total	Public	Banks	Corp.	Total w/DI Debt	Corp. w/DI Debt
log(VIX$_{t-1}$)	-3.269***	0.271	-1.595**	-1.945***	-4.248***	-2.832***	-0.927	1.465	-2.047**	-0.345	-0.249	0.165
	(0.813)	(0.430)	(0.586)	(0.380)	(0.898)	(0.517)	(1.022)	(1.132)	(0.780)	(0.282)	(1.315)	(0.611)
GDP Growth$_{it-1}$	0.00421	-0.00331	0.0152	-0.00764	0.00699	-0.00503	0.0717***	-0.0377***	0.0747***	0.0348***	0.108***	0.0718***
	(0.0171)	(0.00843)	(0.0148)	(0.00885)	(0.0192)	(0.0114)	(0.0197)	(0.0135)	(0.0173)	(0.00876)	(0.0374)	(0.0235)
Observations	588	588	588	588	558	558	784	784	784	784	752	752
R^2	0.037	0.001	0.018	0.073	0.051	0.084	0.025	0.018	0.072	0.045	0.031	0.038
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table B.13: Robustness on Controls: Drivers of Total Debt Inflows, All Sectors - Advanced Economies (Quarterly AHKS data, missing filled from Public Sources)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(\text{VIX}_{t-1})$	-9.101***	-4.154	-3.733	-11.27***	-11.45***	-2.690	-5.111
	(2.676)	(2.294)	(2.260)	(3.134)	(3.138)	(1.592)	(2.618)
GDP Growth$_{it-1}$	0.506***	0.402**	0.539***	0.526**	0.275**	0.285	0.276**
	(0.179)	(0.150)	(0.185)	(0.189)	(0.122)	(0.138)	(0.133)
FFR$_{t-1}$		3.199***				5.404***	3.397***
		(0.871)				(1.266)	(0.977)
Yield Curve$_{t-1}$			-3.892***			3.016**	1.101
			(1.109)			(1.087)	(1.337)
TED Spread$_{t-1}$				4.422		-4.517	-2.554
				(2.988)		(2.428)	(2.639)
Observations	1127	1127	1127	1127	1127	1127	1127
R^2	0.065	0.105	0.086	0.069	0.100	0.112	0.114
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeTrend					Yes		Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. FFR is the effective US Federal Funds Rate, lagged one quarter. Yield Curve is the difference between 10 year US Treasury constant maturity rate and 3 month US Treasury constant maturity rate, lagged one quarter. TED Spread is the difference between the 3 month US dollar LIBOR rate and the 3 month US Treasury rate, lagged one quarter. FFR is the effective US Federal Funds Rate, lagged one quarter. Yield Curve is the difference between 10 year US Treasury constant maturity rate and 3 month US Treasury constant maturity rate, lagged one quarter. TED Spread is the difference between the 3 month US dollar LIBOR rate and the 3 month US Treasury rate, lagged one quarter. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table B.14: Robustness on Controls: Drivers of Total Debt Inflows, All Sectors - Emerging Markets (Quarterly AHKS data, missing filled from Public Sources)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(\text{VIX}_{t-1})$	-2.261**	-1.197	-0.824	-2.539***	-2.637***	0.0743	0.554
	(0.829)	(0.745)	(0.681)	(0.858)	(0.948)	(0.622)	(0.840)
GDP Growth_{it-1}	0.116***	0.0828***	0.108***	0.114***	0.0946***	0.0826***	0.0836***
	(0.0347)	(0.0252)	(0.0317)	(0.0342)	(0.0254)	(0.0234)	(0.0234)
FFR_{t-1}		0.796***				0.900	1.297***
		(0.282)				(0.485)	(0.449)
Yield Curve_{t-1}			-1.107***			-0.209	0.173
			(0.313)			(0.463)	(0.407)
TED Spread_{t-1}				0.524		-1.624	-2.018
				(0.727)		(0.892)	(1.000)
Observations	1372	1372	1372	1372	1372	1372	1372
R^2	0.071	0.100	0.093	0.071	0.079	0.105	0.106
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeTrend					Yes		Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. FFR is the effective US Federal Funds Rate, lagged one quarter. Yield Curve is the difference between 10 year US Treasury constant maturity rate and 3 month US Treasury constant maturity rate, lagged one quarter. TED Spread is the difference between the 3 month US dollar LIBOR rate and the 3 month US Treasury rate, lagged one quarter. FFR is the effective US Federal Funds Rate, lagged one quarter. Yield Curve is the difference between 10 year US Treasury constant maturity rate and 3 month US Treasury constant maturity rate, lagged one quarter. TED Spread is the difference between the 3 month US dollar LIBOR rate and the 3 month US Treasury rate, lagged one quarter. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table B.15: Robustness on GDP Growth: Drivers of Total Debt Inflows, by Sector - Advanced Economies (Quarterly AHKS data, missing filled from Public Sources)

	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-10.48***	0.614	-8.600***	-2.495**
	(2.986)	(1.418)	(2.301)	(1.064)
GDP Growth$_{it-1}$	0.566**	0.00402	0.446**	0.116
	(0.241)	(0.0688)	(0.211)	(0.0737)
Observations	1127	1127	1127	1127
R^2	0.047	0.000	0.046	0.025
CountryFE	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as country year-on-year percentage GDP growth minus aggregate advanced economy year-on-year GDP growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Table B.16: Robustness on GDP Growth: Drivers of Total Debt Inflows, by Sector - Emerging Markets (Quarterly AHKS data, missing filled from Public Sources)

	(1) Total	(2) Public	(3) Banks	(4) Corp.
$\log(\text{VIX}_{t-1})$	-2.505***	1.188	-2.562***	-1.132***
	(0.862)	(0.677)	(0.747)	(0.253)
GDP Growth$_{it-1}$	0.133***	-0.0390***	0.124***	0.0478***
	(0.0440)	(0.0136)	(0.0430)	(0.0112)
Observations	1372	1372	1372	1372
R^2	0.066	0.017	0.099	0.078
CountryFE	Yes	Yes	Yes	Yes

Sample is from 2002q4-2014q4, countries as listed in Appendix B.5. Total Debt is the sum of Portfolio Debt and Other Investment Debt inflow data, constructed by AHKS as described in Section 3.2. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as country year-on-year percentage GDP growth minus aggregate advanced economy year-on-year GDP growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

B.6.8 Outflow Regressions

Table B.17: Drivers of Capital Outflows, by Instrument (Quarterly BOP data, missing filled with Zero)

	(1) Total	(2) Direct Investment	(3) Portfolio Equity	(4) Portfolio Debt	(5) Other Investment Debt	(6) Reserves
Panel A: All Countries						
log(VIX$_{t-1}$)	-7.173***	-0.0898	-0.409	-1.469***	-5.321***	0.115
	(2.166)	(0.884)	(0.522)	(0.503)	(1.909)	(0.485)
GDP Growth$_{it-1}$	0.196***	0.0515	-0.0142	0.00391	0.126***	0.0280***
	(0.0604)	(0.0338)	(0.00930)	(0.0159)	(0.0411)	(0.0100)
Observations	1408	1408	1408	1408	1408	1408
R^2	0.048	0.006	0.005	0.011	0.041	0.007
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Advanced Economies						
	(1) Total	(2) Direct Investment	(3) Portfolio Equity	(4) Portfolio Debt	(5) Other Investment Debt	(6) Reserves
log(VIX$_{t-1}$)	-11.89***	-0.492	-0.743	-2.232**	-9.375**	0.951
	(3.869)	(1.862)	(1.102)	(0.958)	(3.614)	(0.583)
GDP Growth$_{it-1}$	0.392**	0.0824	-0.0271	0.0329	0.306**	-0.00203
	(0.146)	(0.0424)	(0.0224)	(0.0467)	(0.111)	(0.00951)
Observations	660	660	660	660	660	660
R^2	0.075	0.009	0.009	0.018	0.071	0.021
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: EM						
	(1) Total	(2) Direct Investment	(3) Portfolio Equity	(4) Portfolio Debt	(5) Other Investment Debt	(6) Reserves
log(VIX$_{t-1}$)	-2.678**	0.370	-0.142	-0.775**	-1.447***	-0.683
	(1.226)	(0.407)	(0.296)	(0.351)	(0.461)	(0.774)
GDP Growth$_{it-1}$	0.105	0.0384	-0.00761	-0.00891	0.0477**	0.0358**
	(0.0523)	(0.0470)	(0.00721)	(0.00879)	(0.0187)	(0.0129)
Observations	704	704	704	704	704	704
R^2	0.037	0.004	0.005	0.014	0.040	0.017
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes

Sample is from 2004q1-2014q4, countries as listed in Appendix B.5. Capital outflow data is from Balance of Payments, with any missing data replaced with zeros. Dependent variables are expressed as a percentage of GDP. VIX is the implied volatility of S&P 500 index options. GDP growth is calculated as a year-on-year percentage growth. Errors are clustered at the country level. ** $p < 0.05$, *** $p < 0.01$

Appendix C: Chapter 4 Appendix

C.1 Appendix

C.1.1 Macro Data

This section details the sources, definitions, and construction of the data and variables used in the macro analysis.

VIX is taken from global liquidity indicators produce by the BIS. The VIX is the Chicago Board Options Exchange Market Volatility Index, which is a measure of the implied volatility of the S&P 500 index options. FFR is the Effective Federal Funds Rate obtained from FRED (the database of the St. Louis Federal Reserve). Spread is defined as the difference between the domestic monetary policy rate and FFR. The domestic monetary policy rate is obtained from the IMF International Financial Statistics. When the monetary policy rate is not available, the rate on Treasury Bills is used. When neither of those are avaiable, the Money Market rate is used.

GDP Growth is annual nominal GDP growth from the World Bank WDI data, publically available online. Real GDP per capita is missing recent data for Argentina, but using real GDP per capita growth yields similar results, so

I use the nominal figure to reatin more observations in the dataset. Exports as a percentage of GDP is likewise taken from the public World Bank data, except for the most recent data for Latvia and Lithuania, which was missing. This data is filled in from Eurostat. KAOPEN is a de jure measure of capital account openness Chinn and Ito (2006). I use the version of this variable that is normalized between 0 and 1, downloaded from `http://web.pdx.edu/~ito/Chinn-Ito_website.htm`, which has this measure updated through 2012. An increase in the value of KAOPEN indicates domestic policies more open to capital flows (less restrictive). For a time invariant measure of openness, I use the median value over the sample. Measures of financial development are taken from the World Bank database produced by Beck, Demirgüç-Kunt, and Levine (2000). I use the ratio of bank assets to GDP as a measure of banking sector development, using the median value over the sample to get a time invariant version (so as to not capture fluctuations in the banking sector due to the expansion and contraction in global credit). My measure of institutional quality comes from publically available annual data derived from the International Country Risk Guide (ICRG) commercial dataset. This consists of year end values of subindicators, made available by the World Bank. I construct my measure of institutional quality from the average of the Government Effectiveness, Regulatory Quality, Corruption Control, and Rule of Law indicators for each year. For a time invariant measure of institutional quality, I use the median value over the sample. For exchange rate classification, I draw on Ilzetski, Reinhart, and Rogoff (2009). I use the monthly coarse classification, and convert to quarterly data using end of quarter values. I classify the exchange rate as rigid if it takes a value of 1 or 2, which encompasses explicit and de facto pegs and crawling pegs, and de facto crawling bands narrower than +/- 2%. I construct a dummy variable equal to 1 if the exchange rate is rigid, and 0 otherwise. I use the median value over the sample for a time invariant measure of exchange rate regime.

For measures of external debt, I draw on the Quarterly External Debt Statistics database published jointly by the IMF and World Bank. I construct the share of external debt held by the banking sector from the Quarterly External Debt Statistics (QEDS), published jointly by the IMF and World Bank. Share of bank debt relative to private debt is constructed by dividing banking sector external debt by the sum of bank external debt and the "Other" sector external debt.[1] Share of credit to the domestic non-financial sector extended by domestic banks is calucalted from the BIS long series on credit to the private sector.[2] I use the series adjusted for breaks in the data. The sample used from this data is Argentina, Brazil, China, Czech Republic, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Poland, Russia, South Africa, Thailand, and Turkey. For the fraction of external bank liabilities in foreign currencies (plotted in panel (b) of Tables C.1-C.17) is obtained from BIS Locational Banking Statistics, Tables 2A and 2C.

The balanced sample is data from 2006q2-2013q4 for the following countries: Argentina, Brazil, Chile, Colombia, Costa Rica, Croatia, Czech Republic,

[1]Data is available for all of my balanced sample, except for Croatia. The banking sector is "Deposit taking corporations, except the central bank", while the "other" sector is composed of other financial corporations, non-financial corporations, households, and non-profit institutions serving households.

[2]see Dembiermont et al. (2013) for a discussion of this data.

Hungary, Indonesia, Israel, Latvia, Lithuania, Mexico, Poland, South Africa, Turkey,and Ukraine.

The sample of all emerging and developing markets has data from 1990q1-2014q2 and consists of: Afghanistan, Albania, Argentina, Bhutan, Bosnia and Herzegovina, Brazil, Chile, China, Colombia, Costa Rica, Croatia, Czech Republic, Estonia, Georgia, Hungary, India, Indonesia, Israel, Kazakhstan, Kenya, Korea, Latvia, Lithuania, Mexico, Moldova, Namibia, Nigeria, Peru, Poland, Romania, Russian Federation, Rwanda, Slovak Republic, South Africa, Sri Lanka, Swaziland, Tajikistan, Tanzania, Turkey, Ukraine, Uganda, West Bank and Gaza, and Zambia.[3]

C.1.2 FX Loans

The FX Loans variable is defined as fraction of gross loans made by the domestic banking sector denominated in a non-domestic currency.[4] A primary source for this data is the Financial Soundness Indicators (FSI) produced by the IMF. However, this data has been voluntarily reported, and so data is only available for select countries, and usually only for very recent years. I extend this dataset with data from National sources. A description of the source of the national data and variable construction is described below. All data not from the

[3]Other countries with FX Loan data available from FSI: Austria, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong SAR China, Italy, Lebanon, Luxembourg, Macao SAR China, Malta, Maritius, Netherlands, Portugal, Singapore, Spain, and United Kingdom

[4]With some exceptions, based on data availability with data drawn from national sources. For instance, data for currency composition of external loans of the Albania banking sector are unavailable, but it is assumed that external loans are small enough that the domestic ratio will match the total.

national sources described below are from the FSI database. In the below descriptions, MFI stands for Monetary Financial Institutions, usually those institutions which report to the central bank, comprising deposit taking corporations.

- **Albania:** The Bank of Albania reports loans of banks by district, with breakdowns by foreign and national currency. The largest districts have a full breakdown, while a residual group of districts only had breakdown for short term loans. I use only the districts with a full breakdown, comprising 93-94% of all loans. The correlation between this measure and the measure including the Other districts short term loans is $> .99$. Data is quarterly from 2007q4-2014q3. This is domestic loans.

- **Argentina:** The Central Bank of the Argentine Republic (BCRA) publishes balance sheet data for financial institutions (excludes the central bank, data is the exact same as that of the banking sector). The data details assets, including loans, are broken down by external and domestic sector, and by foreign and domestic currency. Data is consolidated. The series is monthly starting from 1940, but most of the detail in the breakdowns begins in 1994.

- **Chile:** The Central Bank of Chile reports figures for loan balances by domestic and foreign currency for the banking sector. Data is from 1990q1-2014q2.

- **China:** The People's Bank of China publishes figures on the sources and uses of funds of financial institutions, which includes the People's Bank of

China,[5] the banking industry deposit-taking financial institutions, trust and investment companies, financial leasing companies and auto finance companies. The data contains a breakdown of deposits and loans in total and foreign currency. Data is monthly from 2007m1-2010m12, with quarterly data for 2006.

- **Colombia:** The Central Bank of the Republic of Colombia (BCRP) publishes data on the currency composition of loans granted by the financial sector. This data is weekly from 2002m5-2014m12, and "includes loans given by depository corporations." I use the series "Total Gross Loans without Mortgage Loans Securitization". The figures including securitization yield a slightly smaller ratio.

- **Costa Rica:** Harmonized balance sheets of other depository corporations (with breakdown by currency) is published by the Central Bank of Costa Rica. Loans by sector are listed, and the sum of loans to all sectors is used to compute the variable. Data is monthly from 2001m12-2014m12.

- **Czech Republic:** The Czech National Bank reports loans made by commercial banks in foreign and domestic currency monthly from 1997m1-2014m12.

- **Estonia:** The Bank of Estonia publishes statistics on the financial sector. Data on loans from credit institutions (Banking sector, excluding savings and loan associations and central bank) is broken down by sector and currency from 1997m1-2014m12. Estonia joined the Euro in 2011, so domestic

[5] The People's Bank has very few claims on the non-financial sector.

currency changes from the Estonian Kroon to the Euro at that point.

- **Hungary:** The Central bank of Hungary publishes financial accounts by institutional sector. They include a currency breakdown for loans. Hungary posts this data for both consolidated and non-consolidated positions, including and excluding Special Investment Vehicles (SPE), and by stocks, flows, and revaluations. I use non-consolidated stocks (not including SPEs) from the Monetary Institutions secgion (S.122), which includes deposit taking banks, but excludes the central bank. This data is quarterly from 1989q4-2014q2.

- **Indonesia:** The Central Bank of Indonesia reports loans in total and in domestic currency by commercial and rural banks. Data is 2002m1-2014m11.

- **Latvia:** Data for Latvia was drawn from the central bank of Latvia. Table 20 of the MFI Balance Sheet and Monetary Statistics produced by the Bank of Latvia reports the percentage of loans in foreign currency granted by MFI's (except the central bank), covering 2002m1-2013m12. These figures do not report loans made to resident MFIs, and are reported separately for the other sectors. To get an estimate for currency composition of gross loans, I average the ratios to the resident non-MFI sector, non-resident MFI's, and non-resident non-MFI's, weighting by total loans to each. Latvia adopted the Euro in 2014m1.

- **Lithuania:** The Central Bank of the Republic of Lithuania publishes balance sheet data for MFIs. Currency breakdown of loans to residents is in section 2.8. Currency breakdown is not available for the external sector, so I use the domestic sector for my calculation of the composition. Comparing this to the available numbers reported by FSI, we see that they match. Hence, I use this series to give a larger range for the data. (Lithuania does not use the Euro until 2015). Data is monthly, spanning 1993m12-2014m12.

- **Mexico:** The Central Bank of Mexico reports credit extended by commercial banks in domestic and foreign currencies. FX Loans is calculated as the sum of domestic and external credit, and interbank credit (to be as consistent as possible with the definition of the variable from other sources, the interbank market is included). Data is 1994m12-2014m11.

- **Poland:** The National Bank of Poland reports currency breakdown loans and claims of the banking system. Data for loans separate from other claims is listed for residents that are not general government or other MFIs. ("Other claims" do not include debt securities). I estimate the currency composition of gross loans by using "loans and other claims" for loans vis-a-vis resident MFIs and the external sector. "Loans" and "Other Claims" are listed separately for the general government, but currency composition is only available for their sum. I estimate the loans in foreign currency by using the composition of the sum and multiplying by the loan total. Total gross loans is then computed from all of these estimates. Data is from monthly from 1996m12-2014m9.

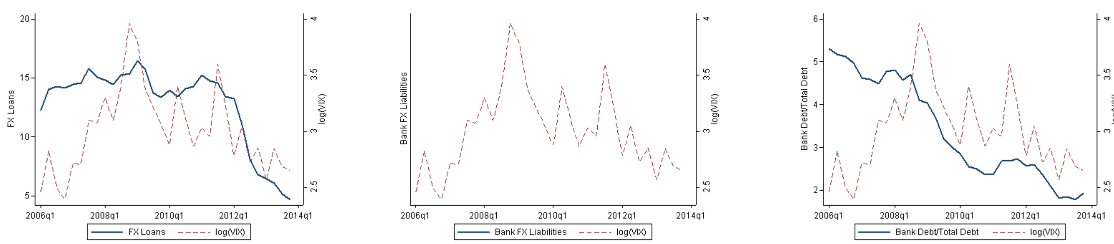
- **Romania:** The Central Bank of Romania reports data on loans outstanding from MFIs with breakdown by currency for the Private Non-Financial sector. I assume that the loans there are representative of the total gross loans composition. Checking this data with that reported for FSI shows that they match, and so I use this series to give a larger range. Data is monthly from 2000m1-2014m12.

- **South Africa:** The Reserve Bank of South Africa reports data on assets of banking institutions in total and in foreign currency. Data is 1997m1-2014m9.

C.1.3 Figures

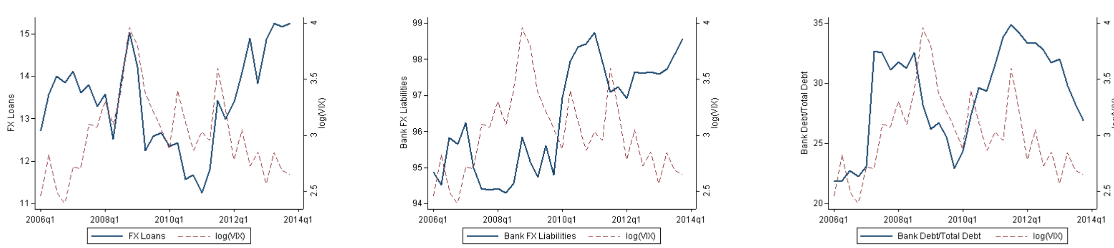
In panel (a), the solid line is the share of loans outstanding from the domestic banking sector in FX. Source: IMF Financial Soundness Indicators and National Sources. In panel (b), the solid line is the share of banking sector external liabilities in FX. Source: BIS Locational Banking Statistics. In panel (c), the solid line is the share of a country's external debt attributable to the banking sector. Source: QEDS. In all panels, the dashed line is the logged value of the VIX.

Figure C.1: Argentina



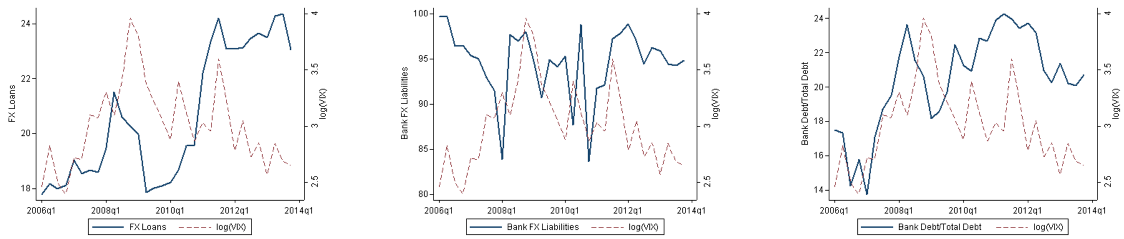
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.2: Brazil



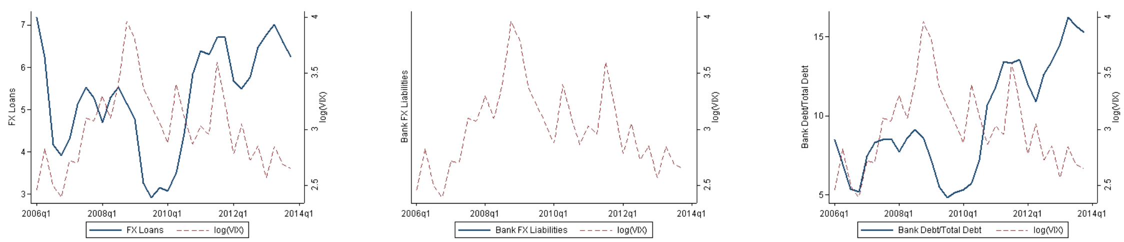
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.3: Chile



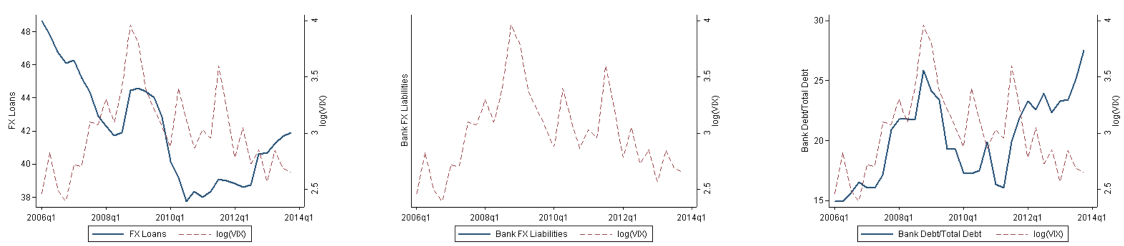
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.4: Colombia



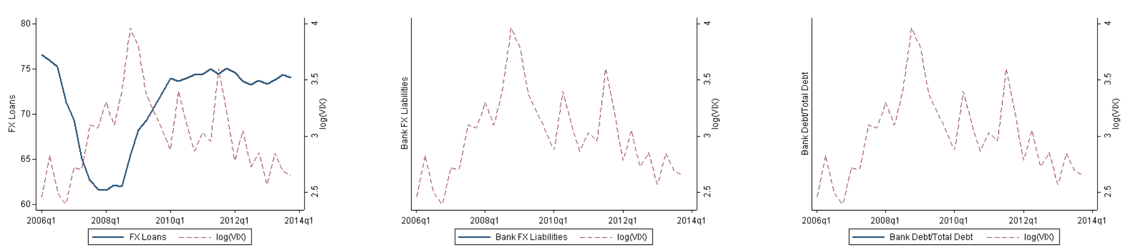
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.5: Costa Rica



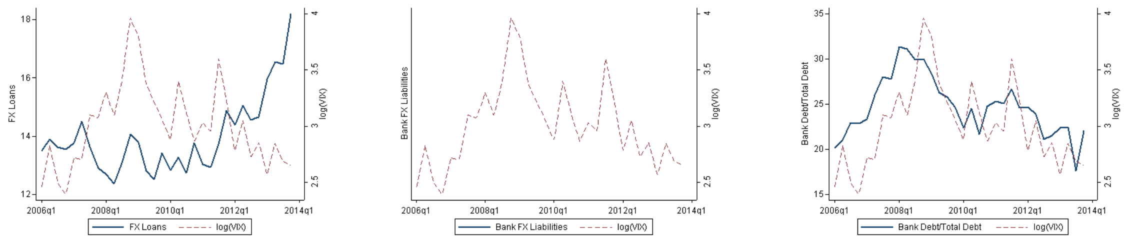
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.6: Croatia



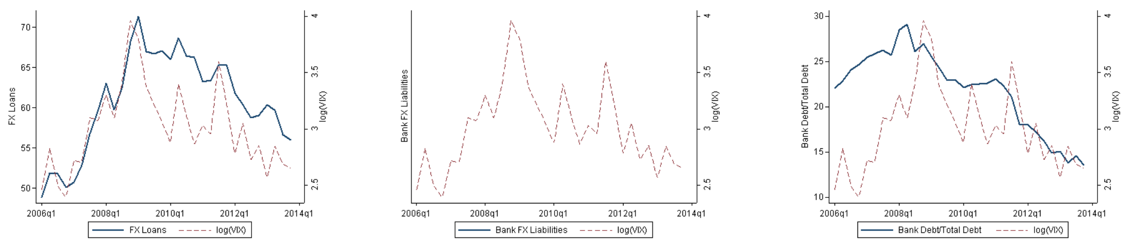
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.7: Czech Republic



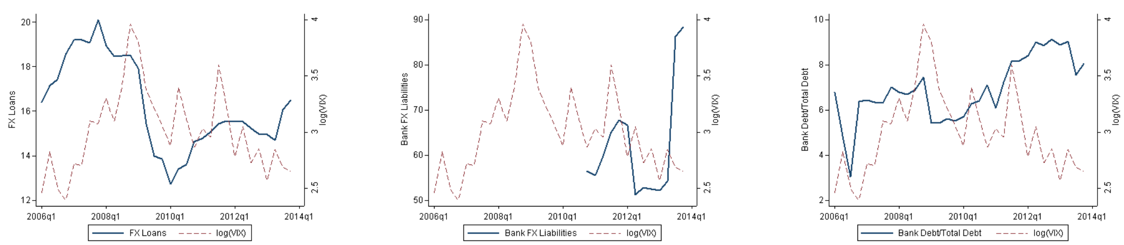
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.8: Hungary



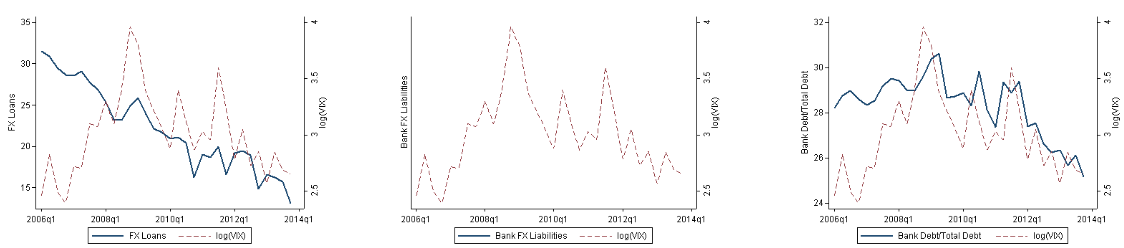
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.9: Indonesia



(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

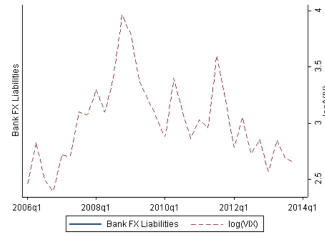
Figure C.10: Israel



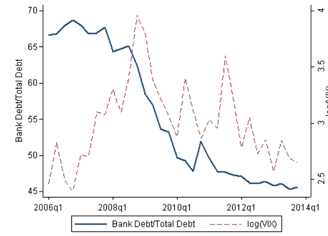
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.11: Latvia

(a) FX Loans

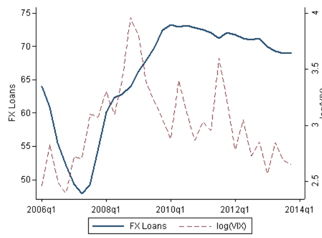


(b) Bank FX Liabilities

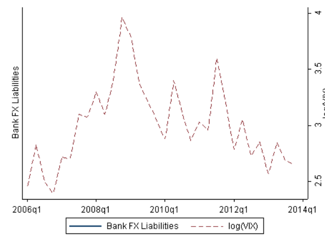


(c) Bank Share Ext. Debt

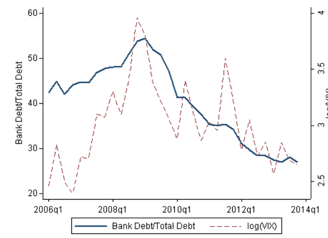
Figure C.12: Lithuania



(a) FX Loans

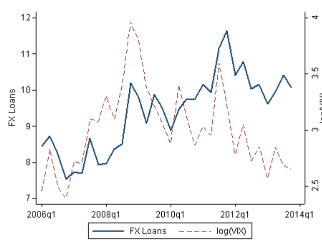


(b) Bank FX Liabilities

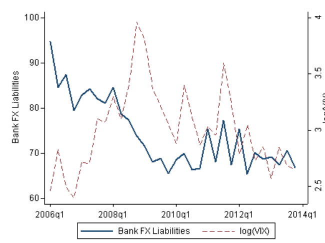


(c) Bank Share Ext. Debt

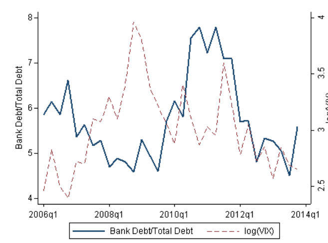
Figure C.13: Mexico



(a) FX Loans



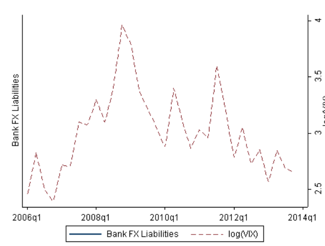
(b) Bank FX Liabilities



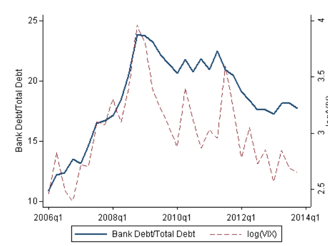
(c) Bank Share Ext. Debt

Figure C.14: Poland

(a) FX Loans

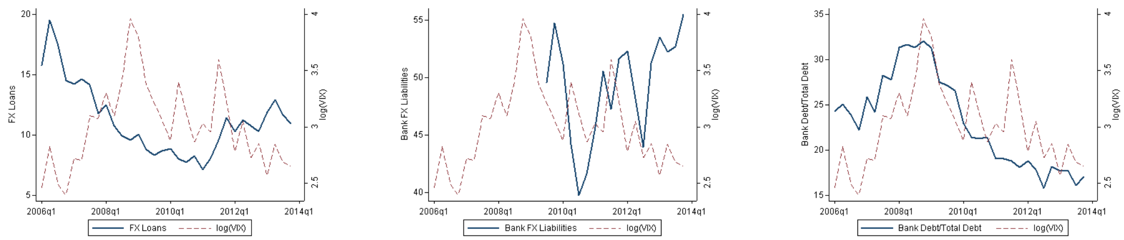


(b) Bank FX Liabilities



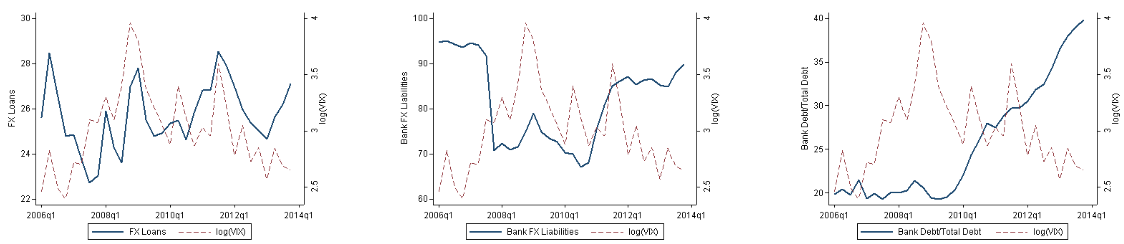
(c) Bank Share Ext. Debt

Figure C.15: South Africa



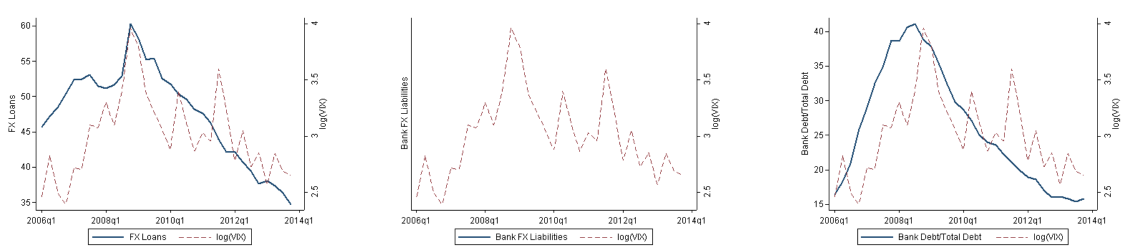
(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.16: Turkey



(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

Figure C.17: Ukraine



(a) FX Loans (b) Bank FX Liabilities (c) Bank Share Ext. Debt

C.1.4 Macro Tables

Table C.1: Descriptive Statistics

	N	mean	median	std. dev.	min	max
Panel A: Full Sample (Unbalanced), 1990-2014						
FX Loans	1769	35.779	28.984	25.94634	0	100
Monetary Policy Spread	1529	6.589	5.11	8.694	-3.288	178.17
Depreciation Rate	1674	0.897	0.020	7.794	-19.062	195.148
Exports/GDP	1683	36.622	32.940	17.356	5.517	92.953
GDP Growth	1683	4.026	4.491	4.274	-17.955	20.941
Openness	1769	0.621	1	0.485	0	1
Good Institutions	1769	0.831	1	0.375	0	1
Pegged Exchange Rate	1745	0.307	0	0.461	0	1
NonBank Private External Debt Growth	1013	2.662	2.273	10.150	-100.000	194.304
Bank External Debt Growth	1015	3.650	1.876	20.736	-100.000	523.670
Bank Share of External Debt	1043	22.890	21.676	14.312	0	68.716
Countries	42					
Quarters	98					
Panel B: Balanced Sample, 2006-2013	N	mean	median	std. dev.	min	max
FX Loans	544	32.795	23.406	24.862	2.921	92.831
Monetary Policy Spread	544	4.335	4.02	4.137	-3.288	30.628
Depreciation Rate	544	0.500	-0.032	6.933	-19.063	58.404
Exports/GDP	544	39.518	37.389	19.177	10.872	88.761
GDP Growth	544	3.142	3.937	4.396	-17.955	12.233
Openness	544	0.647	1	0.478	0	1
Institutional Quaity	544	0.824	1	0.382	0	1
Pegged Exchange Rate	544	0.221	0	0.415	0	1
NonBank Private External Debt Growth	512	2.161	2.151	7.970	-1.000	35.606
Bank External Debt Growth	512	3.298	2.249	0.132	-100.000	130.617
Bank Share of External Debt	512	22.469	21.817	13.665	1.780	68.716
Countries	17					
Quarters	32					

FX Loans is the proportion outstanding of loans from the domestic banking sector denominated in foreign currencies. Monetary Policy Spread is defined as the difference between the domestic monetary policy rate and the US Effective Federal Funds Rate. Depreciation Rate is the rate of local currency depreciation vis-a-vis the US Dollar, expressed in percent. Exports/GDP is total exports of the country normalized by GDP (annual data). GDP Growth is Nominal GDP Growth (annual data). Openness is a dummy variable equal to 1 if KAOPEN, the Chinn-Ito index of capital account openness, is greater than 0.5. Good Institutions is a dummy variable equal to 1 if an index constructed from ICRG subindicators is greater than 0.5. Pegged Exchange Rate is a dummy equal to one if the exchange rate is pegged, and 0 if it is flexible. All percentages are expressed as whole numbers, i.e. 35 represents 35%.

Table C.2: FX Loans and VIX, Country Specific Regressions

Country	2006-2013	Full Sample	Country	Full Sample
Argentina	1.317*	-1.501	Afghanistan	-0.598
Brazil	1.705***	1.786***	Albania	0.520
Chile	0.727	0.439	Bhutan	-0.0791
Colombia	0.796	0.954*	Bosnia and Herzegovina	1.005
Costa Rica	1.118	0.949	China	-0.964**
Croatia	-0.844	-0.770	Estonia	2.391***
Czech Republic	0.859*	1.243***	India	-1.273
Hungary	7.008***	3.398***	Kazakhstan	0.897
Indonesia	1.139	0.632	Kenya	2.313***
Israel	2.428**	1.779**	Korea	2.483***
Latvia	0.285	-0.958	Macedonia, FYR	-0.271
Lithuania	0.551	-1.027	Moldova	-2.421
Mexico	1.467***	1.956***	Namibia	-0.0317
Poland	4.961***	3.718***	Peru	0.340
South Africa	0.907	0.750	Romania	2.761**
Turkey	2.324***	2.313***	Russia	2.480**
Ukraine	3.395	3.221	Rwanda	0.160
			Slovak Republic	-0.105
			Sri Lanka	1.873
			Swaxiland	0.411
			Tajikistan	4.437
			Tanzania	2.871*
			Uganda	0.161
			Zambia	3.015

Dependent variable is the share of domestic bank loans outstanding in foreign currencies, independent variable is the logged value of the VIX. Data is quarterly. Each coefficient is its own regression. Year fixed effects are included. Standard errors are max of two way cluster at country and date levels, robust, and OLS. P-values were calculated using a wild bootstrap on the country-cluster. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1.5 Micro Tables

Table C.3: Global Liquidity and Loan Growth: Mexico Bank-Firm Level - Lag Effects

	(1)	(2)	(3)	(4)	(5)	(6)
FX	-0.0832	0.0291	0.0250	0.0330***	0.0160	0.0112
	(0.0775)	(0.132)	(0.0173)	(0.00742)	(0.0163)	(0.0179)
FX × VIX$_{q-1}$	0.0318*	-0.00611				
	(0.0180)	(0.0391)				
FX × FFR$_{q-1}$			-0.0307	-0.0593*		
			(0.0304)	(0.0300)		
FX × Bank Inflows/GDP$_{q-1}$					-0.00329***	-0.00192
					(0.000746)	(0.00218)
Observations	7197	7112	7197	7112	7197	7112
R^2	0.353	0.408	0.353	0.409	0.353	0.408
Banks	53	49	53	49	53	49
Firms	100	99	100	99	100	99
Quarters	26	26	26	26	26	26
BankFirmFE	No	Yes	No	Yes	No	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes

Sample is loans from domestic banks to listed non-financial firms over 2008q1-2014q3. Dependent variable is the log difference of loans outstanding in FX or Peso at the Bank-Firm level in each period, winsorized by 1%. VIX is the logged value of the CBOE S&P 500 implied volatility index. FFR is the effective federal funds rate. Banks Inflows/GDP is capital inflows to the domestic banking sector as a share of GDP, as constructed in Avdjiev, Hardy, Kalemli-Özcan, and Servèn (2017). FX is a dummy equal to 1 if the loan is denominated in a foreign currency. Regressions are weighted by the lagged value of the log of loan volume. Standard errors are triple clustered at the bank, firm, and date levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: US Dollar and Loan Growth: Mexico Bank-Firm Level

	(1)	(2)	(3)	(4)	(5)	(6)
FX $\times$ Equity/Assets$_b$	-0.334			2.017		
	(0.492)			(10.65)		
FX $\times$ FFR$_q$ $\times$ Equity/Assets$_b$	1.049					
	(0.749)					
FX $\times$ Capital Ratio$_b$		-1.293**			8.888	
		(0.560)			(16.55)	
FX $\times$ FFR$_q$ $\times$ Capital Ratio$_b$		2.043				
		(1.249)				
FX $\times$ Bank Size$_b$			0.00230			-0.389
			(0.0132)			(0.246)
FX $\times$ FFR$_q$ $\times$ Bank Size$_b$			-0.0420**			
			(0.0153)			
FX $\times$ USD Index$_q$ $\times$ Equity/Assets$_b$				-0.0213		
				(0.108)		
FX $\times$ USD Index$_q$ $\times$ Capital Ratio$_b$					-0.0968	
					(0.167)	
FX $\times$ USD Index$_q$ $\times$ Bank Size$_b$						0.00374
						(0.00245)
Observations	6167	5765	6167	6167	5765	6167
R^2	0.462	0.459	0.462	0.461	0.459	0.462
Banks	38	32	38	38	32	38
Firms	91	89	91	91	89	91
Quarters	26	26	26	26	26	26
BankFirmFE	Yes	Yes	Yes	Yes	Yes	Yes
BankQuarterFE	Yes	Yes	Yes	Yes	Yes	Yes
FirmQuarterCurrencyFE	Yes	Yes	Yes	Yes	Yes	Yes

Sample is loans from domestic banks to listed non-financial firms over 2008q1-2014q3. Dependent variable is the log difference of loans outstanding in FX or Peso at the Bank-Firm level in each period, winsorized by 1%. FFR is the effective federal funds rate. USD Index is the broad trade weighted value of the US dollar (from FRED). FX is a dummy equal to 1 if the loan is denominated in a foreign currency. Equity/Assets is the average ratio of the bank's total equity to total assets. Capital Ratio is the bank's average Tier 1 capital ratio. Bank Size is the logged value of the bank's average asset size. Regressions are weighted by the lagged value of the log of loan volume. Standard errors are triple clustered at the bank, firm, and date levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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