Non-Core Bank Liabilities and Financial Vulnerability[*]

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October 17, 2012

Abstract

A lending boom is reflected in the composition of bank liabilities when traditional retail deposits (core liabilities) cannot keep pace with asset growth and banks turn to other funding sources (non-core liabilities) to finance their lending. We formulate a model of credit supply as the flip side of a credit risk model where a large stock of non-core liabilities serves as an indicator of the erosion of risk premiums and hence of vulnerability to a crisis. We find supporting empirical evidence in a panel probit study of emerging and developing economies.

JEL Codes: F32, F33, F34
Keywords: Currency crises, credit booms, cross-border banking

[*]Paper presented at the Federal Reserve Board and JMCB conference on "Regulation of Systemic Risk", Washington, DC, September 15-16, 2011. We are grateful to Stijn Claessens for his comments as discussant, and to Ken West and other participants at the conference for their feedback. The authors thank Yongwhan Jung and Ilsoo Hahn for their excellent research assistance.

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1 Introduction

Banks are the most important financial intermediaries in emerging and developing economies. As intermediaries who borrow in order to lend, banks must raise funding in order to lend to their borrowers. In an economy with domestic savers, the main source of funding available to the bank is the retail deposits of the household sector. However, retail deposits grow in line with the size of the economy and the wealth of the household sector. When credit is growing faster than the pool of available retail deposits, the bank will turn to other sources of funding to support its credit growth. If we classify retail deposits as the core liabilities of the banking sector and label the other components of bank funding as the *non-core* liabilities, then the ratio of the non-core to core liabilities will reflect the underlying pace of credit growth relative to trend and may be expected to give a window on the risk premiums ruling in the economy.

Our paper investigates the role of non-core banking sector liabilities in signaling financial vulnerability. There are two parts to our inquiry. First, we formulate a model of credit supply as the flip side of a credit risk model where a bank maximizes profit subject to a Value-at-Risk (VaR) constraint. The bank maintains a large enough capital cushion to limit the probability of failure to a fixed threshold. When measured risks are low, the bank can expand lending without violating its VaR constraint, leading to higher credit supply to the economy, with consequent impact on the risk premium implicit in the price of credit. When core deposits are "sticky" and do not grow in line with credit supply, the liabilities side of banks' balance sheets will be filled with non-core funding from the capital market. In this way, a higher incidence of non-core funding will be associated with above-trend growth in credit and compressed risk premiums.

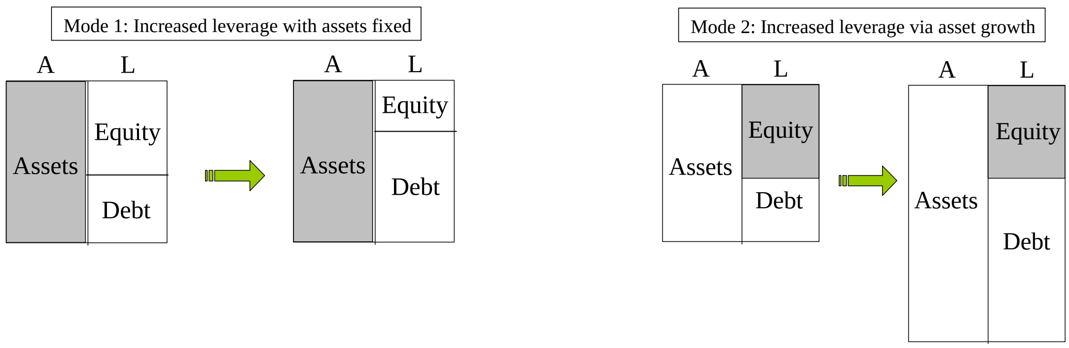

Figure 1. **Two Modes of Leveraging Up.** In the left panel, the firm keeps assets fixed but replaces equity with debt. In the right panel, the firm keeps equity fixed and increases the size of its balance sheet.

The second part of our paper is an empirical investigation where we put the main prediction of our model to the test. We conduct a panel probit study of the susceptibility of emerging and developing economies to a financial crisis using the non-core liabilities of the banking sector as the conditioning variable. We find evidence that various measures of non-core liabilities, and especially the liabilities to the foreign sector, serve as a good indicator of the vulnerability to a crisis, both of a collapse in the value of the currency as well as a credit crisis where lending rates rise sharply.

In formulating our model of credit supply as the flip side of a credit risk model, our approach rests on the corporate finance of bank balance sheet management. In textbook discussions of corporate financing decisions, the set of positive net present value (NPV) projects is often taken as being given, with the implication that the size of the balance sheet is fixed. Instead, attention falls on how those assets are financed. Leverage increases by substituting equity for debt, such as through an equity buy-back financed by a debt issue, as depicted by the left hand panel in Figure 1.

However, the left hand panel in Figure 1 turns out not to be a good

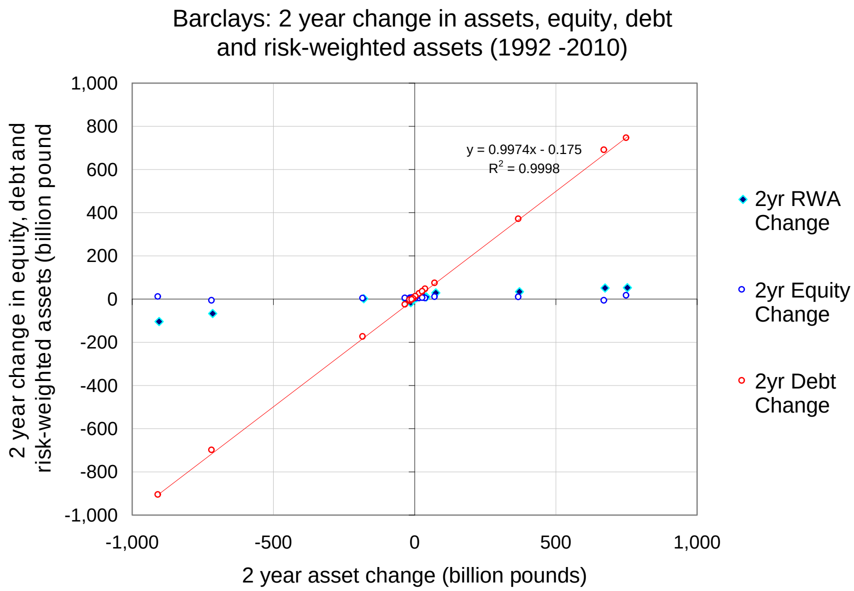

Figure 2. Scatter chart of relationship between the two year change in total assets of Barclays against two-year changes in debt, equity and risk-weighted assets (Source: Bankscope)

description of the way that the banking sector leverage varies over the financial cycle. Instead, leverage and total assets tend to move in lock-step, as depicted in the right hand panel of Figure 1.

Bank balance sheet management can be illustrated in Figure 2 that shows the scatter chart of the two-year changes in debt, equity and risk-weighted assets to changes in total assets of Barclays. The pattern in Figure 2 is typical of banks across countries and across business sectors.[1] More precisely, Figure 2 plots $\{(\Delta A_t, \Delta E_t)\}$, $\{(\Delta A_t, \Delta D_t)\}$ and $\{(\Delta A_t, \Delta RWA_t)\}$ where ΔA_t is the two-year change in assets at quarter t, and where ΔE_t, ΔD_t and ΔRWA_t are the two-year changes in equity, debt, and risk-weighted assets, respectively.

[1]See Adrian and Shin (2010) for a more detailed study of the US investment banks.

The fitted line through $\{(\Delta A_t, \Delta D_t)\}$ has slope very close to 1, while the slope of the fitted line through the points $\{(\Delta A_t, \Delta E_t)\}$ is close to zero. Both features capture the picture of bank balance sheet management given by the right hand panel in Figure 1.

The upshot is that there is a near one-for-one relation between the change in assets and the change in debt, meaning that assets expand or contract dollar for dollar (or pound for pound) through a change in debt. What is especially notable is how the risk-weighted assets of the bank barely change, even as the raw assets change by several hundred billion pounds. The fact that risk-weighted assets barely increase even as raw assets are increasing rapidly attests to the lowering of measured risks during upswings. Lower measured risks and lending booms thus go together. Bank lending appears to expand to fill up any spare balance sheet capacity when measured risks are low.

The causation in the reverse direction may also be operating – that is, the compression of risk spreads is induced by the rapid increase in credit supply chasing available credits. In the presence of such two-way causation, there may well be the potential for a feedback loop in which greater credit supply by banks and the compression of risk spreads interact to generate an amplification of the credit boom. Borio and Disyatat (2011) have coined the term "excess elasticity" to describe the tendency of the banking system to expand when financial constraints are relaxed.

Such procyclical behavior of the banking sector has consequences for capital flows. Banks are intermediaries who borrow in order to lend, and they must raise funding in order to lend to their borrowers. When credit is expanding rapidly, outstripping the pool of available retail deposits, the bank will turn to other sources of funding to support its credit growth, typically from other banks operating as wholesale lenders in the capital market. In this respect, there are close parallels between *currency crises* and *credit crises*. The link comes from the fact that the procyclical behavior of banking that fuels the credit boom is financed through capital inflows via the banking sector. Indeed, one of the key results unearthed by our empirical investigation below is that the most consistently reliable indicator of the vulnerability of both a currency crisis and a credit crisis is a high level of bank liabilities to the foreign sector.

By addressing the up-phase of the financial cycle, and the potential for the compression of risk premiums during lending booms, our approach differs from models of leverage constraints or collateral constraints that bind only in the downturn. In such models, lending is always below the first best. As well as on the downturn, our focus is on the up-phase of the cycle when risk premiums become compressed, leaving the economy vulnerable to a potential reversal.

Our model is not sufficiently refined to address issues of the optimal level of risk premium or quantity of credit. However, the model delivers the feature that a large stock of non-core liabilities of the banking sector will be associated with compressed risk premiums in the market for bank credit - a feature that proves useful in our empirical investigation. We conduct a panel probit investigation for the incidence of financial crises in a large sample of emerging and developing economies and find that non-core bank liabilities do, indeed, have explanatory power for subsequent crises.

Figure 3 is a schematic illustration of the build-up of vulnerabilities associated with the growth of non-core liabilites. The bottom panel is the banking sector before a credit boom, while the top panel illustrates the sys-

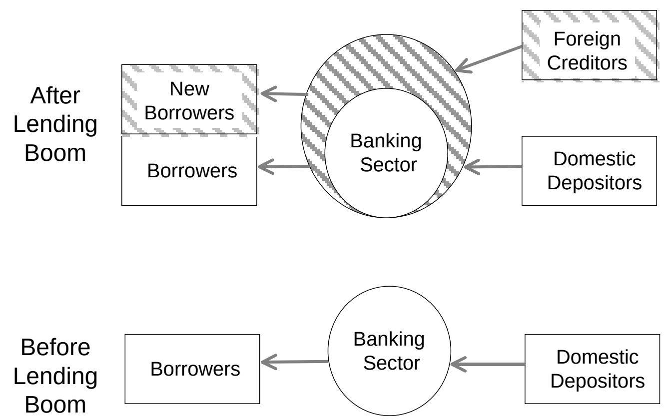

Figure 3. **Lending Boom Financed by Non-Core Liabilities.** This figure depicts the banking sector balance sheet before and after a credit boom. Increased lending during a credit boom is financed by non-core liabilities.

tem after the boom. As traditional deposit funding does not keep up with the credit growth, the banking sector's expansion is funded by non-core liabilities (in this case, from foreign creditors), building up vulnerabilities to deleveraging by foreign creditors.

Figure 4 is an illustration from Korea. The right panel of Figure 4 plots six categories of non-core liabilities of the Korean banking sector, taken from Shin and Shin (2010). It is notable how the first peak in non-core liabilities coincides with the 1997 crisis. After a lull in the early 2000s, non-core liabilities increase rapidly in the run-up to the 2008 crisis.[2] The left panel of Figure 4 is the plot of non-core liabilities as a fraction of M2, and highlights the highly procyclical nature of non-core liabilities. There is substantial variation in the ratio of non-core liabilities to M2, ranging from around 15% of M2 to a peak of 50% at the height of the 2008 crisis following the bankruptcy of Lehman Brothers.

[2] The peaks in the series occur some weeks after the start of the crisis, as the non-core series are measured in Korean Won and the Won depreciated sharply during the 1997 and 2008 crises, increasing the Won value of foreign exchange-denominated liabilities.

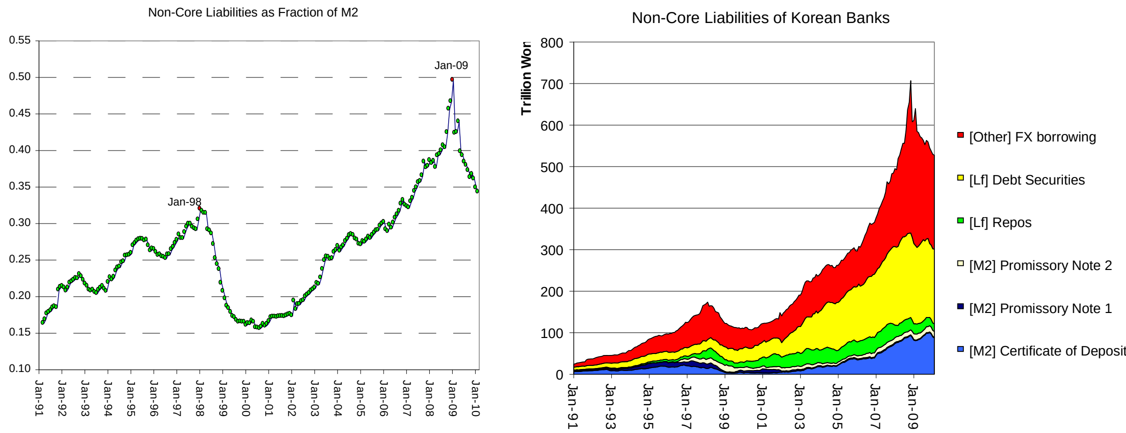

Figure 4. **Non-Core Liabilites of Korean Banks.** Panel on right plots six categories of non-core liabilities of Korean banks measured in Korean Won. Panel on the left plots the non-core series as a fraction of M2. Source: Bank of Korea and Shin and Shin (2010)

There is an extensive literature on leading indicators of emerging market financial crises. Using a panel of over 100 developing countries from 1971 to 1992, Frankel and Rose (1996) find that currency crises tend to occur when output growth is sluggish, domestic credit growth is high, foreign interest rates are high, and the ratio of FDI to debt is low. Kaminsky and Reinhart (1999) explored the linkages between banking crises and currency crises, and found that financial liberalization and capital inflows, credit booms, and an overvalued currency often precede "twin crises" that combine banking and currency crises.[3]

Drawing on the earlier literature, Goldstein, Kaminsky and Reinhart (2000) conducted a comprehensive battery of empirical tests for the effectiveness of early warning systems that rely on macroeconomic (and some microeconomic) variables at various frequencies. Using the "signals" method-

[3]See Berg and Pattillo (1999) for a survey of the early literature and comparison of methodologies.

ology of comparing Type I and Type II errors, they conclude that many of their in-sample leading indicators remain effective in out-of-sample analyses.

The recent global financial crisis has also stimulated renewed interest in measuring vulnerability. However, the fact that the crisis affected advanced and emerging economies alike, with outwardly disparate causes in the two groups, has meant that consistent indicators of vulnerability have been rare. Claessens et al. (2010) examine many candidate indicators of vulnerability but find support only for house price appreciation, current account deficits and bank credit growth. Using a Multiple Indicator Multiple Cause model based on 107 country data, Rose and Spiegel (2008, 2010) find that commonly cited causes of financial crises implicating a host of variables - macroeconomic, financial conditions, regulatory, and institutional - are in fact only weakly related to the incidence of crises, leading them to somewhat more skeptical conclusions on the usefulness of early warning systems.

Our objective differs from these earlier papers. Our motivation is primarily to draw attention to the role of the intermediary sector in driving fluctuations in risk premiums. For this reason, we employ only a small selection of key variables motivated by the theory, and we do not attempt to maximize goodness of fit by employing a large number of explanatory variables from disparate categories. Nevertheless, we conduct a robustness analysis by considering other variables considered in the literature.

Overall, the empirical performance of non-core liabilities measures is encouraging and gives some cause for optimism that more elaborate versions of such models may be a useful input into early warning exercises. In any case, we note that previous research on forecasting crises did not focus explicitly on fluctuation of non-core bank liabilities as a potential indicator of financial vulnerability, focusing instead on the asset side of the banking sector balance sheet, such as on credit growth or credit to GDP ratios. Although our non-core liability measures are closely related to asset side measures, we show that they carry considerable information value over and above credit aggregates.

Liabilities of banks to the foreign sector constitute a major component of non-core bank liabilities in many emerging market countries as the domestic wholesale bank funding market is not sufficiently developed to support rapid bank lending growth. Earlier empirical studies cited above have examined the size and maturity structure of aggregate external debt positions - an example being the ratio of short-term external debt to official foreign exchange reserves. These ratios were employed as an indicator of vulnerability to foreign exchange liquidity shocks. Our contribution is to point to the banking sector as the likely engine of accumulating vulnerability.

Our investigation complements that in Gourinchas and Obstfeld (2012), who conduct an empirical study using data from 1973 to 2010 for both advanced and emerging economies on the determinants of financial crises. They find that two factors emerge consistently as the most robust and significant predictors of financial crises, namely a rapid increase in leverage and a sharp real appreciation of the currency.

Our study also builds on Shin and Shin (2010), who laid out the conceptual distinction between core- and non-core banking sector liabilities, and how these aggregates relate to traditional monetary aggregates. Using Korean bank data, this earlier study finds that non-core bank liabilities as defined as the sum of foreign exchange liabilities and wholesale bank funding are associated with vulnerability to sharp depreciation of the Won and increased borrowing spreads. Hahm, Mishkin, Shin and Shin (2010) further elaborate on the role of non-core bank liabilities as an indicator of financial procyclicality. Using more disaggregated series by claim-holders of non-core liabilities in Korea, they find that, relative to core liabilities, non-core bank liabilities are more procyclical on various measures. Drawing on these earlier studies, the objective of our empirical analysis is to explore the potential usefulness of non-core bank liabilities as conditioning variables in a panel probit study of potential vulnerability of emerging economies to financial crises.

The outline of the paper is as follows. We begin in the next section by formulating our model of credit supply based on the Vasicek (2002) model of credit risk, and draw implications on the relationship between credit, non-core liabilities and risk premiums in the bank credit market. We then follow with our empirical investigation by conducting a panel probit study of financial crises in emerging and developing economies using the IMF's International Financial Statistics (IFS) data. In order to allow for persistent heterogeneity across countries in our sample, we use the random effects version of the panel probit model, and confirm the strong explanatory role of non-core banking sector liabilities in explaining crises.

2 Model

Our model is a static model of credit supply with two dates - dates 0 and 1. Loans are made at date 0 and repaid at date 1. A bank makes loans financed from three funding sources - the bank's equity E, its deposits D and its non-core liabilities, denoted by N. The notation for the components of the bank's balance sheet is given as in Figure 5.

The bank's equity E and total deposit funding D are both fixed. Deposits are fully insured by the government, and so earn the risk-free rate of return, which we set to zero. Total lending L satisfies the balance sheet identity:

$$L = E + D + N \tag{1}$$

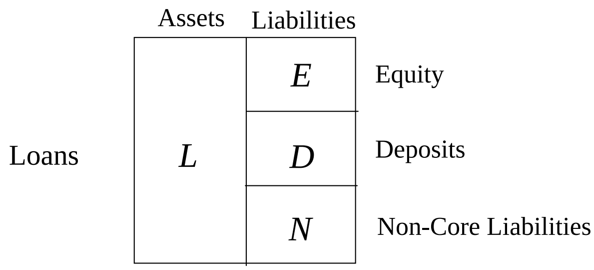

Figure 5. Balance Sheet of Bank

The bank has a well-diversified loan portfolio consisting of loans to many borrowers, and credit risk follows the Vasicek (2002) model, which is the basis for the Basel capital requirements (BCBS (2005)). Borrower j repays the loan when $Z_j > 0$, where Z_j is the random variable given by

$$Z_j = -\Phi^{-1}(\varepsilon) + \sqrt{\rho}Y + \sqrt{1-\rho}X_j \tag{2}$$

where $\Phi(.)$ is the c.d.f. of the standard normal, ε is the probability of default on the loan and Y and $\{X_j\}$ are mutually independent standard normal random variables. Y is the common factor that drives credit risk while each X_j are the idiosyncratic component of credit risk for the particular borrower j. The parameter $\rho \in (0,1)$ is the exposure of each loan to the common factor Y. To verify that ε is the probability of default, note that

$$\begin{aligned} \Pr(Z_j < 0) &= \Pr\left(\sqrt{\rho}Y + \sqrt{1-\rho}X_j < \Phi^{-1}(\varepsilon)\right) \\ &= \Phi\left(\Phi^{-1}(\varepsilon)\right) = \varepsilon \end{aligned}$$

Conditional on the common factor Y, defaults are independent. Denote the loan interest rate as r so that the notional value of assets (the amount due to the bank at date 1) is $(1+r)L$. By the law of large numbers, the realized value of the loan book at date 1 is the random variable $w(Y)$ defined as:

$$
\begin{aligned}
w(Y) &\equiv (1+r)\,L \cdot \Pr\left(Z_j \geq 0 | Y\right) \\
&= (1+r)\,L \cdot \Pr\left(\sqrt{\rho}Y + \sqrt{1-\rho}X_j \geq \Phi^{-1}(\varepsilon)\,|Y\right) \\
&= (1+r)\,L \cdot \Phi\left(\tfrac{Y\sqrt{\rho}-\Phi^{-1}(\varepsilon)}{\sqrt{1-\rho}}\right) \qquad (3)
\end{aligned}
$$

The quantiles of the asset realizations can be derived as follows. The c.d.f. of the realized value of the loan portfolio at date 1 is given by

$$
\begin{aligned}
F(z) &= \Pr(w \leq z) \\
&= \Pr\left(Y \leq w^{-1}(z)\right) \\
&= \Phi\left(w^{-1}(z)\right) \\
&= \Phi\left(\frac{\Phi^{-1}(\varepsilon)+\sqrt{1-\rho}\Phi^{-1}\left(\frac{z}{(1+r)L}\right)}{\sqrt{\rho}}\right) \qquad (4)
\end{aligned}
$$

As prescribed by the Basel capital requirements (BCBS (2005))[4], the bank follows the Value-at-Risk (VaR) rule of keeping enough equity to limit the insolvency probability of the bank to be some small $\alpha > 0$. We impose the condition that $\alpha < \varepsilon$. That is, the bank defaults with a smaller probability than an individual borrower.[5] The bank is risk-neutral otherwise. The bank's objective is to maximize expected profit subject only to its Value-at-Risk constaint.

The bank remains solvent as long as the realized value of $w(Y)$ is above its notional liabilities at date 1. Since the interest on deposits is zero while the funding rate on non-core liabilities[6] is f, the notional liability of the bank

[4]The regulatory requirement was intended to emulate private sector best practice. See Adrian and Shin (2008) for a possible derivation of the VaR rule in a contracting setting.

[5]This conditions is useful in our comparative statics results that follow. It ensures that increasing ρ (and hence greater systematic risk in the loan portfolio) leads to lower leverage.

[6]The funding rate f is fixed and determined outside our model. See Bruno and Shin (2011) for a model of credit supply that endogenizes f by modeling the global banking sector.

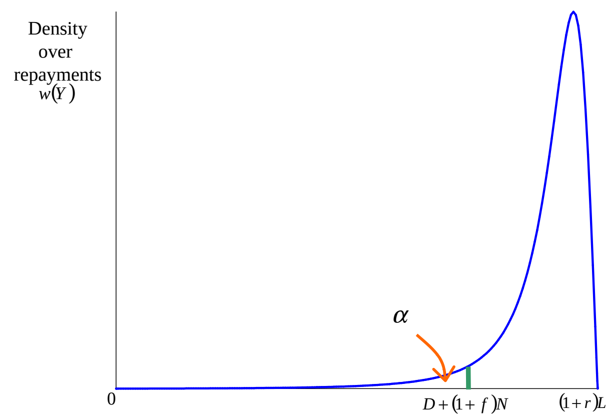

Figure 6. Probability density of $w\,(Y)$

at date 1 is

$$D + (1 + f)\,N \tag{5}$$

The optimal size of the loan book L for the bank keeps the insolvency probability at α, as illustrated in Figure 6. If $L > E + D$, then the shortfall in funding is made up by borrowing in the wholesale market. The bank's use of wholesale funding N and its loan supply L therefore satisfies:

$$\Pr\left(w < D + (1 + f)\,N\right) = \Phi\left(\frac{\Phi^{-1}(\varepsilon)+\sqrt{1-\rho}\,\Phi^{-1}\left(\frac{D+(1+f)N}{(1+r)L}\right)}{\sqrt{\rho}}\right) = \alpha \tag{6}$$

Re-arranging (6), we can derive an expression for the ratio of notional liabilities to notional assets.

$$\frac{\text{Notional liabilities}}{\text{Notional assets}} = \frac{D + (1 + f)\,N}{(1 + r)\,L} = \Phi\left(\frac{\sqrt{\rho}\,\Phi^{-1}(\alpha) - \Phi^{-1}(\varepsilon)}{\sqrt{1-\rho}}\right) \tag{7}$$

We use the notational shorthand:

$$\varphi\,(\alpha, \varepsilon, \rho) \equiv \Phi\left(\frac{\sqrt{\rho}\,\Phi^{-1}(\alpha)-\Phi^{-1}(\varepsilon)}{\sqrt{1-\rho}}\right) \tag{8}$$

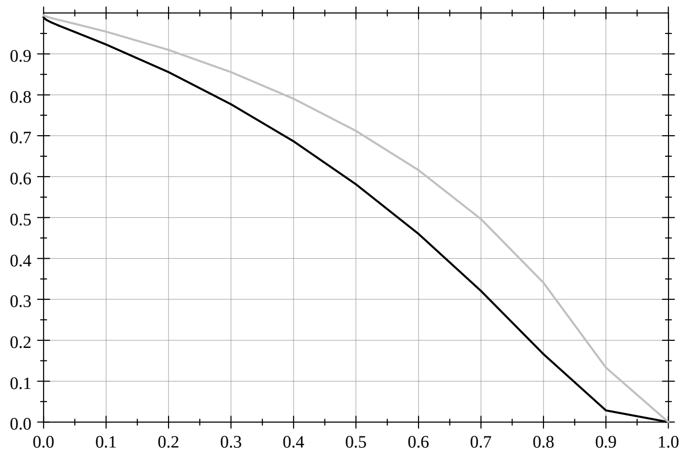

Figure 7. **Plot of notional debt to assets ratio** $\varphi(\alpha, \varepsilon, \rho)$. This chart plots φ as a function of ρ with $\alpha = 0.001$. Dark line is when $\varepsilon = 0.01$. Light line is when $\varepsilon = 0.005$.

Clearly, $\varphi \in (0, 1)$. Our condition that $\alpha < \varepsilon$ ensures that the expression inside $\Phi(.)$ in (8) flips sign from negative to positive as ρ increases from zero to one. Figure 7 plots the notional debt to assets ratio φ as a function of the common risk factor ρ. The Value-at-Risk threshold level is fixed at $\alpha = 0.1\%$. The dark line is when the default probability ε is 1%, while the light line is when ε is 0.5%. We see that the debt to assets ratio is decreasing in both ρ and ε. Since the bank's leverage is monotonic in φ, leverage declines in ρ and ε.

From (7), we can solve for the bank's stock of non-core liabilities N.

$$N = \frac{\varphi(1+r)(E+D) - D}{1 + f - \varphi(1+r)} \tag{9}$$

Using the balance sheet identity $L = E + D + N$, we can also solve for the bank's loan supply function

$$L_S(r) = \frac{E + \frac{f}{1+f} \cdot D}{1 - \frac{1+r}{1+f} \cdot \varphi} \tag{10}$$

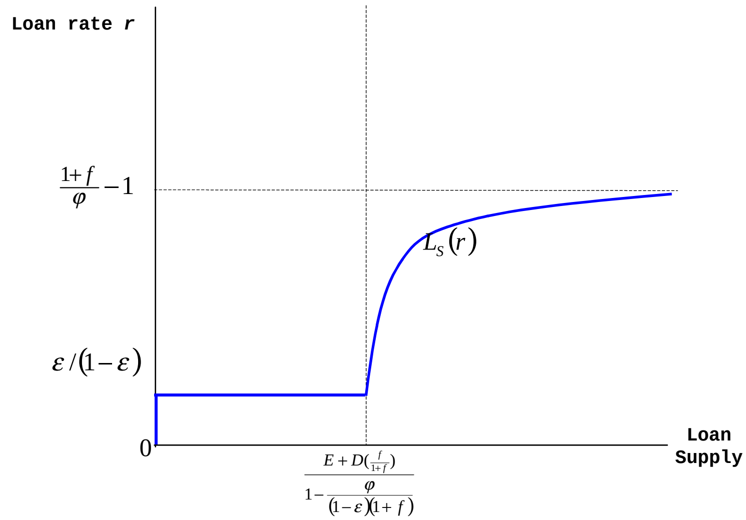

Figure 8. Loan Supply $L_S(r)$

Note that the loan supply by the bank is increasing in E and D. Loan supply is well-defined only when $1+f > \varphi(1+r)$. Loan supply goes to infinity as the ratio $(1+f)/(1+r)$ approaches φ. Since the probability of default is ε, the expected profit to the bank from one dollar's worth of loans is

$$(1-\varepsilon)(1+r)-1 \tag{11}$$

Since the bank maximizes expected profit, its loan supply is zero if r falls below $\varepsilon/(1-\varepsilon)$. Otherwise, it will supply the full amount of loans constrained only by the VaR constraint (6). Figure 8 plots the loan supply curve of the bank as a function of the loan interest rate r. Note that the loan supply is zero if $r < \varepsilon/(1-\varepsilon)$, and goes to infinity as r approaches the asymptote $((1+f)/\varphi)-1$ from below. We summarize our results as follows.

Proposition 1 *Non-core funding N is increasing in φ and decreasing in f.*

Corollary 2 *Bank credit supply L is increasing in φ and decreasing in f.*

Corollary 2 follows from the balance sheet identity $L = E + D + N$ and the fact that bank equity and deposit funding are fixed, so that total credit and non-core funding move together.

Credit market clearing determines the equilibrium loan rate r, and hence the risk premium. Denoting loan demand as $L_D(r)$, the equilibrium condition for the loan market is

$$L_D(r) = \frac{E + \frac{f}{1+f} \cdot D}{1 - \frac{1+r}{1+f} \cdot \varphi} \tag{12}$$

The market-clearing condition (12) determines the equilibrium loan rate r. Since the default probability of loans is ε, the risk premium in the credit market is given by

$$\pi \equiv (1 - \varepsilon)(1 + r) - 1 \tag{13}$$

When N is high, loan supply is high and hence the risk premium π is low. For fixed ε, the risk premium is monotonic in the lending rate r, so that the comparative statics of the risk premium inherit the comparative statics of the total credit supply given by Corollary 2.

Proposition 3 *The risk premium π is low when N is high. The risk premium increases when the funding rate f increases, or when φ falls.*

In a credit boom when the systematic risk factor ρ is small, the measured risks in the loan portfolio is low, implying that less equity is needed to meet the bank's Value-at-Risk constraint, allowing the bank to increase its lending funded by an expansion in its wholesale funding N. In Figure 6, a decrease in ρ implies the shrinkage of the size of the left tail of the density of repayments, meaning that the bank can have a larger loan book for any given equity base E. Also, during a period of permissive funding conditions when the funding rate f is low, the bank can maintain a larger stock of non-core liabilities N.

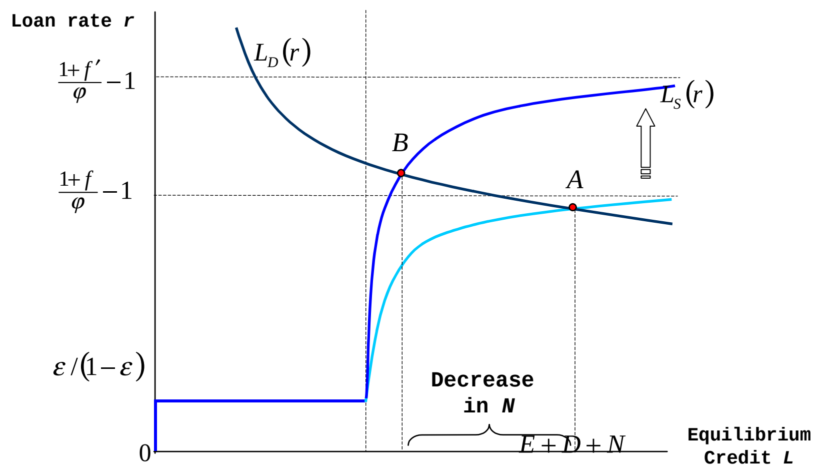

Figure 9. Effect of rise in funding rate f

However, after such a period of permissive financial conditions, risk premiums are low and the sector is vulnerable to a shock that reverses the permissive financial conditions. When eventually a shock arrives that either increases ρ, or when the funding rate f increases due to an overall deterioration of the wholesale funding market, there will be a sharp contraction in the stock N of wholesale funding and in overall lending. Figure 9 shows the effect of a sharp increase in the funding rate f. The increase in the funding rate shifts up the loan supply curve of the bank. For any given loan demand curve $L_D(r)$, the shift upward in loan supply results in a sharp decrease in credit and in the use of non-core liabilities N.

In open emerging economies, a substantial fraction of the non-core liabilities of the banks are foreign exchange-denominated liabilities, often short-term. Therefore, a sharp reduction in N will be associated with capital outflows through the contraction of banking sector debt, and a depreciation of the domestic currency.

3 Evidence from Panel Probit

3.1 Data Description and Methodology

The primary data source for our study is the IMF's International Financial Statistics (IFS) database, focusing on the banking sector indicators at the country level. Although the country coverage of the IFS data is broad, the range of variables that can serve as the empirical counterpart of our non-core concept is somewhat limited. The IFS database lists 105 countries that have measures of banking sector liabilities to the foreign sector, 60 countries with liabilities of banks to non-bank financial sectors (with 50 that have both), and only 14 countries that list bonds issued by banking institutions. We also examine the difference M3 – M2 between two measures of broad money, M3 and M2 (reported by 64 countries) in order to get another fix on non-core liabilities of the banking sector.[7] The sample period spans January 2000 to December 2010. All variables are monthly except for the credit to GDP ratio, which is annual. All missing values are replaced by using the linear interpolation method.

As measures of core liabilities, we sum demand deposits (reported by 121 countries), time, savings and foreign currency deposits (120 countries) and restricted deposits (80 countries). As an alternative, we use monetary aggregates M1 (reported by 120 countries) and M2 (120 countries). Eurozone countries do not report separate monetary aggregates and hence are excluded here. Use of the M3 measure in our study also reduces our sample. For instance, Korea does not figure in the regressions below, as it does not report

[7] Although the detailed breakdown of M2 and M3 categories differs across financial systems, the US is a useful benchmark (although the Federal Reserve no longer reports M3). For the US, the difference between M3 and M2 is given by large time deposits, institutional money market mutual funds, and repurchase agreements. In this respect it captures some aspects of wholesale bank funding.

M3 within IFS.

To investigate the predictive power of non-core bank liabilities for impending financial crises, we use three definitions of crises - *currency crises*, *credit crises* and *stock market crises*.

Currency crises are episodes where the value of the local currency drops abruptly and substantially. Following Frankel and Rose (1996) we define a currency crisis in terms of a currency depreciation of more than 25% in one year, and where the depreciation is at least 10% more than the depreciation in the previous year. That is

$$\ln e_t - \ln e_{t-12} \geq 0.25 \tag{14}$$

$$(\ln e_t - \ln e_{t-12}) - (\ln e_{t-12} - \ln e_{t-24}) \geq 0.10 \tag{15}$$

The second condition was introduced by Frankel and Rose (1996) to take account of countries that undergo rapid but steady depreciation due to high inflation.

The credit crisis definition captures episodes of sharply higher market interest rates. Specifically, we use the money market interest rate, and define a credit crisis as an episode where the money market rate reaches a level that is in the top 3% tail of the pooled in-sample distribution. A more standard measure of credit crisis would have been in terms of the spread between the local risk-free rate and the local rate on private liabilities, but data limitations due to the sample of countries examined in our study precludes the use of this more standard (and desirable) measure. By analogy with our definition of a credit crisis, we define a stock market crisis as an episode where the rate of change in stock price index belongs to the bottom 3% tail of the pooled in-sample distribution.

Our investigation complements that in Gourinchas and Obstfeld (2012), who find that a rapid increase in leverage and a sharp real appreciation of the currency emerge as being important in explaining crises. Our model suggests that the common thread between currency crises and credit crises is the procyclical behavior of the banking sector, and the implication for capital flows, as mentioned at the outset. Banks are intermediaries who borrow in order to lend, and they must raise funding in order to lend to their borrowers. When credit is expanding rapidly, outstripping the pool of available domestic deposits, the bank will turn to other sources of funding to support its credit growth, typically from other banks operating as wholesale lenders in the capital market. The link comes from the fact that the procyclical behavior of banking that fuels the credit boom is financed through capital inflows via the banking sector. When the cycle turns, the decline in credit is accompanied by the "sudden stop" in capital flows and the associated collapse of the currency. As we see below, the most consistently reliable indicator of the vulnerability of both a currency crisis and a credit crisis turns out to be a high level of bank liabilities to the foreign sector.

A stock market crisis will reflect the direct distress of banking sector stocks, as well as the associated distress of firms whose access to credit is impaired by the crisis. The sharp increase in credit spreads will also increase the discount rate, pushing down stock prices. Thus we would expect a close connection between all three measures of crises - currency crisis, credit crisis and stock market crisis. We explore the connections in our empirical investigation below.

Once the crisis month is identified, we define a crisis episode by following the procedure used by Hausmann, Pritchett and Rodrik (2005)[8], and assign the dummy value of 1 to the ± 6 month period centered on the month of a crisis. That is, when the crisis happens at date t, the crisis dummy equals

[8]Hausmann, Pritchett and Rodrik (2005) used a probit model to identify factors in growth accelerations.

to 1 at dates

$$t-6, t-5, \cdots, t, t+1, \cdots, t+6$$

We drop data for the six months before and after the crisis period so as to remove the ambiguity associated with the transition period when 1 or 0 may not be clearly assigned. The comparison group is the group of the countries that did not have a crisis in that same month.

By using a binary definition of crisis, we may be neglecting those episodes where the financial system is under considerable stress, but just manages to weather the storm. In order to capture such "near misses", we also examine alternative definitions of crises, such as the currency pressure index to be introduced below.

Our definition of non-core bank liabilities follows the approach in Shin and Shin (2010). Non-core bank liabilities will be classified (in the first instance) broadly as claims on banks held by financial institutions and held by foreign creditors. In principle, non-core bank liabilities should include inter-bank liabilities, but data limitations for emerging economies prevent us from using interbank liabilities in gross terms. We adopt two alternative measures of non-core bank liabilities:

$$\begin{aligned} \text{Non-core 1} = \quad & \text{Liability of banks to the foreign sector} \\ & + \text{Liability of banks to the} \\ & \quad \text{non-banking financial sector} \end{aligned} \tag{16}$$

$$\begin{aligned} \text{Non-core 2} \quad = \quad & \text{Liability of banks to the foreign sector} \\ & + (\text{M3} - \text{M2}) \end{aligned} \tag{17}$$

Both measures of non-core bank liabilities include bank liabilities to the foreign sector, which constitutes an important source of non-deposit wholesale funding for banks in emerging and developing economies. In addition to foreign liabilities, non-core 1 adds bank liabilities to non-bank financial institutions such as insurance companies and pension funds, and non-core 2 adds M3 – M2 as additional components of non-core liabilities.

In actual estimations of the probit models below, we use various ratios of non-core to core. As a measure of core liabilities, we use three alternative measures – M1, M2 and core deposits. Core deposits are obtained by summing demand deposits, time and savings deposits, foreign currency deposits, and restricted deposits. Finally, to obtain the credit to GDP ratio, we use deposit-taking banks' claims on other residents as a measure of bank credit.

The appendix presents the full list of countries that experienced a currency crisis, credit crisis or stock market crisis as identified above, together with the crisis dates. The appendix also reports which countries have data on non-core bank liabilities and the credit to GDP ratio. 37 countries had currency crises during our sample period, and several countries had two or more currency crises according to our definition (Brazil, Colombia, Lesotho, Mozambique, Namibia, South Africa, Swaziland, Turkey and Zambia). We have18 countries that underwent credit crises in the sample period and 27 countries that underwent stock market crises.

Table 1 reports summary statistics for the monthly variables used in the probit analysis. When non-core liability is defined as the sum of bank liabilities to the foreign sector and non-bank financial sector (Non-core I), the non-core liability is 70% of M1 and around 30% of M2 or core deposits. The currency and credit crisis variables are dummy variables with a value of 1 for the crisis period. Credit to GDP is an annual variable with a mean of 45% in our sample.

Table 1. **Summary Statistics.** This table gives the summary statistics for the monthly variables. Missing values are replaced by using a linear interpolation. The appendix contains the list of crisis episodes studied in this paper.

Variable	Obs	Mean	Std.Dev	Min	Max
Noncore1/M1	4228	0.70	0.92	0.00	9.13
Noncore1/M2	4239	0.27	0.46	0.00	5.10
Noncore1/Core	4510	0.22	0.24	0.00	1.80
Foreign/M1	6029	0.63	0.93	0.00	9.11
Foreign/M2	6040	0.31	0.52	0.00	5.09
Foreign/Core	6286	0.26	0.44	0.00	8.37
Nonbank/M1	4228	0.17	0.28	0.00	1.66
Nonbank/M2	4239	0.06	0.09	0.00	0.85
Nonbank/Core	4510	0.05	0.09	0.00	0.90
Noncore2/M1	4506	1.41	1.38	0.09	10.10
Noncore2/M2	4610	0.66	0.64	0.02	5.98
Noncore2/Core	4585	0.55	0.57	0.03	10.02
(M3-M2)/M1	4506	0.77	1.05	0.00	6.50
(M3-M2)/M2	4610	0.34	0.40	0.00	3.84
(M3-M2)/Core	4585	0.26	0.27	0.00	1.95
Exchange rate growth	6026	0.01	0.13	-0.54	0.86
Interest rate	3974	8.09	11.24	0.00	400.27
Currency crisis	5547	0.11	0.31	0.00	1.00
Credit crisis	3885	0.11	0.31	0.00	1.00
Stock market crisis	1796	0.27	0.44	0.00	1.00

3.2 Probit Estimation Results

We estimate panel probit models to investigate the linkage between our crisis measures and the non-core bank liabilities constructed above. Under the probit model, the inverse standard normal c.d.f. of the probability of crisis is modeled as a linear function of the explanatory variables. We run separate probit regressions for each crisis definition, and use the random effects panel probit method to allow for country differences that persist over time. As a robustness check, we also ran all regressions using the pooled probit (no random effects) and the fixed effects logit method, and confirmed that the results to be reported below are qualitatively unchanged.[9] The panels are estimated by maximum likelihood, where the explanatory variables are detrended. In each probit regression, the binary outcome variable is the crisis dummy variable for either the currency crisis or credit crisis. All the regressors are lagged by six months in regressions with monthly data and by one year in regressions with annual data.

3.2.1 Currency Crisis

Table 2 presents the random effects panel probit regression results for currency crises. As described above, we have two measures of noncore bank liabilities – non-core 1 (using liabilities to financial institutions) and non-core 2 (using M3 minus M2), and three proxies for core liabilities - M1, M2 and core deposits. Hence, we have six alternative ways of constructing the ratio of non-core to core liabilities. In Table 2, all non-core liability ratios

[9] The fixed effects logit model has the advantage of being robust to potential correlation between cross-section country heterogeneity and the error term, but we lose sample observations of countries that did not have a crisis (when the dependent variable is constant at 0). The robustness of our results to the choice of regression method is a case in favor of the random effects model used here. See Wooldridge (2010, ch.15) for a discussion of relative advantages of probit and logit.

Table 2. **Random Effects Panel Probit Regression for Currency Crisis: Monthly Data for Non-Core Sum.** The binary outcome variable is the currency crisis dummy. Regressors are six months-lagged values of the noncore-core ratios. Standard errors are in parentheses. Statistical significance at 10% ,5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1/M1	2.80***					
	(0.24)					
Noncore1/M2		4.17***				
		(0.50)				
Noncore1/Core			3.95***			
			(0.55)			
Noncore2/M1				0.93***		
				(0.09)		
Noncore2/M2					1.44***	
					(0.17)	
Noncore2/Core						1.54***
						(0.22)
Pseudo R^2	0.15	0.10	0.04	0.07	0.05	0.05
Log-likelihood	-638.93	-681.89	-766.36	-932.94	-952.67	-947.40
Observations	3,304	3,310	3,552	3,482	3,586	3,581
Countries	38	38	40	41	42	42

are 6 months-lagged and detrended, and we report coefficient estimates along with standard errors in the parenthesis.

As can be seen in Table 2, for both non-core 1 and non-core 2 measures, and regardless of the form of core liabilities, all the non-core liability ratios have a positive and statistically significant coefficient at the 1% level. The results indicate that an increase in the non-core bank liability ratio is associated with an increase in the predicted probability of having a currency crisis. This finding is in line with the predictions from our theory section. Fluctuations in the non-core to core liability ratio can be interpreted as reflecting fluctuations in the changing degree of financial vulnerability to a crisis.

In Table 3, we present the panel probit regression results when we decompose the two non-core bank liability variables into their two respective separate components. As before, we introduce the non-core components as

Table 3. **Random Effects Panel Probit Regression for Currency Crisis: Monthly Data for Separate Non-Core to Core Ratios.**

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1						
Foreign/M1	4.39***					
	(0.33)					
Nonbank/M1	0.89*					
	(0.51)					
Foreign/M2		7.08***				
		(0.70)				
Nonbank/M2		5.45***				
		(1.84)				
Foreign/Core			4.70***			
			(0.55)			
Nonbank/Core			8.57***			
			(2.18)			
Noncore2						
Foreign/M1				3.40***		
				(0.24)		
(M3-M2)/M1				-0.33**		
				(0.15)		
Foreign/M2					5.47***	
					(0.47)	
(M3-M2)/M2					-0.85***	
					(0.26)	
Foreign/Core						2.77***
						(0.34)
Nonbank/Core						-0.79
						(0.57)
Pseudo R^2	0.22	0.15	0.06	0.16	0.11	0.07
Log-likelihood	-588.95	-641.59	-744.29	-836.13	-891.69	-934.04
Observations	3,304	3,310	3,552	3,482	3,487	3,581
Countries	38	38	40	41	41	42

ratios of core liabilities.

The results reveal some insights on which components are relatively more important. When we use non-core 1, both foreign and non-bank components have a statistically significant positive effect. However, when we use non-core 2, only foreign liability terms are significantly positive. The coefficients on M3 – M2 have the "wrong" sign, suggesting that the broad money aggregate may not be capturing non-core liabilities. This suggests that foreign liabilities play a more robust role as a predictor of currency crises in emerging economies. Nonetheless, there seems to be an additional and independent role of domestic non-core liabilities, although the non-core measure constructed from traditional monetary aggregates have little explanatory power. Monetary aggregates such as M2 and M3 are based on the legal form of the claim rather than on who holds the claim. Shin and Shin (2010) propose that classification by holder is more important for how "sticky" the claim is, rather than the legal form of the claim. Hahm, Mishkin, Shin and Shin (2010) provide evidence for this claim from disaggregated Korean banking sector data.

In Table 4, we check the robustness of our results by comparing our non-core measures to the much better known credit to GDP ratio. Borio and Lowe (2004) argued for the informativeness of credit aggregates in signalling financial excesses that expose an economy to potential crises, and have given prominence to the ratio of credit to GDP as an indicator. As the credit to GDP ratio is available at an annual frequency only, we run annual regressions. However, instead of re-identifying crisis episodes for annual data, we used the crisis episodes identified in the monthly data. Namely, the year in which the crisis occurs in the monthly data is identified as a crisis episode.

As can be seen in Table 4, we re-confirm the credit to GDP ratio as a

Table 4. **Random Effects Panel Probit Regression for Currency Crisis: Annual Data with Credit to GDP Ratio Included.**

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	9.77***	21.29***	21.23***	13.44***	19.18***	13.62***
	(2.28)	(6.54)	(6.64)	(3.58)	(5.64)	(3.48)
Noncore1/M2		2.91				
		(2.02)				
Foreign/M2			3.34			
			(2.27)			
Nonbank/M2			3.35			
			(4.98)			
Noncore2/M2				2.40**		
				(1.11)		
Foreign/M2					14.06**	4.45**
					(5.57)	(1.84)
(M3-M2)/M2					-2.57	
					(1.99)	
Pseudo R^2	0.08	0.21	0.21	0.14	0.19	0.16
Log-likelihood	-129.06	-61.46	-61.10	-79.41	-74.48	-107.19
Observations	454	233	233	256	256	385
Countries	66	35	35	39	39	58

significant indicator of an impending currency crisis. In every regression, it has a positive coefficient, and significant at the 1% level. Interestingly, however, note how non-core ratios still retain significance even in the presence of the credit to GDP ratio. In contrast with the monthly regressions above, non-core 2 measures seem to fare better than non-core 1 ratios when the credit to GDP ratio is included. This weak performance of non-core 1 may reflect the potential positive correlation between the credit to GDP ratio and the liability to non-bank financial institutions. The insignificant coefficient estimates of non-core 1 ratios may have also resulted from the weak power of test due to the loss of observations in the switch to annual data in these regressions.

It is noteworthy that the significance of the non-core 2 ratio relies heavily on foreign liabilities. We see this in the regression where we break out the non-core measures into their respective components. In column (5) only the foreign liability ratio remains significantly positive while the ratio using the M3 – M2 measure is insignificant. The predictive power of foreign bank liability ratio is again confirmed when it is included as the sole explanatory variable alongside the credit to GDP ratio in column (6).

The empirical results in Table 4 suggest that, independently from the credit to GDP ratio, the non-core liability ratio retains predictive power for currency crises in emerging and developing economies. This predictive power springs mainly from the foreign liabilities of banks, suggesting that liability side measures of vulnerability retain additional explanatory value that is not captured by the credit to GDP ratio.

The informativeness of liability side measures take on added significance when considering the more timely and higher frequency nature of such measures. Credit to GDP ratios are available at an annual frequency in most countries, while liability side aggregates are available more frequently, often monthly and sometimes even weekly. For purposes of real time surveillance exercises where timely identification of emerging vulnerabilities are important, the liability side aggregates identified in our paper may be promising as early warning indicators.

3.2.2 Credit Crisis

We now turn to consider credit crises. Credit crises are often associated with currency crises (as part of a "twin crisis"), but credit crises have occurred independently of currency crises, as is clear from the list of crisis episodes listed in the appendix to our paper. As explained above, our definition of credit crisis is constructed from the money market interest rate being in the 3% tail of the in-sample distribution. Tables 5 to 7 report the random effects panel probit estimation results for credit crises. .

Table 5. **Random Effects Panel Probit Regression for Credit Crisis (Money Market rate only) with Monthly Data.** The binary outcome variable is the credit crisis dummy based on the money market interest rate. Regressors are six month-lagged values of noncore-to-core ratios. Standard errors are in parantheses. The statistical significance at the 10% ,5% and 1% level are indicated by by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1/M1	0.77***					
	(0.12)					
Noncore1/M2		1.63***				
		(0.26)				
Noncore1/Core			11.16***			
			(0.95)			
Noncore2/M1				0.43***		
				(0.09)		
Noncore2/M2					1.08***	
					(0.16)	
Noncore2/Core						0.36***
						(0.08)
Pseudo R^2	0.05	0.05	0.17	0.03	0.05	0.02
Log-likelihood	-504.86	-550.58	-490.27	-432.08	-468.92	-480.91
Observations	2,389	2,365	2,697	2,684	2,753	2,728
Countries	26	26	29	30	31	31

The evidence from the credit crisis regressions indicate considerable explanatory role for the noncore measures. Consider the results shown in Table 5. All our non-core measures have positive coefficients and are significant at the 1% level.

In Table 6, as we did for the currency crisis regression, we break out the non-core liability aggregates into their respective components. Again, we see that liabilities to the foreign sector are an important explanatory variable for a credit crisis, as it was for a currency crisis. Note also how the foreign liability ratios remain statistically significant and of the correct sign even as the other components become insignificant in the regression.

Even more encouraging is the fact that for credit crisis episodes, our liabilities side measures perform better than the better known credit to GDP ratio. In Table 7, although the credit to GDP ratio is significant when it

Table 6. **Random Effects Panel Probit Regression for Credit Crisis (Money Market rate only) with Monthly Data for Separate Non-core to Core Ratios.**

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1						
Foreign/M1	0.71***					
	(0.12)					
Nonbank/M1	-0.13					
	(0.35)					
Foreign/M2		1.60***				
		(0.26)				
Nonbank/M2		0.84				
		(1.19)				
Foreign/Core			12.49***			
			(1.04)			
Nonbank/Core			3.39			
			(2.60)			
Noncore2						
Foreign/M1				0.73***		
				(0.11)		
(M3-M2)/M1				-0.84***		
				(0.24)		
Foreign/M2					1.21***	
					(0.19)	
(M3-M2)/M2					-0.75	
					(0.49)	
Foreign/Core						0.50***
						(0.18)
Nonbank/Core						-0.68
						(0.90)
Pseudo R^2	0.04	0.05	0.19	0.07	0.05	0.02
Log-likelihood	-509.45	-511.76	-474.95	-411.07	-419.97	-483.10
Observations	2,389	2,365	2,679	2,684	2,684	2,728
Countries	26	26	29	30	30	31

Table 7. **Random Effects Panel Probit Regression for Credit Crisis (Money Market rate only): Annual Data with Credit to GDP Ratio Included.**

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	4.17**	6.73	6.80	2.50	1.93	1.48
	(1.71)	(4.55)	(4.80)	(2.41)	(3.17)	(2.28)
Noncore1/M2		1.07				
		(1.21)				
Foreign/M2			0.94			
			(1.28)			
Nonbank/M2			0.94			
			(3.79)			
Noncore2/M2				7.55***		
				(2.03)		
Foreign/M2					12.42***	4.58***
					(3.59)	(1.57)
(M3-M2)/M2					1.91	
					(2.65)	
Pseudo R^2	0.03	0.07	0.07	0.26	0.31	0.11
Log-likelihood	-102.64	-48.31	-48.42	-38.29	-35.72	-86.91
Observations	488	165	165	216	216	412
Countries	62	25	25	31	31	55

enters as the sole explanatory variable, it is knocked out when our liabilities side variables are introduced. In particular, in columns (4) to (6), the non-core 2 ratio as well as the decomposed foreign liability ratio have a positive coefficient that is significant at the 1% level, even though the credit to GDP ratio becomes insignificant. These results confirm the intuition that liabilities to the foreign sector have implications for distress in the domestic financial market, also. By highlighting the explanatory role of banking sector liabilities, we train the spotlight on the behavior of the banking sector in the period preceding the crisis. Overall, these results for credit crises indicate that the non-core liability ratio may have an independent and even superior predictive power relative to measures of credit to GDP.

Table 8. **Random effects Panel Probit Regression for Stock Market Crisis: Monthly Data for Non-Core Sum.** The binary outcome variable is the stock market crisis dummy based on monthly stock returns. Regressors are six month-lagged values of noncore-to-core ratios. Standard errors are in parantheses. The statistical significance at the 10% ,5% and 1% level are indicated by by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1/M1	1.55***					
	(0.28)					
Noncore1/M2		13.92***				
		(1.67)				
Noncore1/Core			-0.36			
			(0.70)			
Noncore2/M1				0.76***		
				(0.11)		
Noncore2/M2					1.08***	
					(0.20)	
Noncore2/Core						0.39***
						(0.09)
Pseudo R^2	0.04	0.11	0.00	0.04	0.02	0.02
Log-likelihood	-432.14	-352.75	-469.34	-746.04	-755.55	-761.11
Observations	819	737	899	1,408	1,408	1,406
Countries	10	9	11	17	17	17

3.2.3 Stock Market Crises

Table 8 presents the random effects panel probit regression results for stock market crises. As in the case of credit crisis, we define a stock market crisis as an episode where the rate of change in stock price index belongs to the bottom 3% tail of the pooled in-sample distribution. As can be seen in Table 8, all non-core liability ratios except for the noncore 1 to core ratio have a positive and statistically significant coefficient at the 1% level.

When we consider decomposed non-core liability measures in Table 9, we find that bank liabilities to the foreign sector are strongly positively related to the probability of a stock market crisis. Liabilities of banks to non-banking financial sector are significant in two regressions, but M3-M2 measures have an opposite sign. These findings indicate that bank foreign borrowings are more important in predicting a future stock market crisis than other forms

Table 9. **Random effects Panel Probit Regression for Stock Market Crisis: Monthly Data for Separate Non-Core to Core Ratios.** The binary outcome variable is the stock market crisis dummy based on monthly stock returns. Regressors are six month-lagged values of noncore-to-core ratios. Standard errors are in parantheses. The statistical significance at the 10% ,5% and 1% level are indicated by by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Noncore1						
Foreign/M1	1.47***					
	(0.30)					
Nonbank/M1	2.87***					
	(0.57)					
Foreign/M2		15.68***				
		(1.76)				
Nonbank/M2		13.21***				
		(2.57)				
Foreign/Core			-0.40			
			(0.71)			
Nonbank/Core			-0.26			
			(2.58)			
Noncore2						
Foreign/M1				1.90***		
				(0.20)		
(M3-M2)/M1				-0.41*		
				(0.22)		
Foreign/M2					3.20***	
					(0.44)	
(M3-M2)/M2					-1.64**	
					(0.79)	
Foreign/Core						2.76***
						(0.37)
Nonbank/Core						-7.21***
						(1.06)
Pseudo R^2	0.06	0.14	0.00	0.08	0.06	0.06
Log-likelihood	-422.69	-338.50	-469.31	-708.20	-726.86	-729.18
Observations	819	737	899	1,408	1,408	1,406
Countries	10	9	11	17	17	17

Table 10. **Random effects Panel Probit Regression for Stock Market Crisis: Anuual Data with Credit to GDP Ratio Included.** The binary outcome variable is the stock market crisis dummy. Standard errors are in parantheses. The statistical significance at the 10% ,5% and 1% level are indicated by by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	4.12***	20.73**	17.62*	4.65***	4.62***	4.51***
	(1.41)	(9.63)	(9.15)	(1.59)	(1.61)	(1.56)
Noncore1/M2		0.78				
		(7.24)				
Foreign/M2			6.02			
			(8.60)			
Nonbank/M2			4.07			
			(10.98)			
Noncore2/M2				1.42		
				(1.81)		
Foreign/M2					1.91	2.07
					(1.88)	(1.75)
(M3-M2)/M2					0.70	
					(3.96)	
Pseudo R^2	0.05	0.24	0.25	0.10	0.10	0.09
Log-likelihood	-92.94	-20.50	-20.22	-56.54	-56.31	-66.49
Observations	159	45	45	98	98	117
Countries	25	8	8	17	17	19

of non-core bank liabilities, which is consistent with our previous results for currency and credit crises.

Note however that, when we include the credit to GDP ratio as an additional explanatory variable, all of non-core bank liabilities become insignificant as shown in Table 10. This result suggests that non-core bank liabilities play a less important role for stock market crises than in currency and credit market crises. Indeed, sudden reversals of foreign bank lending could exert a more direct first order effect on the foreign exchange rate and interbank money market conditions in the recipient countries, but may have a secondary and indirect effect on stock market prices. Boom bust cycles in domestic credit markets may have a more direct effect on stock market prices.

4 Robustness Checks

We now proceed to extend our empirical investigation in three directions so as to check the robustness of our findings. First, we re-examine our results when we use quarterly data for GDP and credit for those countries where quarterly data are available. As we show below, our results become sharper, with greater statistical significance. Second, we introduce a number of control variables to gauge the impact of global variables. Third, we examine a number of alternative dependent variables for crises, taking account of the currency pressures and other distress measures that may not be captured by our binary variables for crises.

4.1 Analysis with Quarterly Credit to GDP Ratio

Using yearly data we have found that the non-core bank liability ratio, especially foreign borrowing of banks, has independent predictive power not captured by the better known credit to GDP ratio, in both currency and credit crisis regressions. For the subsample of countries for which quarterly credit to GDP ratios can be obtained, we run the analogous panel probit regressions for our three alternative measures of crises. Tables 11, 12 and 13 report the quarterly regression results for currency crisis, credit crisis, and stock market crisis respectively. In the regressions, all explanatory variables were lagged by one quarter.

Empirical results confirm our previous findings in that the non-core bank liability measures turn out to be even more significant and fare better than the better known credit to GDP ratio in both currency and credit crisis regressions. For currency crisis, non-core bank liabilities have a significantly positive coefficient in every regression even in the presence of the credit to GDP ratio in Table 11, and non-core liabilities are in general a better predic-

Table 11. **Random effects Panel Probit Regression for Currency Crisis: Quarterly Data with Credit to GDP Ratio Included.** The binary dependent variable is the currency crisis dummy. Regressors are one quarter-lagged values of noncore-to-core ratios. We use quarterly data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by $*$, $**$ and $***$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	-0.15	3.11***	3.23***	0.14	3.65***	3.01***
	(0.22)	(0.89)	(0.97)	(0.29)	(0.94)	(0.71)
Noncore1/M2		4.10**				
		(1.85)				
Foreign/M2			8.90***			
			(3.03)			
Nonbank/M2			2.07			
			(3.88)			
Noncore2/M2				1.14***		
				(0.30)		
Foreign/M2					15.64***	12.04***
					(3.20)	(2.41)
(M3-M2)/M2					-2.28**	
					(0.93)	
Pseudo R^2	0.00	0.14	0.17	0.09	0.29	0.23
Log-likelihood	-143.98	-97.50	-94.20	-97.14	-75.18	-96.78
Observations	914	598	598	492	460	659
Countries	30	22	22	18	17	24

Table 12. **Random effects Panel Probit Regression for Credit Crisis: Quarterly Data with Credit to GDP Ratio Included.** The binary dependent variable is the currency crisis dummy. Regressors are one quarter-lagged values of noncore-to-core ratios. We use quarterly data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by $*$, $**$ and $***$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	0.44	1.14	1.49*	0.53	0.32	1.02***
	(0.29)	(0.80)	(0.82)	(0.36)	(0.41)	(0.35)
Noncore1/M2		4.67***				
		(1.34)				
Foreign/M2			3.27**			
			(1.46)			
Nonbank/M2			3.72*			
			(2.15)			
Noncore2/M2				0.70		
				(0.47)		
Foreign/M2					0.96	2.15***
					(0.89)	(0.65)
(M3-M2)/M2					-9.63***	
					(3.54)	
Pseudo R^2	0.01	0.12	0.09	0.02	0.13	0.06
Log-likelihood	-117.71	-89.77	-92.43	-68.69	-48.35	-105.95
Observations	868	577	577	456	433	641
Countries	27	20	20	17	16	22

Table 13. **Random effects Panel Probit Regression for Stock Market Crisis: Quarterly Data with Credit to GDP Ratio Included.** The binary dependent variable is the currency crisis dummy. Regressors are one quarter-lagged values of noncore-to-core ratios. We use quarterly data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by $*$, $**$ and $***$ respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	-0.81**	0.52	0.42	-0.82*	-1.23	-0.95*
	(0.39)	(1.17)	(1.18)	(0.43)	(0.81)	(0.57)
Noncore1/M2		3.98				
		(3.72)				
Foreign/M2			5.42			
			(3.69)			
Nonbank/M2			0.35			
			(6.23)			
Noncore2/M2				0.29		
				(0.34)		
Foreign/M2					3.97	2.13*
					(2.73)	(1.17)
(M3-M2)/M2					-1.87	
					(2.19)	
Pseudo R^2	0.03	0.01	0.03	0.08	0.17	0.11
Log-likelihood	-102.98	-48.71	-48.18	-41.98	-38.02	-53.03
Observations	423	221	221	208	208	249
Countries	14	8	8	8	8	9

tor of a credit crisis as shown in Table 12. However, non-core bank liabilities are not significant in stock market regressions in Table 13, which is consistent with our findings above with monthly data.

4.2 Global Factors as Control Variables

We also investigate the robustness of our results by considering a set of global factors as additional independent control variables. External conditions, such as the stage of the global business cycle or global liquidity flows may affect the volume of non-core bank liabilities as well as financial vulnerability of open emerging market countries. Commodity price shocks are also an important factor that exerts a crucial impact on both capital and current accounts in emerging market countries. Hence, we include world GDP

Table 14. **Random effects Panel Probit Regression for Currency Crisis: Anuual Data with Credit to GDP Ratio and Common Factors Included.** The binary dependent variable is the currency crisis dummy. Regressors are one year-lagged values of noncore-to-core ratios and common factors such as the federal funds rate, the commodity inflation rate and the real growth rate of world GDP. We use annual data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	7.39***	15.02**	14.80**	7.86*	10.00*	9.67***
	(2.53)	(6.19)	(6.23)	(4.10)	(5.11)	(3.64)
Noncore1/M2		2.17				
		(1.87)				
Foreign/M2			2.33			
			(2.00)			
Nonbank/M2			4.29			
			(5.35)			
Noncore2/M2				2.29*		
				(1.32)		
Foreign/M2					7.52*	3.40**
					(4.03)	(1.65)
(M3-M2)/M2					-1.14	
					(2.02)	
Fed Funds	0.16*	0.28*	0.28*	0.35**	0.30*	0.14
	(0.09)	(0.15)	(0.15)	(0.14)	(0.15)	(0.10)
Commodity	9.20***	5.10	4.87	7.02*	5.90	7.04**
	(2.98)	(4.52)	(4.54)	(3.97)	(4.41)	(3.32)
World GDP	-55.47***	-57.49***	-58.25***	-73.70***	-71.44***	-49.46***
	(12.57)	(20.88)	(21.11)	(19.30)	(20.97)	(14.41)
Pseudo R^2	0.18	0.27	0.27	0.25	0.27	0.22
Log-likelihood	-114.54	-56.76	-56.45	-69.36	-67.51	-99.63
Observations	454	233	233	256	256	385
Countries	66	35	35	39	39	58

Table 15. **Random effects Panel Probit Regression for Credit Crisis: Anuual Data with Credit to GDP Ratio and Common Factors Included.** The binary dependent variable is the currency crisis dummy. Regressors are one year-lagged values of noncore-to-core ratios and common factors such as the federal funds rate, the commodity inflation rate and the real growth rate of world GDP. We use annual data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	1.62	16.43*	12.72	-1.42	-4.88	-1.75
	(2.71)	(9.84)	(10.10)	(5.22)	(8.08)	(5.97)
Noncore1/M2		3.68				
		(3.33)				
Foreign/M2			9.20			
			(6.56)			
Nonbank/M2			-1.54			
			(7.06)			
Noncore2/M2				9.22***		
				(3.08)		
Foreign/M2					16.94***	14.07***
					(6.28)	(4.33)
(M3-M2)/M2					2.62	
					(3.97)	
Fed Funds	0.17	-0.07	-0.14	0.05	0.10	0.17
	(0.14)	(0.23)	(0.24)	(0.21)	(0.24)	(0.18)
Commodity	-9.09**	-17.19**	-18.41**	-8.00	-11.11	-15.42**
	(4.58)	(7.74)	(7.93)	(6.76)	(7.27)	(6.23)
World GDP	-73.57***	-18.26	-4.11	-61.06*	-51.83	-51.21*
	(23.36)	(38.15)	(40.94)	(32.28)	(34.86)	(27.77)
Pseudo R^2	0.17	0.28	0.30	0.35	0.39	0.33
Log-likelihood	-68.99	-33.64	-32.95	-30.24	-28.28	-54.19
Observations	432	156	156	199	199	375
Countries	62	25	25	31	31	55

growth rate, change in commodity price index, and the US Fed Fund target rate as global factor variables in addition to the credit to GDP ratio. We run yearly regressions as the world GDP growth rate is available only at annual frequency. To avoid a potential endogeneity problem, the global factor variables were also lagged by one year.

Tables 14, 15 and 16 report the regression results for currency crisis, credit crisis, and stock market crisis respectively. As can be seen in Table 14, for

Table 16. **Random effects Panel Probit Regression for Stock Market Crisis: Anuual Data with Credit to GDP Ratio and Common Factors Included.** The binary dependent variable is the currency crisis dummy. Regressors are one year-lagged values of noncore-to-core ratios and common factors such as the federal funds rate, the commodity inflation rate and the real growth rate of world GDP. We use annual data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	6.97*	16.73	50.80	13.56*	15.96*	16.56**
	(3.98)	(16.89)	(88.44)	(7.68)	(8.15)	(7.05)
Noncore1/M2		1.15				
		(10.20)				
Foreign/M2			223.92***			
			(79.74)			
Nonbank/M2			-226.45**			
			(102.94)			
Noncore2/M2				2.86		
				(3.13)		
Foreign/M2					1.78	1.87
					(2.94)	(2.64)
(M3-M2)/M2					16.87*	
					(8.44)	
Fed Funds	0.72***	0.47	4.31*	0.64**	0.83**	0.45**
	(0.17)	(0.33)	(2.37)	(0.27)	(0.34)	(0.20)
Commodity	33.05***	27.27	163.33	35.69***	39.14***	31.08***
	(8.96)	(21.94)	(134.52)	(13.64)	(15.13)	(11.06)
World GDP	-24.59	10.77	807.18	-10.76	-22.08	5.47
	(19.61)	(53.23)	(525.01)	(30.18)	(34.21)	(25.63)
Pseudo R^2	0.45	0.50	0.46	0.47	0.38	0.39
Log-likelihood	-34.95	-26.64	-28.94	-12.11	-14.20	-51.55
Observations	139	42	42	87	87	103
Countries	25	8	8	8	17	17

currency crisis, non-core bank liability measures seem to be less significant in the presence of both credit to GDP ratio and global factor variables. Note however that foreign liabilities seem to remain significant. Note also that the world GDP growth rate has a significantly negative coefficient in all regressions, which indicates that downturns in global business cycle lead to higher probabilities of a currency crisis in emerging market economies.

Table 15 shows regression results for credit crisis. Interestingly, non-core bank liability measures seem to fare better than the credit to GDP ratio even in the presence of global factor variables. Note that a fall in commodity prices tends to raise the probability of a credit crisis. Table 16 reports results for stock market crisis. Again non-core bank liabilities seem to have less information as a predictor of a future crisis in the case of stock market prices. It is also interesting that the US fed fund rate is positively associated with the probability of a stock market crisis, which may be due to reversals in portfolio investment flows in response to higher US interest rates.

4.3 Alternative Dependent Variables

Finally we examine alternative dependent variables for our currency and credit crises measures. First, as an alternative to the currency crisis measure, we examine foreign exchange market pressure. The foreign exchange market pressure index is constructed as a simple average of the following three variables – rate of depreciation in local currency, rate of decrease in central bank international reserves, and the increase in money market interest rate. Instead of the panel probit model, we estimate an outright panel regression using the pressure index as a dependent variable. As can be seen in Table 17, non-core bank liability measures, especially foreign borrowings, are significantly positive and seem to fare better than the credit to GDP ratio, which again confirms our previous results.

Next, we examine an alternative credit crisis measure constructed from the interest rate spread. Note that we used money market interest rates above to identify crisis episodes. However, in principle, using the interest rate spread would be preferable in identifying the episode of domestic credit market crises. The interest rate spread was defined as the difference between

Table 17. **Panel Regression for Foreign Exchange Market Pressure: Yearly Data with Credit to GDP Ratio Included.** The dependent variable is an index of foreign exchange market pressures based on the exchange rate, the interest rate and foreign reserves. Regressors are six months-lagged values of noncore-to-core ratios. We use monthly data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit/GDP		-1.61		-34.35		51.30**		37.69*	15.18
		(68.15)		(68.13)		(20.37)		(20.60)	(27.87)
Noncore1/M2	41.81**	42.05**							
	(17.51)	(20.20)							
Foreign/M2			57.59***	63.11***			50.71***	58.33***	56.09***
			(18.27)	(21.46)			(13.66)	(16.75)	(14.37)
Nonbank/M2			-92.92	-93.78					
			(58.67)	(59.49)					
Noncore2/M2					38.59***	36.49**			
					(13.42)	(15.10)			
(M3-M2)/M2							-32.68	-26.52	
							(29.79)	(29.53)	
R^2	0.04	0.04	0.08	0.08	0.05	0.09	0.09	0.13	0.07
Observations	141	138	141	138	166	165	166	165	256
Countries	19	18	19	18	23	23	23	23	33

the money market interest rate and the Treasury bill rate in each country, and a credit crisis was identified if the spread rises to the upper three percent tail of the pooled in-sample distribution. Table 18 reports the regression results, which again confirm that non-core bank liability measures fare better than the credit to GDP ratio which becomes insignificant in all cases while non-core liability measures, especially foreign borrowings, remain significantly positive.

Table 18. **Random effects Panel Probit Regression for Credit Crisis based on Spread Measure: Annual Data with Credit to GDP Ratio Included.** The binary dependent variable is the credit crisis dummy based on the spread measure between money market rate and treasury rate. Regressors are six months-lagged values of noncore-to-core ratios. We use monthly data. Standard errors are in parentheses. Statistical significance at 10%, 5% and 1% level is denoted by *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Credit/GDP	2.87*	0.38	-2.08	1.72	1.19	0.82
	(1.74)	(4.45)	(5.15)	(2.14)	(3.22)	(2.51)
Noncore1/M2		2.13*				
		(1.26)				
Foreign/M2			6.38*			
			(3.66)			
Nonbank/M2			-4.76			
			(4.23)			
Noncore2/M2				2.73*		
				(1.62)		
Foreign/M2					6.16**	5.48***
					(2.44)	(1.98)
(M3-M2)/M2					-9.44*	
					(4.90)	
Pseudo R^2	0.02	0.06	0.11	0.07	0.19	0.11
Log-likelihood	-90.47	-35.37	-33.31	-40.63	-35.04	-71.94
Observations	293	100	100	133	133	253
Countries	41	16	16	21	21	37

5 Summary and Concluding Remarks

Our empirical results paint a remarkably consistent picture across all the regressions (both binary and standard panel regressions) and can be summarized as follows.

First, our measures of the non-core bank liability ratio has significant predictive power for currency crises and credit crises. The predictive power of non-core liabilities seem to be weakest for stock market crises, although even here, there is some empirical support for the usefulness of non-core liabilities as a predictive variable..

Second, most of the predictive power of the non-core liability ratio stems from the information contained in the banking sector's liabilities to the foreign sector.

Third, the non-core bank liability ratio has independent predictive power over the much better-known and debated credit to GDP ratio. Moreover, the non-core liability ratio remains significant in the presence of the credit to GDP ratio and other control variables in the regressions, and the non-core liability ratio seems to fare better than the credit to GDP ratio in the key crisis regressions.

Taken together, the empirical evidence strongly suggests that non-core liability measures contain considerable information value for financial vulnerability, and provides an additional support for the "excess elasticity" hypothesis of Borio and Disyatat (2011), as formalized in our theory section. Our findings suggest that, at least in emerging and developing economies, non-core bank liabilities may be usefully monitored as a complementary measure to the credit to GDP ratio in gauging the stage of financial cycles and the build up of financial risk.

The discussion in our paper serves to focus attention on the banking sector and its role in the fluctuations in financial conditions. Through its pivotal role in the determination of risk premiums and overall financial conditions, the banking sector can be seen to lie at the heart of issues of financial stability.

Our discussion has focused mainly on the theoretical underpinnings of the possible information value of non-core banking sector liabilities and their empirical properties in forecasting crisis episodes. Although much more work is necessary in refining the results, there are some lessons for the broader application of balance sheet aggregates in questions of financial regulation and the mitigation of financial vulnerability.

Our empirical result that non-core liability aggregates perform at least as well as the credit to GDP ratio (and sometimes much better) has far-reaching implications for the choice of aggregate measures to be used in surveillance and regulatory frameworks. As part of the Basel III overhaul of bank regulation, the Basel Committee on Banking Supervision (BCBS) has agreed on a countercyclical capital buffer. In operational terms, the countercyclical buffer will make use of the credit to GDP ratio as the indicator of procyclicality that triggers increased capital requirements on banks (BCBS 2010). However, as seen in our results above, the simple credit to GDP ratio may be a somewhat coarse indicator, as well as being available only at a low frequency.

One of the main reasons for the lack of universal support for the cyclical capital surcharge under Basel III has been the concern that the simple credit to GDP aggregate may be too noisy in capturing finer institutional details that are relevant when considering harmonized international standards for bank capital regulation. Our results concerning the informativeness of liabilities side measures raise the prospect of having possibly more finely distinguished measures of financial vulnerability that tie up better with the underlying cyclical trends in the banking sector. Further research will be illuminating in shedding more light on these questions.

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Appendix: Crisis Episodes

This appendix lists the crisis episodes that qualify as crises according to the criteria for a currency crisis, a credit crisis or a stock market crisis. See the text for the methodology to identify the three types of crises. Crisis countries for which noncore1, noncore2 and credit/GDP ratio data are available are marked with "o".

Country Name	Non -Core1	Non Core2	Credit /GDP	Currency Crisis	Credit Crisis	Stock Market Crisis
Armenia			O		00m2-02m8	
Belarus	O	O	O	08m8-10m6		
Botswana	O	O	O	08m4-09m7		
Brazil	O	O	O	02m6-03m10 08m6-09m10	02m6-04m2	01m3-04m11 08m4-09m4
Burundi		O	O	02m10-03m10		
Canada	O					08m4-09m4
Chile	O	O	O	08m5-09m10		
China	O					01m1-02m1 07m10-10m11
China (Hong Kong)			O			00m9-02m3 08m4-09m4
Colombia	O	O	O	02m8-03m10 08m8-09m10		
Croatia	O		O			07m8-09m9
Czech Republic		O	O	08m8-09m9		08m4-09m8
Denmark	O		O			01m3-02m3 08m4-09m4
Dominican Republic	O		O	02m7-04m11	02m9-05m6	
Egypt	O		O	02m11-04m7		
Eritrea		O		01m7-03m2		
Estonia			O			08m4-09m5
Finland			O			
Georgia	O	O	O		00m1-00m8 01m2-03m7	
Ghana	O				02m10-04m5 08m10-10m4	
Haiti		O	O	02m5-04m4		
Hungary		O	O	08m8-10m1		05m12-06m12 08m4-09m5
Iceland		O	O	08m1-10m2	00m8-02m8	07m5-09m9
Indonesia	O		O	08m8-09m9	00m8-01m8	
Jamaica	O		O		02m8-04m8 08m6-09m6	
Japan	O	O	O			08m4-09m4
Latvia		O	O		08m12-09m12	01m3-02m3 08m4-09m8
Lesotho			O	01m07-02m10 08m4-09m9		
Lithuania		O	O			08m4-09m9
Malaysia	O		O			00m10-01m10
Malta		O	O	07m7-08m7		
Mauritius	O		O	08m10-09m10		08m8-09m8

Country Name	Non -Core1	Non Core2	Credit /GDP	Currency Crisis	Credit Crisis	Stock Market Crisis
Mexico	O	O		08m8-10m2		00m1-02m3 08m4-09m4
Moldova	O	O	O		00m1-01m4	
Mongolia			O	08m9-09m9		
Mozambique			O	05m5-06m8 09m12-10m12	00m5-02m11	
Namibia	O		O	01m7-02m10 08m4-09m9		
Nigeria	O		O	09m2-10m3		
Pakistan			O	08m4-09m9		
Papua New Guinea			O			02m1-03m1 08m4-09m4
Paraguay	O	O	O	01m7-03m10	03m1-04m3 08m7-09m9	
Philippines			O			00m1-03m5 05m6-09m11
Poland		O	O	08m7-10m2		07m7-09m8
Romania		O	O	08m8-10m1	00m01-03m5	
Russian Federation			O	08m7-10m2	01m6-02m6	00m6-01m6 04m6-05m6 08m2-09m6
Serbia		O	O		05m7-07m2	05m4-06m4 07m5-09m9
Seychelles	O		O	07m4-10m3		
Slovak	O		O			08m8-10m7
Solomon Islands		O	O	01m12-03m7		
South Africa	O	O		01m7-02m10 08m4-10m2		08m4-09m10
Swaziland	O		O	01m7-02m10 08m4-09m9		
Sweden		O	O	08m8-09m12		
Thailand	O	O				00m1-00m11 08m4-09m4
Turkey	O	O	O	01m7-02m8 08m5-09m9	00m1-05m2	00m6-02m12 05m12-06m12 08m4-09m4
United States	O	O	O			01m3-02m3 08m4-09m4
Uganda	O	O	O	08m10-10m1		
Ukraine	O	O	O	08m6-10m5	00m1-02m2 08m5-09m9	
Uruguay	O		O	01m11-03m12	00m3-03m11 08m4-09m4	
Zambia	O	O	O	02m3-03m3 06m8-07m10 08m7-10m3		08m5-09m5