The Causes and Consequences of Credit Expansion: Evidence from Stock Prices*

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Abstract

This paper examines the causes and consequences of credit expansion in a set of developed and emerging economies through its joint dynamics with stock prices. We find that credit expansion, measured by the three-year change in bank credit to GDP ratio, predicts a significantly increased crash risk in the returns of the equity market index and bank equity index in the subsequent two to eight quarters. Despite the increased crash risk, credit expansion predicts both lower mean and median returns of these indices in the subsequent quarters, even after controlling for a host of variables known to predict the equity premium. These findings suggest that credit expansion is not simply driven by risk-seeking of financial intermediaries against the will of shareholders or by expanded risk appetite, but is likely accompanied by widespread optimism of financial intermediaries and stock investors.

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A strand of the economic literature emphasizes that in the presence of information and agency frictions, the credit channel of financial intermediaries can have significant and persistent impacts on the real economy, e.g., Bernanke and Gertler (1989), Kashyap, Stein and Wilcox (1993), Kiyotaki and Moore (1997), and Holmstrom and Tirole (1997). In particular, economists have long argued that credit expansion by banks and other intermediaries can lead to instability of the financial system and the economy, e.g., Fisher (1933), Minsky (1977), and Kindleberger (1978). The more recent literature has highlighted a set of economic mechanisms, such as capital outflows (Shleifer and Vishny, 1997), wealth effects (Xiong, 2001; Kyle and Xiong, 2001; He and Krishnamurthy, 2012, 2013), collateral capacities (Geanakoplos, 2010), and margin constraints and spirals (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), through which credit expansions make financial intermediaries more exposed to adverse economic shocks and increase probabilities of financial crises.

Given the potentially severe consequences of credit expansion, which were evident from the experience of the recent global financial crisis, it is important to understand its origin. There are several distinct views. First, credit expansion may reflect active risk seeking by bankers and financial intermediaries as a result of agency problems. Such risk-seeking incentives can arise from the misaligned incentives of financial intermediaries with their shareholders, e.g., Allen and Gale (2000), and Bebchuk, Cohen, and Spamann (2010) or from the implicit too-big-to-fail guarantees provided by the government, e.g., Rajan (2006, 2010) and Acharya, et al. (2010). A second view posits that credit expansion may be driven by widespread optimism shared by financial intermediaries and other agents in the economy. This view can be traced back to Minsky (1977) and Kindleberger (1978), who emphasize that prolonged periods of economic booms tend to breed optimism, which in turn leads to credit expansions that can eventually destabilize the financial system and the economy. The recent literature has proposed various mechanisms that can lead to such optimism, such as neglected risk (Gennaioli, Shleifer and Vishny, 2012, 2013), group think (Benabou, 2013), extrapolative expectations (Barberis, 2012), and this-time-is-different syndrome (Reinhart and Rogoff, 2010). Finally, credit expansion may also reflect largely increased risk appetite of financial intermediaries due to the reduced market volatility during economic booms, which relaxes Value-at-Risk constraints faced by financial intermediaries (Danielsson, Shin and Zigrand, 2012; Adrian, Moench and Shin, 2013).

In this paper, we empirically examine the causes and consequences of credit expansion through its joint dynamics with stock prices. Several reasons motivate such an analysis. First, price fluctuations of equity market indices and bank stocks, which are readily available for a large set of countries and going back for substantial periods of time, provide a convenient measure of financial instability induced by credit expansion on the overall economy and the banking sector. Second, stock prices also provide a channel to examine the causes of credit expansion as stock prices aggregate the expectations and risk preferences of stock investors regarding financial instability induced by credit expansion.

We focus on testing two hypotheses. First, motivated by the aforementioned theories on financial instability induced by credit expansion, we hypothesize that credit expansion predicts an increase in the crash risk of bank stocks and the equity market index. We measure credit expansion by the three-year change in bank credit to GDP ratio in a country and test whether this variable predicts a significant increase in the negative skewness of future returns of the bank equity index and broad equity market index. Our analysis adopts a panel quantile regression approach with the credit expansion variable and other control variables as predictive variables for various quantiles of stock returns in the subsequent one to eight quarters. We use two measures of negative skewness in stock returns: the main measure by the distance from the median to the lower tail (10^{th} quantile) minus the distance to the upper tail (90^{th} quantile), and an alternative by the difference between the mean and median. To increase statistical power, we pool together a data sample of 19 developed and 14 emerging countries. Interestingly, bank credit expansions in these countries exhibit only small cross-country correlations throughout history.

Our analysis shows that bank credit expansion predicts a significant increase in the negative skewness in the subsequent returns of the equity market index and bank equity index. The increase in the negative skewness is particularly strong for the bank equity index, and is robust in different subsamples of countries and in periods even excluding the recent post-2008 global financial crisis period or excluding years before 1950. This finding confirms that financial instability induced by credit expansion is not unique to the recent crisis and is present across many countries in different periods of time.

Next, we examine a second hypothesis that the increased stock crash risk induced by credit expansion is compensated by a higher equity premium. If bank credit expansions are just driven by risk seeking of financial intermediaries against the will of shareholders, we expect stock investors to demand a higher equity premium as both protection and compensation for the increased crash risk they have to bear. On the other hand, there may not be any higher equity premium, if bank credit expansions are caused by widespread optimism among both financial intermediaries and stock investors.

We find that in one to eight quarters after bank credit expansions, despite the increased crash risk, the mean returns of the bank equity index and equity market index are significantly *lower* rather than higher. One concern is that the lower mean returns might be caused by a small number of price crashes in our sample. Interestingly, bank credit expansion also predicts significantly lower *median* returns of bank equity index and equity market index, which are robust to this small sample concern and, given the increased negative return skewness, provide an upper bound for the mean returns. The lower median returns predicted by bank credit expansion suggests that not only there is no premium to compensate for the increased crash risk, the equity premium conditional on credit expansions is lower even in the absence of the occurrence of tail events.

In this regard, one might argue that the lower mean and median returns predicted by bank credit expansion may be caused by a correlation of bank credit expansion with time-varying equity premium, which is indeed present in the data. However, even after controlling for a host of variables known to be predictors of the equity premium, including dividend yield, inflation, the term spread, the corporate yield spread, real GDP growth, investment to capital, residential investment to capital, and consumption to wealth, bank credit expansion remains strong in predicting lower mean and median returns of the bank equity index and equity market index. Furthermore, we also find that the predictability of bank credit expansion for the equity premium not only works in-sample but also is significant out-of-sample.

Taken together, our analysis shows that bank credit expansion predicts increased crash risk in the equity market index and bank equity index and the increased crash risk is accompanied by a lower, rather than higher, equity premium. These joint patterns suggest that bank credit expansions cannot be simply driven by risk-seeking by financial intermediaries against the will

of shareholders. Alternatively, one might argue that during economic booms both financial intermediaries and stock investors may experience expansions of risk appetite, which can lead to both credit expansions and a largely reduced equity premium. However, based on the coefficient estimates of our predictive regressions, the predicted equity premium drops to substantially below zero in some countries after large credit expansions. It will be challenging for any model to fully explain such large drops in the equity premium simply based on expansion of risk appetite. Instead, there is a need to account for the role of optimism in driving credit expansions.

A large literature investigates the real and financial effects of credit expansions from both domestic macro and international finance perspectives and has highlighted various consequences of credit expansions, such as bank runs, output losses, capital outflows, and currency crashes.[1] In contrast to this literature, our paper highlights asset pricing implications of credit expansion, as well as the roles of investors' and intermediaries' beliefs and risk-appetite leading up to the crisis.

In closely related work, Schularick and Taylor (2012) construct a historical dataset of bank credit for 12 developed countries over the years of 1870-2008 and find that bank credit growth is a powerful predicator of banking crises. We expand their data sample to a larger set of countries and show that bank credit growth is also a powerful predictor of equity crashes. More importantly, our analysis further finds that the increased crash risk is not compensated for by a higher equity premium, which helps establish an important role played by optimism in driving credit booms. In this regard, our results echo the findings of Greenwood and Hanson (2013) that during credit booms the credit quality of corporate debt borrowers deteriorates and that this deterioration forecasts lower excess returns to corporate bondholders. Mian and Sufi (2009) and Keys, et al. (2010) provide evidence on the effects of credit expansion on households by showing that the credit boom of the U.S. in the 2000's allowed households with poor credit to obtain unwarranted mortgage loans, which led to the subsequent subprime mortgage default crisis.

By highlighting a possible role of optimism in driving credit booms, our analysis echoes some earlier studies regarding distorted beliefs of financial intermediaries during the housing boom before the recent global financial crisis, which originated from the U.S. housing bubble.

[1] See, for example, Mishkin (1978), Bernanke (1983), and Eichengreen and Mitchener (2003) for the role of credit in the propagation of the Great Depression in the U.S.; for the role of credit in international financial crises, see, for example, Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), Eichengreen and Arteta (2002), Borio and Lowe (2002), Laeven and Valencia (2008), and Mendoza and Terrones (2008).

Foote, Gerardi, and Willen (2012) argue that before the crisis top investment banks were fully aware of the possibility of a housing market crash but "irrationally" assigned a small probability to this possibility, as revealed by their investment reports. Cheng, Raina and Xiong (2013) find that employees in the securitization finance industry were more aggressive in buying second homes for their own personal accounts than some control groups during the housing bubble and, as a result, performed worse. It is important to note that our findings, as well as these other findings in the literature, do not invalidate the important effects of misaligned incentives of financial intermediaries in driving credit booms, but help establish belief distortions as an additional cause.

Our study is also related to the growing literature on analyzing asset pricing implications of balance sheet quantities of financial intermediaries. Adrian, Moench and Shin (2013) and Adrian, Etula and Muir (2013) provide theory and empirical evidence for intermediary book leverage as a relevant pricing factor for both the time-series and cross-section of asset prices. Our study differs from their objective by focusing on analyzing the increased crash risk induced by credit expansion of financial intermediaries. Muir (2013) documents that risk premia increase substantially during financial crises, and highlights reduced equity capital in the financial sector, combined with a binding leverage constraint, as the key in understanding the largely increased risk premia following a financial crisis. Differing from his focus on risk premia after financial crises, our analysis is mostly concerned with the predicted equity premium during credit expansions, which tend to precede crises and thus are fundamentally important for understanding the causes of crises and for designing policies to prevent future crises.

Our paper is structured as follows. Section I presents the two main empirical hypotheses and the key empirical methodology used in our analysis. Section II describes the data, and Section III presents some summary statistics of the data. We then discuss our empirical results in Section IV and conclude in Section V.

I. Empirical Hypotheses and Methodology

In this section, we introduce the main hypotheses for our empirical analysis and the regression methodology we use.

A. Empirical hypotheses

Our analysis focuses on two hypotheses. First, we examine financial instability induced by credit expansion through fluctuations of equity prices. A large volume of recent theoretical work highlights various mechanisms for credit expansion to trigger downward spirals on financial intermediaries' balance sheets after a negative shock. These downward spirals may operate through capital outflows from financial intermediaries after an initial poor performance (e.g., Shleifer and Vishny, 1997), reduced risk bearing capacity as a result of wealth effects (e.g., Xiong, 2001; Kyle and Xiong, 2001; and He and Krishnamurthy, 2011, 2012), margin calls and spirals (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), and reduced collateral capacities (e.g., Geanakoplos, 2010). When such downward spirals occur, we expect prices of bank stocks to crash. Such spirals may further propagate and develop into a banking crisis that threatens the whole economy. Anticipating this possibility, the equity market index may also crash with bank stocks.

Motivated by these models, we hypothesize that bank credit expansion may lead to greater crash risk in both the equity market index and bank equity index, as summarized below.

Hypothesis I: *Bank credit expansion predicts subsequent equity crashes in both the equity index and the bank equity index.*

If credit expansion is indeed accompanied by an increased stock crash risk, it is reasonable to hypothesize a higher equity premium as compensation for the risk, as stated in the following hypothesis.

Hypothesis II: *Bank credit expansion predicts a higher equity premium in both the equity index and bank equity index.*

Equity prices reflect the aggregate expectation and risk appetite of stock investors regarding the increased crash risk induced by credit expansion. If credit expansion is induced by risk-seeking of financial intermediaries against the will of shareholders, we expect stock investors to demand a higher equity premium as compensation. On the other hand, credit expansion may be caused by economy-wide optimism as emphasized by Minsky (1977) and Kindleberger (1978). Such optimism can be induced by neglected risk (Gennaioli, Shleifer and Vishny, 2012, 2013),

and group think (Benabou, 2013), extrapolative expectations (Barberis, 2013), and this-time-is-different syndrome (Reinhart and Rogoff, 2010). Such optimism may cause financial intermediaries to extend more credits to households and non-financial firms and at the same time cause stock investors to ignore the subsequent, increased crash risk.

From an empirical perspective, it is useful to note that bank credit expansion may also be correlated with a time-varying equity premium caused by forces independent of the financial sector, such as by habit formation of representative investors (Campbell and Cochrane, 1998). There is a large finance literature showing that the risk premium in stock prices varies over time, possibly due to changes in investors' risk preferences. A host of variables are known to predict the time variation in the equity premium, such as dividend yield, inflation, the term spread, the corporate yield spread, real GDP growth, investment to capital, residential investment to capital, and consumption to wealth. See Lettau and Ludvigson (2010) for a review of this literature. It is thus important in our analysis to control for these variables to isolate effects induced by credit expansion.

A more subtle conceptual point is that credit expansion might be caused by a reduction in the risk premium, in particular, by an expanded risk appetite of financial intermediaries. Danielsson, Shin and Zigrand (2012) and Adrian, Moench and Shin (2013) develop models to show that falling asset price volatility (which tends to happen during economic booms) relaxes Value-at-Risk constraints faced by financial intermediaries and allows them to extend more credit to the economy. In their framework, the elevated risk appetite leads to not only credit expansions but also reduced equity premia as financial intermediaries are also the marginal investor in stock markets. The qualitative implications of this elevated risk appetite view are rather similar to that of the aforementioned optimism view. Thus, it is challenging to fully separate the effects caused by optimism and by elevated risk appetite. However, there is a difference in the quantitative implication of these two views. An elevated risk appetite can reduce equity premium down to zero but not below zero, while optimism can cause stock prices to be substantially overvalued and thus cause the equity premium to be negative. We will explore the contrasting implication of these two views in the data based on the predicted equity premium by credit expansion.

B. Regression methodology

We now discuss the two types of regressions that form the core of our analysis. The first is an OLS panel regression with fixed effects, which we simply refer to as the "mean regression" to distinguish it from the median and quantile regressions which we run alongside it. OLS estimates the following function using least-squares, where the right-hand side of the equation below is the best linear predictor (BLP) of the mean conditional on the predictor variables:

$$E\left[r_{i,t+K} - r^{f}_{i,t+K} \mid (predictor\ variables)_{i,t}\right]_{BLP} = \alpha_i + \beta'(predictor\ variables)_{i,t} \qquad (1)$$

To test Hypothesis I, we estimate this mean regression with predictor variables (credit expansion and other control variables) to forecast future stock returns. By using a fixed effects model, we focus on the time series co-movements of subsequent equity returns with credit expansion and other controls. Given that many of the predictor variables come from different sources for different countries and their levels are not directly comparable across countries, it is reasonable to focus on the time series dimension within each country, rather than looking at the cross-section.

We write the mean regression in the form above to emphasize the comparison with quantile regressions, which estimate the best linear predictor (BLP) of the qth quantile conditional on the predictor variables:

$$Quantile_q\left[r_{i,t+K} - r^{f}_{i,t+K} \mid (predictor\ variables)_{i,t}\right]_{BLP} = \alpha_{i,q} + \beta'_q(predictor\ variables)_{i,t} \qquad (2)$$

This quantile regression allows us to look at different features of the distribution of stock returns and how explanatory variables predict changes in the *shape of the future returns distribution*, not just changes in the mean. For example, if credit expansion increases the likelihood or severity of a market crash, we should see this in the effect of credit expansion on the 5th or 10th quantiles (lower tail probabilities) of returns.[2]

[2] In section 4.D, we check the robustness of our quantile regression methodology by comparing with OLS regressions with a crash indicator as the dependent variable.

To examine Hypothesis I, we adopt two measures of crash risk in stock returns. First, we use quantile regressions to compute the following negative skew statistic to ask whether credit expansion (or other factors) predict increased tail risk:

$$\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=10}) - (\beta_{q=90} - \beta_{q=50}),$$

where $\beta_{q=x}$ denotes the coefficient estimated for the x quantile. This statistic $\beta_{\text{negative skew}}$ equals the distance from the median to the lower tail minus the distance to the upper tail.[3]

Without relying on a particular choice of quantiles, we also use an alternative measure of the impact of credit expansion on negative skewness of subsequent stock returns by computing ($\beta_{\text{median}} - \beta_{\text{mean}}$), the difference between the coefficient from a median regression (50th quantile regression) and the coefficient from the mean (OLS) regression.

In our test of Hypothesis II, we focus on testing whether β_{mean}, the coefficient of credit expansion in the mean regression, is different from zero. Due to the increased crash risk induced by credit expansion, there is a concern that the estimate of β_{mean} might be strongly influenced by a small number of crashes. To address this concern, we also examine the estimate of β_{median}, which provides an upper bound on β_{mean}.

Taken together, we examine four main statistics: β_{mean}, β_{median}, ($\beta_{\text{mean}} - \beta_{\text{median}}$), and $\beta_{\text{negative skew}}$. Special care must be taken to estimate these predictive return regressions in a financial panel data setting. The main concern is that both outcome variables (e.g. overlapping n-quarter-ahead excess returns, $n = 1, 2, 4, 8$) and explanatory variables (e.g. bank credit expansion and other macro and finance controls) are correlated across countries (due to common global shocks) and over time (due to country-specific shocks that will induce correlations across time). If these concerns are not appropriately accounted for, the standard errors can appear to be much lower than they ought to be. Therefore, we estimate standard errors that are dually clustered on time and countries, following Thompson (2011), to account for correlations across countries and over

[3] We do not measure just ($\beta_{q=50} - \beta_{q=10}$) because a larger number could simply be indicative of increased variance. Instead we measure the asymmetry, the increase in the lower tail minus the increase in the upper tail. In the statistics literature, this measure is called the quantile-based measure of skewness. We use the 10th and 90th quantiles to represent tail events. While looking at more extreme events (5th or 1st quantiles) might be more desirable from the point of view of identifying crashes, there is a trade-off with statistical power since these extreme events get increasing rarer as we choose smaller quantiles. Using the 10th and 90th quantiles is a good compromise, allowing us to still get strong statistical power while being indicative of large negative movements in the prices.

time, and that are also robust to heteroskedasticity (in the case of OLS regressions) and autocorrelation.

For the OLS panel regression model with fixed effects, the standard errors described above are implemented in Stata using Huber-White standard errors first adjusted for clustering on time and country separately, and then combined into a single standard error estimate using the technique described in Thompson (2011). For quantile regression estimates, we estimate standard errors by block bootstrapping, drawing blocks that preserve both the dual-clustering and autocorrelation structure of the data. In the case of testing linear restrictions of coefficients from multivariate regressions, the multivariate regressions are estimated simultaneously to account for correlations in the joint estimates of the coefficients. The difference between the mean and median coefficients is tested (H_0: $\beta_{\text{mean-median}} = 0$) via bootstrapping and using each bootstrapped draw to *simultaneously* estimate the OLS and quantile regression; the resulting Wald statistic is then used to find a p-value.[4] The standard error for $\beta_{\text{negative skew}}$ is generated by bootstrapping simultaneous estimates of the q=10, 50, and 90 quantile regression coefficients with clustered draws to account for the above-mentioned considerations.

II. Data

We construct a panel data set of 33 countries from 1920 to the present. The main outcome variables in our dataset, which we describe in detail below, are equity index excess returns, bank equity index excess returns, and indicator variables associated with stock crashes and bank stock crashes. The main explanatory variables in our dataset are credit variables (bank credit to GDP, leverage variables, etc.), in addition to control variables such as macroeconomic indicators (consumption to assets, investment, inflation, interest rates, etc.) and stock valuation ratios (dividend yield, book to market, etc.).

The countries in our sample are subdivided into two main groups: developed (19 countries) for which we have a mostly complete data set from 1950 to the present, and for many of these countries, from 1920 to the present; and emerging (14 countries) for which we have data from

[4] This procedure is necessary because $\hat{\beta}_{mean}$ and $\hat{\beta}_{\text{median}}$ are not independent random variables.

1970 to the present.[5] We focus our results in this paper mainly on the developed group of countries, both because of better data availability and because these countries show more consistent patterns related to the effects of credit expansion. The sample length for each variable and each country can be found in Table A1 in the appendix.

Below are detailed descriptions of the individual variables used in our analysis and how the time series were constructed.[6] To ensure accuracy, we hand-checked all older historical data by comparing to multiple sources to ensure accuracy. More details on the sources and construction of selected variables for each country, especially when multiple data sets are merged, can be found in the spreadsheet in the online appendix.

A. Credit and leverage data

Our main explanatory variable in this paper is bank credit to GDP. Throughout the paper, **bank credit** refers specifically to credit extended from banks to domestic households and private non-financial corporations. It excludes interbank lending and thus only includes the end users of credit. We also examine a few other closely related credit variables. **Total credit** refers to credit extended from all sources to domestic households and private non-financial corporations. **Total credit to Households** and **total credit to non-financial corporations** refer to the total credit variable above, decomposed into household and corporate components. All variables are normalized by GDP.

Our time series on bank credit to GDP is derived from two sources: "bank credit" from the BIS's "long series on credit to private non-financial sectors" (which covers a large range of countries but generally only extends back a few decades) and from the data of Schularick and Taylor (2012) on "bank loans" (which extends back over a century but only for 14 countries). There are slight discrepancies between the two data sources, presumably coming from: the types of institutions defined as banks, the types of credit instruments considered as “credit”, and the

[5] Given that our data spans a long period, many countries that would be considered "developed" economies today are classified in our study as "emerging" over our sample period. Our classification is somewhat arbitrary and based partly on data availability.

[6] When data comes only in annual time series, as much of the older historical data does, the annual data (assuming it is an explanatory variable, not an outcome variable) is filled forwards for the three subsequent quarters; we fill explanatory variables *forward* to avoid look-ahead bias in forecasting -- filing it forward makes sure that the information for each quarter has already been known at that point.

primary sources for the data. Fortunately, the BIS and Schularick-Taylor data match qualitatively, as their overlap is highly correlated. In merging the two series, we scale the level of "bank loans" to avoid breaks in the series.

The data described above was supplemented with two indirect measures of credit: **bank assets to GDP**, which comes mainly from Schularick and Taylor, and **household housing asset growth**, which is the real growth in housing assets owned by the household sector, from Piketty and Zucman (2013). We also looked at leverage of the household, non-financial corporate, and banking sectors: specifically, **household debt to assets** (which is aggregate household debt to aggregate household assets from Piketty and Zucman), **non-financial corporate equity to assets** and **bank equity to assets** (using book values mainly taken from Thompson-Reuter's Datastream), Lastly, we also examined international credit using the **current account to GDP** (gathered from the IMF's emerging markets external debt data for developing countries and from OECD for developed countries) and **gross external liabilities to GDP** (both public and private liabilities, from Lane and Milesi-Ferretti's (2007) database on countries' external assets and liabilities).

Throughout the paper, we look at *changes* (not levels) in credit variables -- 3-year differences -- for the following reasons. First, credit is rising during booms and falling during busts (though the *level* may still be high *after* the crisis or crash), and thus the change of credit, not the level, is more indicative of the state of the economy. Second, credit as a percentage of GDP exhibits long-term trends presumably related to financial deepening, changes in regulation, etc; differencing remove most of the secular component and allows us to focus on analyzing cyclical credit expansions.[7]

B. Equity data

The main outcome variable is future excess returns for both the equity market index and the bank equity index for each country. For returns on **equity market indices**, our main source was Global Financial Data (GFD). We chose well-known broadly-focused, market cap weighted indices for each country. In countries with several internationally-known equity indices (for

[7] As an alternative approach, we also tried using as our main predictor variable de-trended *levels* of bank credit, using a one-sided Hodrick-Prescott (HP) filter (λ=100,000) to de-trend the series; results were qualitatively similar.

example, the S&P 500, DJIA and NASDAQ in the U.S.), we favored the one with the broadest scope and the longest time-series (the S&P 500 in the U.S.). For **bank equity indices**, we similarly choose market cap weighted indices of banking stocks, or when a bank-specific index was not available, the entire financial sector.

We then construct **equity excess returns** and **bank equity excess returns** for all equity market indices and bank equity indices, respectively, by subtracting the short-term interest rate (described below) from the equity returns. For forecasting purposes, we construct one-quarter-ahead excess returns by applying a lead operator to the excess returns; similarly we construct 2-, 4-, 8-, and 12-quarter-ahead excess returns in an overlapping fashion. Throughout the entire paper, we specifically exclude quarters from our analysis when inflation within ±1 year of the given quarter is greater than 30%, because returns and interest rates become unreliable on the quarterly level, though this happens rarely in developed countries in the post-war period.

We construct a **daily stock volatility** measure for each country and quarter by using daily stock returns from GFD of the equity market index and calculating the standard deviation of daily returns.

Finally, we also construct indicator variables for crash events. Specifically, we construct an **equity crash indicator** (which takes the value of 1 if the real return of the equity index is less than -20% in one quarter or less than -30% in two quarters, and 0 otherwise) and a **bank equity crash indicator** (same, but using the bank equity return).

C. Control variables

We use several equity valuation ratios for the aggregate market in each country as controls for time-varying risk premium. **Dividend yield** and **price-to-earnings** ratios come from GFD (supplemented to a small extent by Datastream), **Book-to-market** ratios come from Datastream and the Emerging Market Database (EMDB, produced by the International Finance Corporation and Standard & Poor's).

We also use several macroeconomic variables. **Inflation** is calculated from the CPI from GFD, and **consumption** is private consumption expenditure from national accounts taken from GFD**. Real GDP growth** (year-over-year) is calculated from nominal GDP taken from GFD.

Long-term interest rates are the yields on 10-year government bonds taken mostly from GFD and OECD. **Short-term interest rates** are almost always the 3-month government t-bill rates taken from GFD, the IMF, OECD, Schularick-Taylor (2012), and other sources. Occasionally, for older data, the short-term interest rate was taken to be the yield on central bank notes, high-grade commercial paper, deposits, or overnight interbank lending; since some of these rates can rise in times of market distress and also historically have been regulated, care was taken to make sure these alternative rates, when used, were representative of the market risk-free rate.

From these variables, we constructed various ratios as additional explanatory variables. **Consumption to wealth**, which is aggregate consumption from GDP divided by the aggregate financial assets held by the household sector from Piketty and Zucman (2013). The **term spread** is the long-term interest rate minus the short-term interest rate. **Investment to capital** is private non-residential fixed investment divided by the outstanding private non-residential fixed capital stock; and housing **investment to capital** is the same but using residential investment and capital.[8] The above investment and capital data all comes from the Kiel Institute's database on investment and capital stock. The **corporate yield spread** is the yield spread between the AAA-rated 10-year-maturity corporate bond index from GFD and the 10-year government bond.

III. Summary Statistics

Table 1 presents summary statistics for equity index returns, bank equity index returns and credit growth. The table is divided into Panel A for developed economies and Panel B for emerging economies. For all the variables in our panel data set, the observations are quarterly and are pooled for all time periods in the sample and for all countries in the subset. In each panel, the asset returns variables we look at are: equity excess returns (index returns - 3-month t-bill rate), equity total excess returns (index returns + dividends - 3-month t-bill rate), equity real returns (index returns - inflation rate), and bank equity excess returns and real returns (defined as above but on the bank equity index). For asset returns, the returns and standard deviations are all

[8] Housing investment to capital and consumption to wealth have long-term trends over the last half-century and are therefore de-trended using a one-sided Hodrick-Prescott filter (λ=100,000 on quarterly data).

expressed as annualized log returns. The credit variables are: Δ (bank credit / GDP), which is the annualized three-year change in bank credit to GDP, and Δ (total credit / GDP), defined similarly.

As can be seen in Table 1, the mean equity excess return is 6.1% for developed economies (2.6% without including dividends) and 10.5% for emerging economies (8.1% without dividends). Equity real returns (without dividends) are 4.6% for developed economies and 10.7% for emerging economies. Bank stocks have seen lower returns (-1.3% excess returns and 1.2% real returns for developed economies), though these numbers exclude dividend payments by bank stocks, on which we unfortunately have no historical data. We also report the median returns for each variables. The standard deviation of returns is around 20% for index returns for developed economies and 35% for emerging economies, with higher numbers for bank stock returns.

Given that we define crash indicator variables and negative skew statistics in our quantile regression based on 10th percentile events, it is useful to get a sense of what magnitude drops these percentiles correspond to. A 10th percentile drop, which occur on average once every 2.5 years, corresponds to a -42.8% annualized real return or a -10.7% quarterly real return (= -42.8% / 4). On this basis, we define the crash indicator to take on the value of 1 if the real return of the equity index is less than -20% in one quarter or less than -30% in two quarters, and 0 otherwise. Thus, a crash as defined here corresponds to an event that occurs 3.6% of quarters, or once every 7 years on average, for developed countries.

In unreported statistics, we also see that historical financial crises, based on data from Reinhart and Rogoff (2010), are accompanied most of the time by crashes in equity markets and especially in bank stocks that occur within ±1 years of the start of the crises.

Table 1 also gives a sense of the magnitudes and variability of credit expansion. On average, bank credit to GDP expanded by 1.3% per year in developed countries and 1.2% in emerging countries. In terms of the variability of credit expansion, bank credit expansion grew as rapidly as 11.5% and 13.2% of GDP per year (99th percentiles for developed and emerging economies, respectively) and contract as rapidly as -5.8% and -15.3% of GDP per year (1st percentiles for developed and emerging economies, respectively).

The variability of bank and total credit expansion can be seen visually in Figure 1, which plots Δ (bank credit / GDP) over time for both developed countries (Panel A) and emerging countries (Panel B). The time series for all countries appear mean-reverting and cyclical, with periods of rapid credit expansion often followed by periods of credit contraction. Stock crash events (blue vertical lines) are added to give a visually sense of the relationship between credit expansion and crashes.

Table 2 presents the time series co-movements of our main credit expansion measure, Δ (bank credit / GDP), with macroeconomic indicators and interest rates (Panel A) and with other credit and banking variables (Panel B). To measure the direction and strength of the within-country time series correlations, we run an OLS panel regression with fixed effects for Δ (bank credit / GDP) against each of the other credit and macro variables in consideration:

$$\Delta(bank\ credit\ /\ GDP)_{\ i,t} = \alpha_i + \beta(independent\ variable)_{i,t} + \varepsilon_{i,t}$$

In Panel A, the independent variables used are: dividend yield (D/P), book to market, daily stock market volatility, non-residential fixed investment to capital, aggregate household consumption to wealth, real GDP growth, the term spread, the corporate yield spread, the sovereign yield spread (versus the U.S.), and the interest rate differential (nominal risk-free rate versus the U.S.'s), and growth of the total value of the household housing stock. In Panel B, the independent variables are alternative measures of credit expansion: Δ (total credit / GDP), Δ (total credit to households / GDP), Δ (total credit to non-financial corporations / GDP), Δ (bank assets / GDP), household debt/assets, non-financial corporate equity/assets, bank equity to assets, growth of household housing assets, Δ (gross external liabilities to GDP), and current account deficits to GDP.

Panel A shows that, in line with expectations, the following variables have a positive correlation with bank credit expansion: daily volatility, investment to capital, real GDP growth, the corporate yield spread, and the short-term interest rate differential (presumably because it leads to capital inflows), and the following variables have a negative correlation with bank credit expansion: dividend yield, book to market, the term spread, and the sovereign yield spread. In particular, the (within-country) R^2 is high for investment and consumption to wealth, because

bank credit is tightly related to real investment and wealth (the latter due to credit boosting asset prices). These correlations all point to credit expansion being pro-cyclical.

Panel B shows that bank credit expansion is positively correlated to changes in other aggregate credit variables (total credit, total credit to households, total credit to non-financial corporations, bank assets, growth of household housing assets) and leverage (the household, corporate, banking sector), and with change in international credit (change in the gross external liabilities to GDP and current account deficits to GDP). In particular, R^2 is high for the three forms of total credit, bank assets, external gross liabilities, and household and corporate leverage, though surprisingly not strong for bank leverage in developed countries. In addition, R^2 is high for bank leverage and the current account in emerging countries. Taken together, we conclude that there are strong correlations, as expected, between different forms of credit and leverage.

Table 3 presents cross-country correlations of a set of variables. To economize on space, we only present the cross-country correlations of other countries with the U.S. (except in the case of the sovereign yield spread, in which case we analyze the correlation with the U.K's., given that the U.S. does not have a sovereign yield spread by definition). Additionally, for space reasons, not all countries in our sample are presented but enough are presented to provide a representative sample of our country set. In general, quarterly excess stock returns are only moderately correlated across countries (average correlation = 0.50) and bank stock excess returns are less so (0.36). Bank credit expansions have historically been quite idiosyncratic in nature (average correlation = 0.02), which is surprising, considering that the two most prominent credit expansions -- those leading up to the recent financial crisis and the Great Depression -- were global in nature. The relatively idiosyncratic nature of historical credit expansions helps our analysis, as their associations with equity returns and crashes are driven by local credit expansions and not spillover effects from global events.

IV. Empirical Results

A. Predicting crash risk

To test Hypothesis I, we run the quantile regression specified in (2) of Section I.B on the subset of developed countries to examine the impact of bank credit expansion on the full distribution of subsequent equity returns. Table 4 reports estimates from the quantile regressions.

The columns correspond to 1-, 2-, 4-, and 8- quarter-ahead excess returns, first for the broad equity market index and then for the bank equity index specifically. The first block of rows reports estimates for quantile regressions on credit expansion with no controls, the second block reports estimates on credit expansion with dividend yield as a control, and the third block of rows reports estimates adding a range of controls: dividend yield, investment to capital, inflation, the corporate yield spread, the term spread, and real GDP growth. The coefficients and t-statistics for credit expansion are reported for the three quantile regressions: $\beta_{q=10}$, $\beta_{q=50}$, $\beta_{q=90}$, followed by the conditional negative skewness coefficient $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=10}) - (\beta_{q=90} - \beta_{q=50})$ and its associated t-statistic. To save space, coefficients on control variables are not reported in Table 4; they are analyzed later in Table 6.

For equity index returns without control variables, the coefficient for negative skewness $\beta_{\text{negative skew}}$ is estimated to be 0.158 (not significant) for a 1-quarter horizon, which increases to 0.605, 0.815, and 0.904 (all significant at the 5% level) for 2-, 4- and 8-quarter horizons, respectively.[9] When dividend yield is added as a control, the coefficients remain similar: 0.128, 0.643, 0.615 and 0.172 at the 1-, 2-, 4-, and 8-quarter horizons, respectively, with only the 2-quarter horizon result being significant at the 5% level. When the rest of the control variables are added, the skewness coefficients are no longer significant.

The interpretation of the conditional skewness coefficient is as follows: using the estimate for 4-quarter horizons, a 1% rise in $\Delta(bank\ credit\ /\ GDP)$ is associated with a 0.815% increased drop for a left tail event relative to a right tail event. In other words, low-probability bad events become increasingly more severe relative to the entire distribution. For a country such as Spain, which had a large credit expansion of $\Delta(bank\ credit\ /\ GDP) \approx 15\%$ leading up to the most recent crisis, the increased severity associated with a tail event would be 12.23% (= 15%*0.815). This number describes the additional loss associated with a left tail event, before taking into account additional losses due to lower conditional mean and median returns (see Table 6) and higher conditional volatility associated with credit expansion.

[9] The coefficients for skewness are generally most significant at 2- and 4-quarter horizons because of two forces: statistical power for the skewness coefficient increases with longer horizons because returns predictability increases, but at longer horizons, skewness disappears due to the central limits theorem, which says that returns become more normally distributed as they become more aggregated.

Similar but stronger and more significant patterns are observed for the bank equity index: the estimate for $\beta_{\text{negative skew}}$ is 0.542 (not significant) for 1-quarter horizons and increases to 1.141, 2.376 and 2.548 (all significant all the 0.1% level) for 2-, 4- and 8-quarter horizons, respectively. Thus, tail risk for bank equity index returns has a quantitatively larger association with bank credit expansion: using the 4-quarter horizon coefficient, a 1% rise in $\Delta(bank\ credit\ /\ GDP)$ is associated with a 2.376% increased severity of a left tail event. In the case of Spain with $\Delta(bank\ credit\ /\ GDP) \approx 15\%$, the associated increased severity of a tail event for the bank equity index is 35.64% (= 15% * 2.376). The coefficients stay roughly the same when dividend yield is added as a control: 0.426, 0.991, 2.496 and 2.53 (all significant at the 1% level) for the 1-, 2-, 4- and 8-quarter horizons, respectively. When all control variables are added, the negative skewness coefficient on bank credit expansion increases slightly and stays significant.

In summary, consistent with Hypothesis I, we find that bank credit expansion predicts an increase in the negative skewness of returns of the equity market index and the bank equity index in the subsequent 2 to 8 quarters. This predictability is particularly strong for the bank equity index.

B. Predicting the equity premium

We now turn to testing Hypothesis II. Table 5 estimates similar regressions of bank credit expansion on equity returns for the subset of developed countries, but this time we focus on the mean regression specified in (1) of Section I.B (the standard OLS fixed effects model) and the median (50th quantile) regression. The mean regression coefficient β_{mean} tells us about the equity premium predictability associated with credit expansion. By comparing β_{mean} to β_{median} from the median regression, we can see when there is credit expansion how much the equity premium changes "most of the time" (the median coefficient) or driven by the increased frequency or severity of tail events (which the mean coefficient is sensitive to).

Table 5 is structured similarly to Table 4. Each column corresponds to 1-, 2-, 4-, and 8-quarter-ahead excess returns, both for the full equity market index and then for bank equity index specifically. The first block of rows presents the results of mean and median regressions on credit expansion without controls, the second block presents coefficient estimates for credit expansion after dividend yield is added as a control, and third block presents the coefficient

estimates after all the controls have been added. Coefficients and t-statistics are reported for the mean and median regressions, along with the (within-country) adjusted R^2 for the mean regressions.[10] The coefficients and t-statistics are reported for the mean and median regressions, along with adjusted R^2 for the mean regressions. In addition, the difference between the mean and median is estimated, along with an associated p-value.[11]

The coefficients from the mean regression measures the change in equity premium associated with credit expansion. For the equity market index, the coefficients are: -0.267, -0.572, -1.256, and -2.472 for 1-, 2-, 4-, and 8-quarter-ahead excess returns, respectively, and are all significant at least at the 5% level (and often at the 1% or 0.1% level). The adjusted R^2 ranges from 0.2% for 1-quarter horizons to 5.3% for 8-quarter horizons. When dividend yield is added as a control, the coefficients generally are slightly lower and have similar statistical significance, and the adjusted R^2 for the 8-quarter horizon increases from 5.3% to 6.7%. When all the controls are added, the coefficients are generally slightly higher and have similar statistical significance, and the adjusted R^2 for the 8-quarter horizon increases even more to 15.8%.

For bank equity indices, the coefficients are higher: -0.378, -0.824, -1.912, and -4.225 (all except the first coefficient significant at the 5% or less significance level) for 1-, 2-, 4-, and 8-quarter-ahead excess returns, respectively. [12] Coefficient estimates remain similar in magnitudes and significance after controlling for dividend yield and also after adding in all the rest of the controls.

[10] R^2 is a measure of the percentage of variation of the dependent variable accounted for by the linear model. In calculating R^2 in the context of a fixed-effects panel regression, we properly exclude the variation accounted by the country fixed-effects (the "between" variation) and only measure the variation due to the coefficients on the predictor variables (the "within" variation).

[11] The difference between the mean and median coefficients is tested (H_0: $\beta_{\text{mean-median}} = 0$) via bootstrapping and using each bootstrapped draw to *simultaneously* estimate the OLS and quantile regression, which is important because the mean and median coefficients are not independent random variables; the resulting Wald statistic is then used to find a p-value.

[12] The higher coefficients for bank equity index are not due to bank stocks just having a high market beta, which would simply magnify the effects that credit expansion has on the broad market. The bank equity index has a market beta of about 1 (results not reported); even after subtracting out the market component of bank returns using a computed time-varying beta, the resulting idiosyncratic component of bank returns still has quantitatively large coefficients when regressed on bank credit expansion (results not shown).

One general point to note is that, for both the equity market index and the bank equity index, all coefficients are roughly proportional to the number of quarters, meaning that the predictability is persistent and constant per quarter for each quarter up to about 2 years.[13]

Due to the increased crash risk induced by credit expansion, one might argue that the lower mean returns might be caused by a small number of crashes in the sample period. To address this concern, we decompose β_{mean} into two components β_{median} and (β_{mean} - β_{median}). β_{median} measures how much the equity premium is lowered "most of the time" when there is credit expansion, while β_{mean} - β_{median} measures how much the equity premium is reduced due to the occurrence of tail events in the sample. β_{mean} - β_{median} also provides an alternative estimate of negative skewness in future equity returns.

Table 5 reports estimates of β_{median} to be -0.150, -0.353, -1.002 and -1.925 for the equity market index and -0.185, -0.547, -1.064, and -2.818 for bank equity index (1-, 2-, 4- and 8-quarter horizons, respectively). All coefficient estimates are significant at the 5% or less significance level.

Table 5 also reports β_{mean} - β_{median} to be 0.017, 0.219, 0.254, and 0.546 for the equity market index and 0.192, 0.277 (not significant), 0.848, and 1.407 for bank equity index (1-, 2-, 4- and 8-quarter horizons, respectively); all except the one noted are significant at the 5% level or less. After adding dividend yield and then all the controls, the estimates are generally the same, though somewhat reduced and only significant at longer horizons. In general, median coefficients are about 1/2 to 3/4 the level of corresponding mean coefficients, which implies in our framework that about 1/4 to 1/2 of the decrease in the equity premium is driven by an increase in the severity or frequency of negative tail events.

Taken together, Table 5 shows that despite the increased negative skewness and crash risk after bank credit expansions, the equity premium falls rather than increases. It is important to note that bank credit expansions are directly observable to the public. Thus, it is rather surprising that stock investors do not demand a higher equity premium to compensate them for the increased crash risk. As such, one cannot attribute bank credit expansions simply to risk seeking

[13] The coefficients level off after about 2-3 years (in unreported results), implying that the predictability is mostly all incorporated into returns within 2-3 years.

by financial intermediaries against the will of shareholders. Instead, our finding suggests the presence of either optimism or expanded risk appetite of stock investors during the periods of bank credit expansions. We will further discuss the roles of optimism and expanded risk appetite in a later subsection based on the magnitude of the drop in the equity premium.

C. Comparing bank credit expansion to other predictors

We now specifically analyze other variables that are known to be predictors of time-varying equity premium: dividend yield, book to market, inflation, the term spread, the corporate yield spread, real GDP growth, investment to capital, residential investment to capital, and consumption to wealth, which we have included as control variables in our regression analysis. Our first goal is to evaluate whether bank credit expansion predicts the equity premium because it is closely related to one of these control variables or whether it adds new predictive power beyond these other variables. We find the latter, as the coefficient on bank credit expansion is unchanged in the presence of other controls. Our second goal is to ask if these control variables can stand on their own as predictors of crash risk and negative skewness in returns. We show that several of these variables also predict crash risk of the equity market index on their own.

To evaluate these variables as controls for bank credit expansion, we estimate mean regressions with bank credit expansion and various subsets of controls. Our subsets start with the controls that are most statistically significant, and we add more variables in decreasing significance. We save consumption to wealth until the end, due to limited data availability restricting its use as a control. As with Tables 4 and 5, all regressions are restricted to developed countries.

Table 6, Panel A, shows mean regressions with future excess returns of the equity market index as the dependent variable, and Panel B shows mean regressions but using the bank stock index. Each column corresponds to a separate multivariable regression. The first block of columns is for 1-quarter-ahead returns, the second for 4-quarter-ahead returns, and the last for 8-quarter ahead returns.

Within each block, the first column uses just credit expansion with no controls. The second column adds one control, dividend yield, which does not affect the coefficient on bank credit expansion and only has a small increased effect on R^2. The third column adds inflation, the term

spread, and real GDP growth; these controls are all highly significant and noticeable increase the R^2 of the regressions. The fourth column adds book to market, non-residential fixed investment to capital, residential investment to capital, and the corporate yield spread. These variables are only significant at longer horizons and collectively do not increase R^2 by much. However, they are common in the literature as known predictors of the equity premium and thus important to control for. The fifth column adds consumption to wealth[14], which has especially strong statistical significance and predictive power as measured by R^2. However, despite its high R^2, consumption to wealth is limited in terms of data availability, so we exclude consumption to wealth as a standard controls in most of this paper. Therefore, in Tables 5 and 6, we used all the control variables in the fourth column.

Next, we ask whether these control variables also predict crash risk on their own. Given that many of these variables are known to predict the equity premium, these variables show the usefulness of our method for quantifying the predictability of crash risk and negative skewness.

Table 7 presents the results of mean, median and negative skewness predictability for these variables for developed countries. For these regressions, the dependent variable is 4-quarter ahead excess returns. As in Tables 5 and 6, for each predictor variable, we estimate univariate mean and quantile regressions and report the coefficients corresponding to the mean, median, the difference between the mean and median, and negative skewness. We report results for the equity market index (columns 1-4) and bank equity index (columns 5-8). Each coefficient in the table corresponds to a separate univariate regression.

In Table 7, we see that for the equity market index, the variables dividend yield, book to market, consumption to wealth, and the real interest rate differential are all associated with a *higher* mean and/or median future equity premium and less negative skew (some of the coefficients are insignificant); while higher bank credit expansion and investment to capital are both associated with a *lower* mean and/or median future equity premium and more negative skew.

[14] Given limited data availability for consumption to wealth and to a lesser extent, book to market, we imputed missing values for consumption to wealth and book to market in the multivariate regressions, so as not to reduce the sample size available for the other variables. We impute values using the mean for each country and an arbitrary constant (the value of which doesn't matter in a fixed effects model) for countries in which there was no data for consumption to wealth or book to market. The R^2 of these regressions is adjusted to account only for non-imputed data.

These results are in line with our prior beliefs about the determinants of the equity premium and crash risk.

Comparing the coefficients for bank equity index with those for the broad equity market index, we also see that mean and/or median coefficients are generally smaller and not statistically significant, implying that traditional predictors of the equity premium work less well for bank stocks; however, the skew coefficients for dividend yield, investment to capital, and consumption to assets are significant and generally larger for bank stocks than for the market index, implying that crash risk for bank stocks is predictable to some extent using these variables.

D. Robustness checks

We perform several robustness checks to make sure that our results are not driven by any particular countries or any particular time period: for example, the recent global financial crisis or the Great Depression. Also, to assess the robustness of our skewness coefficients estimated from quantile regressions, we also run standard probit regressions using crash indicator variables as the dependent variable as a simple alternative to our quantile-based approach. Although the crash indicator regressions have a slightly different interpretation from quantile regressions – the indicator variables suggest the frequency of tail events, while quantile movements indicate the severity of tail events – in practice, we find they yield identical findings.

Table 8 reports mean, median, the difference between mean and median, and negative skewness coefficients for Δ ($bank\ credit\ /\ GDP$) on future excess returns for various subsets of countries and time periods. Using a 4-quarter forecasting horizon, the regressions are exactly the same as those reported above. The only difference here is that, for Panel A, the data is sub-divided into country regions, and separate regressions are run for each of the geographical regions. In Panel B, we restrict ourselves as usual to only developed countries but change the time period: one set of regressions is run on the entire time period (1920-2013), another is run excluding the most recent crisis (1920-2007), and a third is run excluding both the recent crisis and the Great Depression (1950-2007).

In Panel A, for both the equity market index and for bank equity index, we see that the coefficients for the mean are relatively the same for each of the geographical subsets as they are for the full sample of developed countries. The mean coefficients are slightly larger for some

regions (Western Europe, Southern Europe) and slightly less for other regions (Scandinavia, Emerging Markets). For the equity market index but not for bank equity index, the statistical power is reduced for several regions, though that is probably just due to the smaller sample size in certain subsets. Similarly, the skewness coefficients for the market index are similar across geographical regions: slightly higher in some regions (English-speaking developed countries and Scandinavia) and slightly lower in some (Western Europe), and with somewhat less statistical power due to the smaller sample size.

Panel B shows the estimated mean, median, difference, and negative skew coefficients of $\Delta(bank\ credit\ /\ GDP)$ on future excess returns for the full sample of developed countries, excluding the recent financial crisis (1920 – 2007) and excluding also the Great Depression (1950 – 2007). In general, the coefficients are mostly the same and statistically significant regardless of which years are included in the sample period.

As a final robustness check, we analyze stock crashes by using indicator variables in a probit regression framework. The idea is to predict future stock crashes using bank credit expansion and various controls as predictors. If bank credit expansion can predict increased conditional skewness, then it should also be associated with an increased probability of a crash event. A regression with stock crash indicators as dependent variables serves as a second check on our earlier result concerning the increased crash risk based on quantile regressions. We estimate the following probit regression:

$$\Pr\left[Y = 1 \,\middle|\, (predictor\ variables)_{i,t}\right] = \Phi[\alpha_{i,q} + \beta_q'(predictor\ variables)_{i,t}] \qquad (3)$$

where Φ is the CDF of the standard normal distribution, and Y is a future crash indicator, which takes on a value of 1 if there is an equity crash in the next K quarters (K = 1,2,4, and 8) and 0 otherwise. The probit regression is estimated for the subset of developed countries, both for the main equity index and the bank equity index. Given that an increased crash probability may be driven by increased volatility rather than increased negative skewness, we also estimate equation (3) with Y = ($1_{crash} - 1_{boom}$), where 1_{crash} is the stock crash indicator and 1_{boom} is a symmetrically defined positive tail event.

Table 9 reports the marginal effects for the probit regressions and in general reinforces the conclusions from examining negative skewness in Table 4. Panel A uses the just the stock

crash indicator, and Panel B uses $Y = (1_{crash} - 1_{boom})$. Crashes of the equity index are analyzed in columns 1-8, and crashes of the bank equity index are analyzed in columns 9-16. Regressions are estimated with bank credit expansion and two sets of controls: dividend yield only, or the five standard controls from before.

Table 9 shows that, similar to the estimates of conditional skewness from Table 4, bank credit expansion predicts an increased probability of negative tail events. The following control variables also predict increased negative tail risk: lower dividend yield and book to market, higher inflation and real GDP growth, and lower term spread. The pseudo R^2 is about 5-8% for a one-quarter-ahead horizon and rises up to 18% for the two-year-ahead horizon. Therefore, these results give addition confirmation to the negative skewness statistics reported previously.

E. In-sample and out-of-sample predictions

In this subsection, we use the estimated coefficients for the mean regressions to quantitatively predict the equity premium conditional on credit expansion, both in-sample and out-of-sample. The key result is that when credit expansion is substantial, the predicted equity premium can often turn negative and sometimes become very negative. It is difficult to fully explain this negative equity premium simply based on increased risk appetite and risk-bearing capacity of stock investors and financial intermediaries. Instead, it suggests the need to account for shared optimism among stock investors and financial intermediaries. Finally, we assess the validity of out-of-sample prediction by computing adjusted R^2 values for various horizons and comparing them to those for in-sample prediction. The strength of out-of-sample predictability based on credit expansion argues that investors should have been able to forecast future negative equity returns in times and countries when credit was expanding rapidly.

We use the mean regression estimates from Table 5 with a 4-quarter forecast horizon to predict the future equity premium. Figure 2 shows the predicted equity premium plotted over time for each developed countries in our sample. The black line shows the predicted equity premium conditional on just dividend yield (from a univariate regression), and the thicker red line shows the predicted equity premium conditional on both dividend yield and bank credit expansion. Panel A shows the predicted equity premium for the broad equity market index, and

Panel B shows the predicted equity premium for the bank equity index. Equity crash events are marked with a blue vertical line.

To get a sense of the equity premium predictions conditional on credit expansion, consider the predicted time series for the U.S. in Figure 2, Panel A. We know from the summary statistics that the unconditional equity premium has historically been 6.1% for developed economies. In the U.S., up until the 90s, bank credit expansion relative to GDP was small, so there is little deviation of the red line (conditional on both dividend yield and bank credit expansion) from the black line (conditional on dividend yield alone). However, after 1990, credit expansion and credit contraction became more important: the predicted equity premium decreased due to credit expansion in the late 80s, increased sharply in the early 90s due to credit contraction, and decreased to slightly negative levels in the mid-2000s.

The *negative* predicted equity premium in the U.S. leading up to the 2008 financial crisis is not at all unusual compared to credit expansions in other countries throughout history, as shown in Figure 2, Panel A. These plots emphasize that the predicted equity premium often is negative, sometimes highly so, during rapid credit build-up. For example, the predicted equity premium went as low as -5% (or sometimes -10%) in France in the early 60s; Australia, Denmark, France, Norway, Sweden, Switzerland, and the UK in the late 80s; Japan in the early 70s and again the late 80s; and most Western European countries leading up to 2008. These periods of negative predicted equity premia are almost always followed by severe market crashes and financial crises, as shown by the blue vertical lines representing crashes, visually demonstrating that a negative predicted equity premium is a good predictor of impending crash risk (Table 10, described below, quantitatively assesses the out-of-sample predictability). In the U.S., for example, the predicted equity premium dipped sharply leading up to: the 2008 financial crisis, the stock crash of the early 2000s, the 1987 crash, and the 1973 crash. It is difficult to fully explain this negative equity premium simply based on increased risk appetite and risk-bearing capacity of stock investors and financial intermediaries. Instead, it suggests the need to account for shared optimism among stock investors and financial intermediaries.

Turning to Panel B, we see the same patterns hold and are perhaps more prominent when predicting the equity premium of bank stocks. In fact, for bank stocks, the predicted equity premium is less sensitive to dividend yield (the black line) and much more sensitive to bank

credit expansion (the thick red line), and thus the predicted time-varying bank stock equity premium is very volatile, as high as 20% at some point in almost all the countries in the panel and very negative during any period of rapid credit expansion. Again, we emphasize that the predicted equity premium often is negative. In countries such as Japan, Switzerland, and the UK, the predicted equity premium is less than -5% in periods of rapid credit expansion. More extreme examples can be found at different points in history in such countries as Australia, Belgium, Denmark, Germany, Ireland, the Netherlands, Portugal, Spain, and Sweden, where the predicted bank stock equity premium is less than -10% before a crash and in some cases less than -30%! Again, given predictable episodes of rapid credit expansion followed by highly negative returns, it is difficult to fully explain this negative equity premium simply based on increased risk appetite and risk-bearing capacity of stock investors and financial intermediaries.

A final important point illustrated by Figure 2 is that the predicted equity premium is often quite high *after* a crash, as rapid and often forced deleveraging by investors and intermediaries lifts the equity premium, consistent with the findings of Muir (2013) and Adrian et al. (2013a, 2013b).

Finally, we assess the validity of the above exercise by analyzing out-of-sample predictability, which we do by computing adjusted R^2 values for various long-run horizons. The strength of out-of-sample predictability based on credit expansion demonstrates that investors should have been able to forecast future negative equity returns when the credit was expanding very rapidly – in other words, demonstrates that market corrections were foreseeable before the fact.

Table 10 reports adjusted R^2 values for both in-sample and out-of-sample predictions for the subset of developed countries. Out-of-sample prediction is computed by estimating the mean regression using only information from year 1950 to year (t-i), where i is the forecast horizon in years. Regressions are estimated with either just dividend yield as a control or with the five standard control variables from earlier: dividend yield, book to market, inflation, the term spread, and real GDP growth. Both in-sample and out-of-sample equity premium predictions are made for each quarter within three time periods – 1960-1980, 1980-2000, and 2000-2013. The adjusted R^2 values for each time period are reported both as the total R^2 for bank credit expansion plus five controls and as the additional R^2 coming from just bank credit expansion (over the controls).

In Table 10, the out-of-sample adjusted R^2 for predictions using both bank credit expansion and the controls are 6% (4-quarter ahead) , 8% (8-quarter ahead), and 7% (12-quarter ahead) for the 1960-1980 period, similar for the 1980-2000 period, and considerably higher for the 2000-2013 period: 11% (4-quarter ahead) , 20% (8-quarter ahead), and 21% (12-quarter ahead). Separating the R^2 contribution of bank credit expansion from that of the controls, we see that the additional contribution of credit expansion is generally around 4-5% out-of-sample, which interestingly is about the same as it is in-sample. For bank stocks, we see similar out-of-sample predictability with adjusted R^2 values for both the total R^2 and the addition contribution from bank credit expansion. In some cases, the out-of-sample additional R^2 contribution from bank credit expansion goes as high as 9%.

The high and robust out-of-sample R^2 gives validity to the equity premium predictions in Figure 2 and demonstrates that investors should have been able to forecast future negative equity returns when credit was expanding rapidly and that market corrections were in fact foreseeable before the fact.

V. Conclusion

In a set of developed and emerging economies, we find that bank credit expansion predicts significantly increased crash risk in the returns of the equity market index and bank equity index in subsequent two to eight quarters. Despite the increased crash risk, credit expansion predicts both lower mean and median returns of these indices in the same horizons, even after controlling for a host of variables known to predict the equity premium. These findings suggest that credit expansion is not simply driven by risk-seeking of financial intermediaries against the will of shareholders. It is also difficult to fully explain the large drop in the equity premium during credit expansions based on expanded risk appetite of financial intermediaries and stock investors as the predicted equity premium often turns negative and sometimes turns substantially negative in some countries and in some periods. There is thus a need to account for widespread optimism of financial intermediaries and stock investors in order to fully explain credit expansions.

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Figure 1, Panel A - Three-year change in bank credit to GDP for developed country in our sample

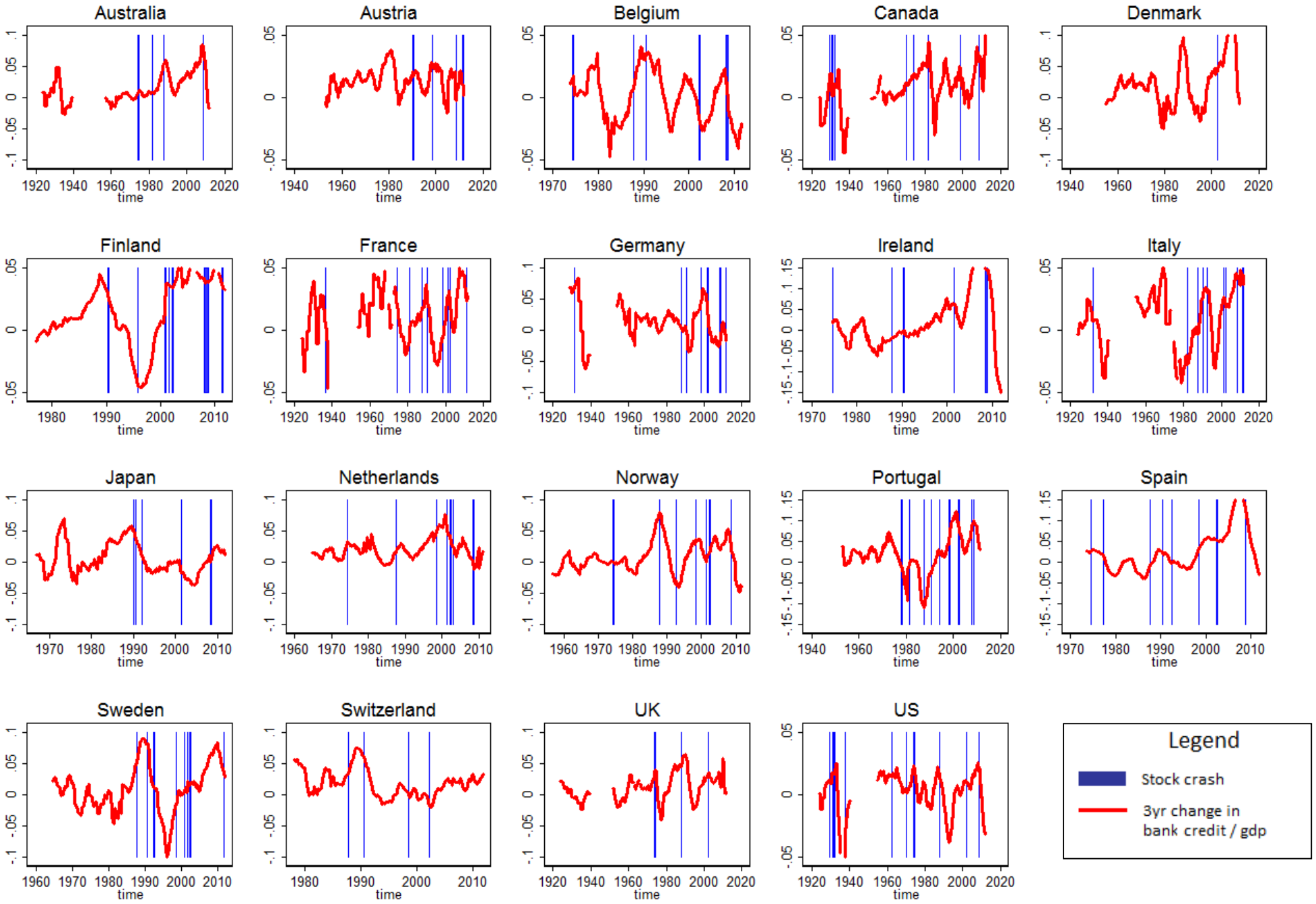


Figure 1, Panel B – Three-year change in bank credit to GDP for emerging economies in our sample

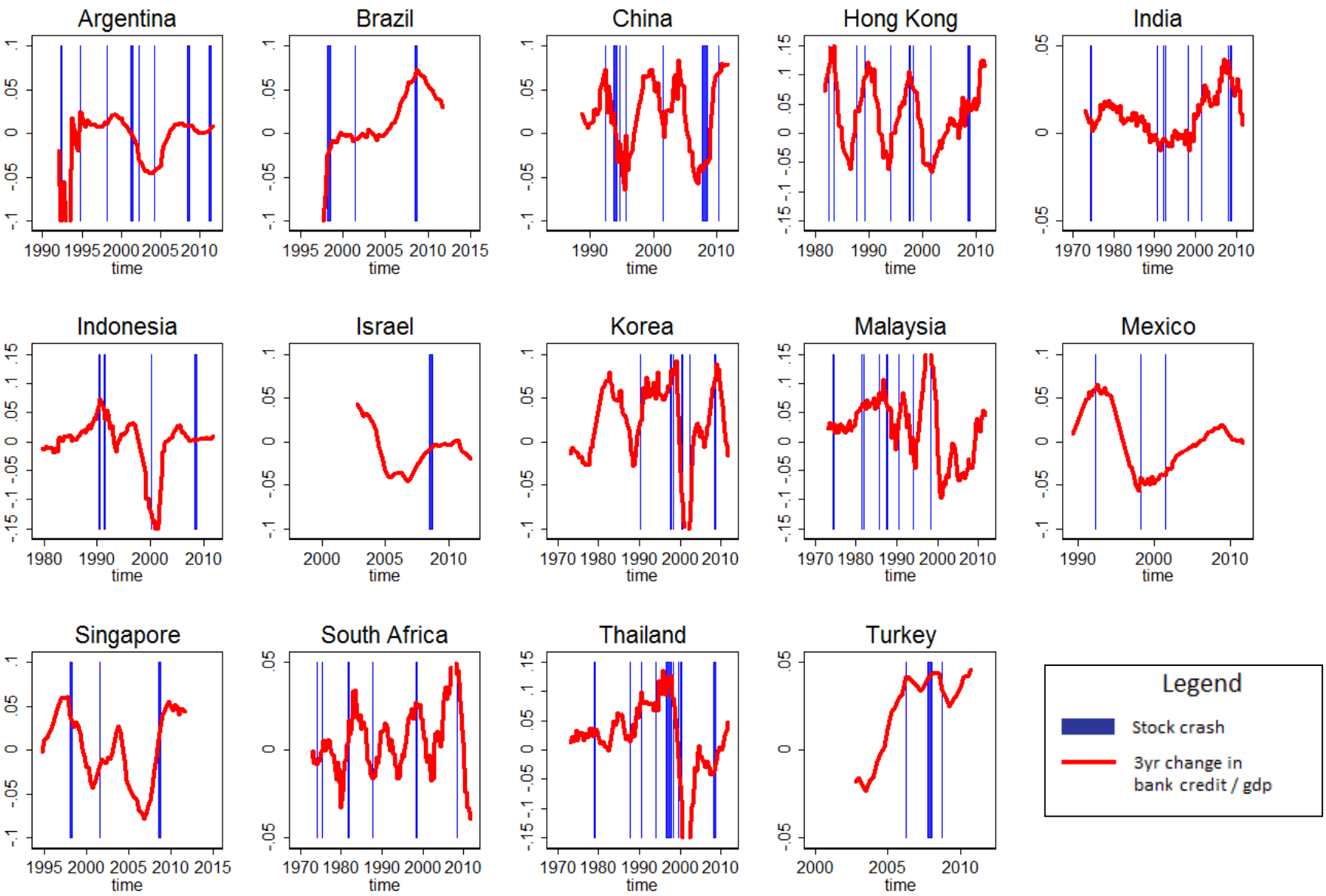


Figure 2, Panel A - Equity premium prediction for market index based on bank credit expansion

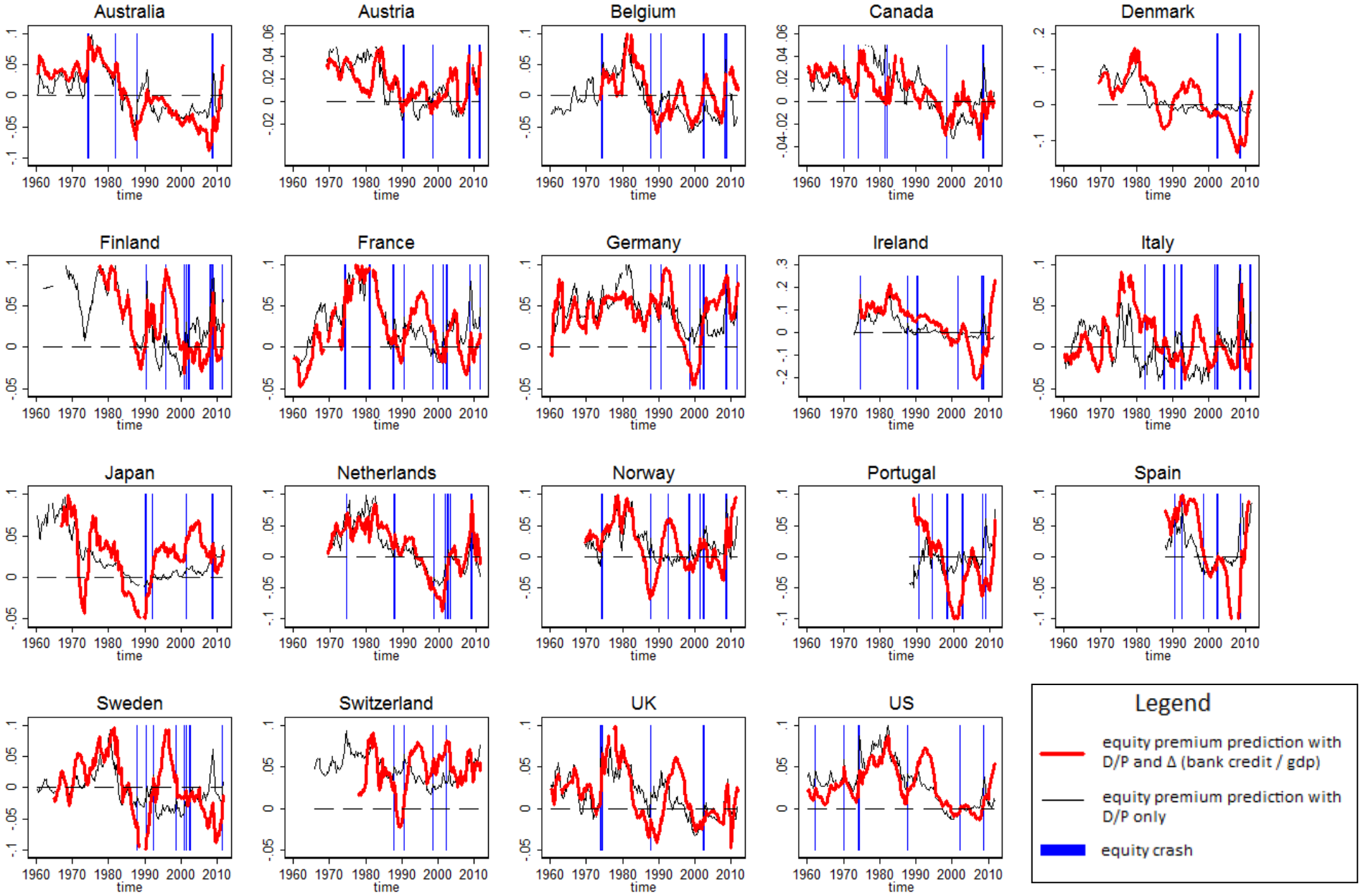


Figure 2, Panel B - Equity premium prediction for bank stock index

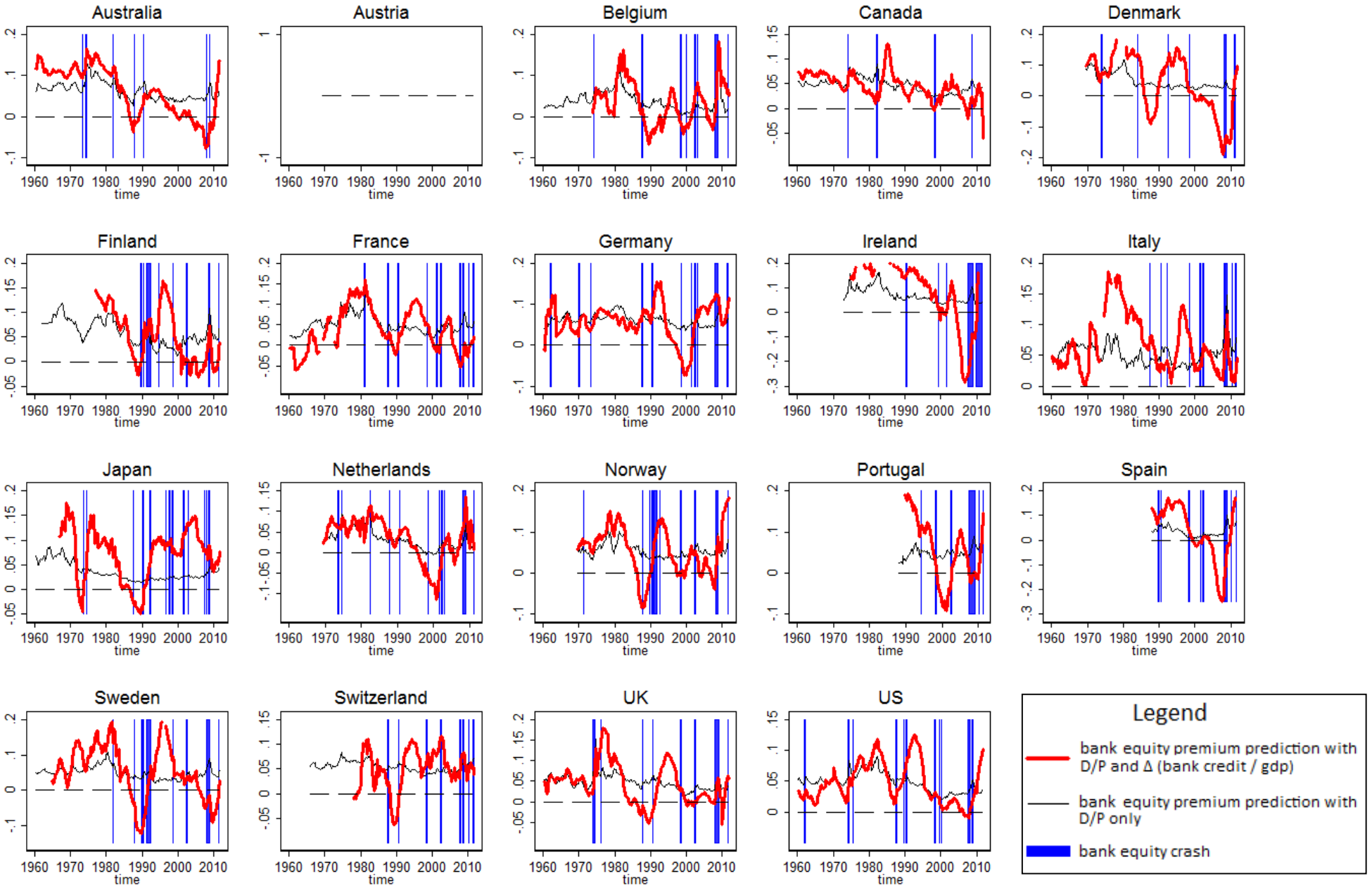


Table 1 - Summary statistics

Panel A: Developed economies

	N	Mean	Median	Stdev.	1%	5%	10%	90%	95%	99%
Quarterly log returns, annualized										
Equity excess returns	4704	2.6%	3.4%	21.5%	-110.1%	-65.8%	-46.2%	48.2%	65.8%	110.1%
Equity total excess returns (incl. dividends)	4307	6.1%	7.4%	21.2%	-106.7%	-63.8%	-43.7%	52.0%	69.2%	110.1%
Equity real returns	5687	4.6%	4.5%	27.8%	-104.1%	-60.2%	-42.8%	48.6%	65.9%	113.5%
Bank stocks excess returns	3904	-1.3%	1.7%	25.8%	-170.6%	-81.9%	-52.7%	49.5%	69.2%	122.4%
Bank stocks real returns	4578	1.2%	2.4%	34.0%	-162.4%	-75.7%	-47.5%	49.7%	69.4%	125.5%
Credit to private households and non-financial corporations, 3 year change										
Δ (Bank credit / GDP)	4197	1.3%	1.1%	3.0%	-5.8%	-3.1%	-2.0%	4.5%	6.0%	11.5%
Δ (Total credit / GDP)	3652	2.3%	2.1%	5.0%	-9.2%	-4.6%	-2.7%	7.9%	10.3%	16.7%

Panel B: Emerging economies

	N	Mean	Median	Stdev.	1%	5%	10%	90%	95%	99%
Quarterly log returns, annualized										
Equity excess returns	2050	8.1%	3.4%	36.1%	-142.8%	-91.0%	-67.7%	79.6%	114.4%	239.8%
Equity total excess returns (incl. dividends)	1782	10.5%	7.6%	33.6%	-138.0%	-88.4%	-66.5%	81.3%	112.0%	238.8%
Equity real returns	2276	10.7%	4.7%	35.8%	-143.1%	-86.4%	-65.0%	84.0%	121.3%	238.7%
Bank stocks excess returns	1460	1.6%	1.3%	38.8%	-219.5%	-117.0%	-81.2%	78.1%	115.1%	242.4%
Bank stocks real returns	1618	4.0%	2.1%	37.6%	-201.8%	-111.6%	-75.0%	79.2%	116.6%	230.3%
Credit to private households and non-financial corporations, 3 year change										
Δ (Bank credit / GDP)	1608	1.2%	1.0%	5.9%	-15.3%	-5.5%	-3.7%	6.8%	8.4%	13.2%
Δ (Total credit / GDP)	1608	1.3%	1.1%	8.9%	-17.4%	-5.4%	-3.4%	7.8%	9.8%	15.9%

Table 2 - Time series correlations

Panel A: Time-series co-movements of macro and interest rate variables with credit

								RHS variable:				
LHS variable:	Country		D/P	book / market	Daily volatility	Invest-ment to capital	Consum-ption to wealth	real GDP growth	term spread	corporate yield spread	sovereign yield spread	interest rate differential
Δ (bank credit / GDP)	Advanced	β	-.377***	-.009***	.374**	.745***	-.108***	.083**	-.184***	.315***	-.288***	.039**
		R^2	0.05	0.05	0.01	0.20	0.14	0.01	0.01	0.07	0.04	0.00
	Emerging	β	.497**	.033***	0.119	1.21***		-0.151	-.245***	.629**	-0.042	0.043
		R^2	0.00	0.00	0.00	0.56		0.00	0.06	0.05	0.03	0.00

Panel B: Time-series co-movements with different forms of credit variables

								RHS variable:				
LHS variable:	Country		Δ (total credit)	Δ (total credit to HHs)	Δ (total credit to private NFCs)	Δ (Bank assets / GDP)	Growth of household housing assets	HH debt / assets	NFC equity / assets	Bank equity / assets	Δ (gross external liabilities / GDP)	current account deficit / GDP
Δ (bank credit / GDP)	Advanced	β	.58***	1.07***	.558***	.249***	.177***	.957***	-.345***	-1.03***	.172***	.053***
		R^2	0.70	0.61	0.56	0.33	0.22	0.14	0.11	0.06	0.21	0.01
	Emerging	β	.604***	1.51***	1.06***	.519***			-.658***	2.94***	.084***	.457***
		R^2	0.85	0.39	0.81	0.42			0.14	0.18	0.02	0.11

Table 3: Cross-country correlations

Correlation with U.S., 1950-2005

	Selected countries	Quarterly equity excess returns	Quarterly bank equity excess returns	Equity Crash indicator	Bank Equity Crash indicator	Δ (Bank credit / GDP)	D/P	C/A	I/K	Current account / GDP	Sovereign Spread (corr. with UK)
	US	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	N/A
Commonwealth	Australia	0.53	0.32	0.60	0.36	0.00	0.59	0.02	0.73	0.60	0.20
	Canada	0.82	0.57	0.35	0.32	-0.34	0.92	0.75	0.66	-0.59	0.58
	UK	0.60	0.51	0.61	0.52	0.17	0.74	0.71	0.79	0.43	1.00
W. Europe	Belgium	0.57	0.45	0.66	0.40	-0.24	0.82		0.43	-0.56	0.46
	France	0.51	0.39	0.47	0.35	0.46	0.68	0.61	0.45	-0.13	0.54
	Netherlands	0.73	0.45	0.50	0.27	0.15	0.91		0.64	-0.47	0.58
	Germany	0.54	0.42	0.32	0.43	0.31	0.22	0.39	0.43	-0.35	0.36
Scandinavia	Denmark	0.43	0.26	0.28	0.20	0.48	0.65		0.64	-0.51	0.60
	Sweden	0.53	0.31	0.25	0.23	0.15	0.71		0.64	-0.70	0.41
	Norway	0.40	0.26	0.53	0.37	0.35	0.64		0.10	-0.67	-0.03
S. Europe	Italy	0.40	0.36	0.47	0.28	0.04	0.51	0.39	0.46	0.18	0.35
	Spain	0.56	0.47	0.41	0.28	0.17	0.89		0.19	0.34	0.44
Asia	Japan	0.37	0.15	-0.03	0.25	0.18	0.54	0.12	-0.24	-0.79	0.35
	Korea	0.39	0.17	0.25	0.11	-0.48	-0.18			-0.66	0.82
	Singapore	0.58	0.34	0.39	0.43	-0.52	0.45				0.24
	Thailand	0.32	0.26	0.15	0.28	-0.38	0.24			-0.68	0.26
S. America	Argentina	0.39		0.33		0.55	-0.31			-0.57	
	Brazil	0.45		-0.04		0.10	-0.40			-0.78	-0.16
	Mexico	0.45		-0.04		-0.86	0.22			-0.71	0.24
	Average	0.50	0.36	0.34	0.32	0.02	0.47	0.43	0.46	-0.37	0.40

Table 4: Quantile regressions and negative skewness coefficients

		All stocks				Bank stocks			
Explanatory variables:	Horizon (quarters):	1	2	4	8	1	2	4	8
Δ (bank credit / GDP)	**Q10**	**-.394****	**-.994*****	**-2.03*****	**-2.643*****	**-.775*****	**-1.663*****	**-3.071*****	**-5.192*****
	(t stat)	(-2.66)	(-5.10)	(-5.83)	(-10.7)	(-4.31)	(-4.72)	(-10.19)	(-15.33)
	Q50 (median)	**-.15***	**-.353****	**-1.002*****	**-1.925*****	**-.185***	**-.547*****	**-1.064*****	**-2.818*****
	(t stat)	(-2.18)	(-2.76)	(-6.09)	(-6.42)	(-2.34)	(-4.52)	(-5.68)	(-10.3)
	Q90	**-0.064**	**-.316***	**-.789*****	**-2.112*****	**-0.137**	**-.573****	**-1.434*****	**-2.992*****
	(t stat)	(-.47)	(-2.27)	(-3.52)	(-4.68)	(-.87)	(-2.82)	(-4.33)	(-7.46)
	Negative skew	**0.158**	**.605***	**.815***	**0.904**	**0.542**	**1.141*****	**2.376*****	**2.548*****
	(t stat)	(0.72)	(2.32)	(2.44)	(1.59)	(1.7)	(3.73)	(5.3)	(4.21)
With D/P as control	**Q10**	**-.42****	**-1.073*****	**-1.924*****	**-2.163*****	**-.749****	**-1.49*****	**-3.042*****	**-5.024*****
	(t stat)	(-3.05)	(-7.34)	(-6.65)	(-7.07)	(-2.72)	(-5.91)	(-10.7)	(-11.4)
	Q50 (median)	**-0.159**	**-.399*****	**-1.027*****	**-1.931*****	**-0.215**	**-.549*****	**-1.071*****	**-2.759*****
	(t stat)	(-1.76)	(-4.57)	(-4.60)	(-8.59)	(-1.89)	(-4.28)	(-4.41)	(-8.59)
	Q90	**-0.026**	**-.368***	**-.745*****	**-1.871*****	**-0.107**	**-.599****	**-1.595*****	**-3.025*****
	(t stat)	(-.23)	(-2.46)	(-3.83)	(-6.46)	(-.70)	(-2.96)	(-4.16)	(-6.56)
	Negative skew	**0.128**	**.643*****	**0.615**	**0.172**	**0.426**	**.991****	**2.496*****	**2.53*****
	(t stat)	(0.55)	(3.35)	(1.56)	(0.31)	(1.48)	(2.74)	(6.43)	(3.74)
With D/P, inflation, i/k, corporate yield spread, term spread, real GDP growth as controls	**Q10**	**-.492**	**-1.045****	**-2.799*****	**-3.964*****	**-1.021****	**-2.039*****	**-4.325*****	**-6.711*****
	(t stat)	(-1.7)	(-2.85)	(-4.08)	(-6.52)	(-2.75)	(-6.01)	(-4.36)	(-5.65)
	Q50 (median)	**-.039**	**-.572****	**-.932****	**-2.824*****	**-.311**	**-.662****	**-1.653*****	**-3.275*****
	(t stat)	(-.28)	(-3.02)	(-2.78)	(-6.48)	(-1.58)	(-2.71)	(-4.03)	(-5.79)
	Q90	**.09**	**-.028**	**-.608**	**-1.507***	**-.052**	**-.349**	**-1.321***	**-2.748****
	(t stat)	(.51)	(-.12)	(-1.86)	(-2.55)	(-.33)	(-1.43)	(-2.49)	(-3.12)
	Negative skew	**.324**	**-.072**	**1.542**	**-.177**	**.451**	**1.064***	**2.34***	**2.908***
	(t stat)	(1.02)	(-.13)	(1.87)	(-.17)	(1.19)	(2.11)	(2.15)	(2.42)

Table 5: Mean and median regressions

Panel A: Mean and median regressions over various horizons with three sets of controls (coefficients on controls not shown)

		All stocks				Bank stocks			
Explanatory variables:	Horizon (quarters):	1	2	4	8	1	2	4	8
Δ (bank credit / GDP)	**mean**	**-.267***	**-.572****	**-1.256*****	**-2.472*****	**-0.378**	**-.824***	**-1.912*****	**-4.225*****
	(t stat)	(-2.35)	(-3.01)	(-4.26)	(-7.12)	(-1.81)	(-2.41)	(-4.05)	(-8.25)
	(R^2, within)	0.002	0.009	0.025	0.053	0.004	0.014	0.041	0.1
	median	**-.15***	**-.353****	**-1.002*****	**-1.925*****	**-.185***	**-.547*****	**-1.064*****	**-2.818*****
	(t stat)	(-2.18)	(-2.76)	(-6.09)	(-6.42)	(-2.34)	(-4.52)	(-5.68)	(-10.3)
	difference	**.117***	**.219****	**.254***	**.546***	**.192***	**0.277**	**.848*****	**1.407*****
	(p value)	0.03	< 0.01	0.05	0.01	0.04	0.10	< 0.001	< 0.001
With D/P as control	**mean**	**-.258***	**-.541****	**-1.19*****	**-2.347*****	**-0.373**	**-.798***	**-1.863*****	**-4.183*****
	(t stat)	(-2.11)	(-2.68)	(-3.96)	(-6.75)	(-1.63)	(-2.14)	(-3.77)	(-8.04)
	(R^2, within)	0.002	0.011	0.03	0.067	0.004	0.015	0.042	0.103
	median	**-0.159**	**-.399*****	**-1.027*****	**-1.931*****	**-0.215**	**-.549*****	**-1.071*****	**-2.759*****
	(t stat)	(-1.76)	(-4.57)	(-4.60)	(-8.59)	(-1.89)	(-4.28)	(-4.41)	(-8.59)
	difference	**0.098**	**0.143**	**0.163**	**.416***	**0.158**	**0.249**	**.793****	**1.424*****
	(p value)	0.11	0.10	0.33	0.02	0.12	0.24	< 0.01	< 0.001
With D/P, inflation, i/k, corporate yield spread, term spread, and real GDP growth as controls	**mean**	**-.199**	**-.566***	**-1.512*****	**-3.025*****	**-.318**	**-.762****	**-2.165*****	**-4.49*****
	(t stat)	(-1.07)	(-2.34)	(-4.21)	(-6.77)	(-1.54)	(-2.67)	(-4.67)	(-7.59)
	(R^2, within)	.017	.042	.084	.158	.02	.047	.096	.166
	median	**-.039**	**-.572****	**-.932****	**-2.824*****	**-.311**	**-.662****	**-1.653*****	**-3.275*****
	(t stat)	(-.28)	(-3.02)	(-2.78)	(-6.48)	(-1.58)	(-2.71)	(-4.03)	(-5.79)
	difference	**0.16**	**-0.006**	**0.58**	**0.201**	**0.007**	**0.1**	**0.512**	**1.215**
	(p value)								

Table 6: Selected mean regressions with controls.

Panel A: Broad stock market index

Explanatory variables:	1 quarter horizon					4 quarter horizon					8 quarter horizon				
Δ (bank credit / GDP)	-.267*	-.258*	-.253*	-0.191	-0.1	-1.26***	-1.19***	-1.59***	-1.48***	-.913*	-2.47***	-2.35***	-3.08***	-2.96***	-1.86***
D/P		0.195	0.672	0.535	0.544		1.26	2.7***	2.49**	2.48**		2.66**	5.08***	4.68***	3.85***
Inflation			-.373**	-0.258	-.404*			-1.3***	-1.06**	-1.63***			-2.15***	-1.94***	-2.5***
Term spread			0.326	0.35	0.216			1.15*	0.978	0.609			1.86**	1.36*	0.706
Real GDP growth			-.411*	-0.372	-0.293			-1.59***	-1.32**	-.974*			-3.19***	-2.44***	-1.94***
Book / market				0.019	0.0165				.0713***	.061**				.146***	.133***
Invest. / Capital				-0.0713	-0.211				-0.397	-0.907				-0.719	-1.66*
Residential invest. / capital				-0.958	-0.907				-2.04	-2.72				-3.96	-6.19**
Corporate yield spread				-0.352	-0.303				-1.28	-1.26				-0.623	-1.18
Consumption / wealth					.261***					1.2***					1.93***
Adj. R^2	0.00	0.00	0.02	0.02	0.04	0.02	0.03	0.09	0.08	0.21	0.05	0.07	0.16	0.16	0.32
N	3738	3572	2865	1919	1833	3738	3572	2865	1919	1833	3738	3572	2865	1919	1833

Panel B: Bank stock index

Explanatory variables:	1 quarter horizon					4 quarter horizon					8 quarter horizon				
Δ (bank credit / GDP)	-0.378	-0.373	-0.316*	-0.314	-0.214	-1.91***	-1.86***	-2.19***	-2.149***	-1.58***	-4.22***	-4.18***	-4.55***	-4.460***	-3.344***
D/P		0.07	0.719	0.578	0.276		1.155	2.98***	2.942**	1.795		1.849	5.66***	4.472***	2.523
Inflation			-0.454**	-0.315	-0.333			-1.57***	-1.374***	-1.51***			-2.64***	-2.037***	-2.242***
Term spread			0.610*	0.674*	0.492			2.255**	2.022*	1.499			3.357***	2.577**	1.905*
Real GDP growth			-0.267	-0.116	0.058			-1.090*	-0.632	-0.078			-2.10***	-1.553*	-1.035
Book / market				0.027*	0.026*				0.096***	0.092***				0.181***	0.175***
Invest. / Capital				0.226	0.046				0.833	0.061				1.801	0.387
Residential invest. / capital				-1.551*	-1.999**				-4.531*	-6.82***				-10.42***	-14.98***
Corporate yield spread				-0.345	-0.402				-1.654	-2.217				-0.845	-2.404
Consumption / wealth					0.312***					1.227***					1.868***
Adj. R^2	0.00	0.00	0.02	0.02	0.03	0.04	0.04	0.09	0.10	0.17	0.10	0.10	0.16	0.17	0.25
N	3306	3180	2557	1726	1671	3306	3180	2557	1726	1671	3306	3180	2557	1726	1671

Table 7: other variables predicting crash risk

Univariate regressions - crash risk, 4 quarter forecast horizon

	All stocks				Bank stocks			
	Mean	**Median**	**Difference**	**Negative Skew**	**Mean**	**Median**	**Difference**	**Negative Skew**
Δ (bank credit / GDP)	-1.256***	-1.002***	-.254*	.815*	-1.912***	-1.064***	-.848***	2.376***
D/P	1.887***	1.346**	.54**	-2.301***	1.05	0.456	.594*	-2.1*
Book / market	.08**	.051**	.029*	-.131***	0.025	0.033	-0.008	-0.083
Invest. / Capital	-1.783**	-.924***	-.859***	2.88***	-1.466	-0.086	-1.38***	4.696***
Consumption / wealth	1.484***	1.278***	.206*	-0.251	1.466***	1.156***	.309**	-1.027*
Sovereign yield spread	-0.366	-1.009***	.643***	-2.391***	-0.438	-.743**	0.305	-1.311
Short-rate differential	0.148	.294***	-.146*	.559**	0.016	.171*	-0.155	0.321

Table 8: Robustness checks

Panel A: Regressions by geographical regions, 4 quarter forecast horizon

		All Developed	Eight Developed	U.S.	English speaking	W. Europe	S. Europe	Scandinavia	Emerging
All stocks	**Mean**	**-1.256*** **	**-1.214*** **	**-.833**	**-.601**	**-1.386*** **	**-1.851*** **	**-.91**	**-.115**
	(t stat)	(-4.26)	(-4.27)	(-.93)	(-1.38)	(-4.58)	(-3.77)	(-1.97)	(-.71)
	Median	**-1.002*** **	**-.926*** **	**-.581**	**-.292**	**-1.13*** **	**-1.104***	**-.406**	**-.21**
	(t stat)	(-5.64)	(-3.85)	(-1.3)	(-.82)	(-5.31)	(-2)	(-1.35)	(-.97)
	Difference	**-.254***	**.288**	**.252**	**.309**	**.257**	**.747***	**.504**	**-.095**
	(p value)	(.024)	(.067)	(.699)	(.105)	(.094)	(.033)	(.075)	(.478)
	Negative Skew	**.815***	**1.053**	**1.163**	**2.268** **	**.5**	**1.455**	**1.918** **	**-.67**
	(t stat)	(2.1)	(1.58)	(.52)	(3.11)	(1.1)	(1.31)	(2.76)	(-1.17)
Bank Stocks	**Mean**	**-1.912*** **	**-1.546*** **	**-2.857** **	**-1.335** **	**-2.062*** **	**-2.267*** **	**-1.803** **	**-1.208** **
	(t stat)	(-4.05)	(-4.92)	(-2.81)	(-2.91)	(-4.08)	(-3.45)	(-2.98)	(-2.69)
	Median	**-1.064*** **	**-1.03*** **	**-2.745** **	**-.795** **	**-1.2*** **	**-1.487*** **	**-.515**	**-.543**
	(t stat)	(-4.56)	(-3.59)	(-2.92)	(-2.88)	(-3.88)	(-3.7)	(-1.04)	(-1.6)
	Difference	**-.848*** **	**-.516***	**-.112**	**-.54**	**-.862*** **	**-.78**	**-1.287*** **	**-.665** **
	(p value)	(< 0.001)	(.014)	(.875)	(.06)	(.001)	(.11)	(< 0.001)	(.006)
	Negative Skew	**2.376*** **	**2.242** **	**.311**	**2.068***	**2.438*** **	**2.743**	**3.594** **	**.178**
	(t stat)	(4.45)	(2.89)	(.13)	(2.39)	(4.31)	(1.61)	(3.23)	(.19)

Panel B: Regressions by time periods, 4 quarter forecast horizon

		1920-2013	1920-2008	1950-2008
All stocks	**Mean**	**-1.256*** **	**-1.388*** **	**-1.473*** **
	(t stat)	(-4.26)	(-4.63)	(-4.49)
	Median	**-1.002*** **	**-1.135*** **	**-1.195*** **
	(t stat)	(-5.64)	(-4.93)	(-6.10)
	Difference	**-.254***	**-.253**	**-.277***
	(p value)	(.024)	(.109)	(.044)
	Negative Skew	**.815***	**.55***	**.683**
	(t stat)	(2.1)	(2.04)	(1.35)
Bank Stocks	**Mean**	**-1.912*** **	**-1.948*** **	**-2.102*** **
	(t stat)	(-4.05)	(-4.51)	(-4.43)
	Median	**-1.064*** **	**-1.112*** **	**-1.364*** **
	(t stat)	(-4.56)	(-4.72)	(-5.54)
	Difference	**-.848*** **	**-.837*** **	**-.738*** **
	(p value)	(< 0.001)	(< 0.001)	(.001)
	Negative Skew	**2.376*** **	**2.573*** **	**2.363*** **
	(t stat)	(4.45)	(6.25)	(6.32)

Table 9: Predictive probit regressions using crash indicators. All reported coefficients are marginal effects.

Panel A: Dependent variable is crash indicator.

	All stocks								Bank stocks							
Horizon:	1		2		4		8		1		2		4		8	
Δ (bank credit / gdp)	.56***	.246*	.921***	.519***	1.54***	1.03***	2.46***	1.81***	.904***	.635***	1.48***	1.12***	2.39***	1.84***	3.79***	3.27***
D/P	-.494*	-.82*	-1.2***	-1.7***	-3.4***	-4.3***	-7.6***	-10.1**	-1.2***	-2.6***	-2.2***	-4.3***	-4.5***	-7.9***	-8***	-11***
Inflation		.362***		.588***		1.05***		1.7***		.861***		1.39***		2.21***		2.58***
Book / market		-.061***		-.095***		-.153***		-.228***		-.0705**		-.0966***		-.146***		-.21***
Term spread		-.4*		-.936***		-1.94***		-2.49***		-.503		-.875*		-1.9***		-.815
Real GDP growth		-.131		.0697		.481		1.92***		-.334		-.0536		.511		2.45***
R^2	0.05	0.08	0.06	0.10	0.09	0.13	0.12	0.18	0.06	0.08	0.07	0.10	0.10	0.13	0.13	0.15
N	3788	2970	3789	2970	3790	2970	3790	2970	3319	2651	3323	2654	3330	2660	3342	2672

Panel B: Dependent variable is $(1_{crash} - 1_{boom})$ **indicator.**

	All stocks								Bank stocks							
	1		2		4		8		1		2		4		8	
Δ (bank credit / gdp)	.471***	.119	.72***	.235	.966***	.467*	1.42***	.617*	1***	.481**	1.47***	.859***	1.8***	1.48***	1.47***	.964**
D/P	-.237	-.96*	-.91**	-2.2**	-2.8***	-4.6**	-4.5***	-6.0**	-.44	-2.57***	-1.52**	-4.25**	-3.9**	-6.64**	-6.77**	-9.09**
Inflation		.571***		.908***		1.48***		1.51***		.809***		1.38***		2.03***		1.95***
Book / market		-.0711***		-.087***		-.126***		-.16**		-.0658**		-.0966**		-.152***		-.13***
Term spread		-.48*		-1.06***		-2.03***		-2.44***		-.98**		-1.42***		-2.13***		-.895
Real GDP growth		-.226		-.01		.339		.902		-.67*		-.394		.518		4.06***
R^2	0.04	0.08	0.05	0.08	0.07	0.10	0.07	0.09	0.06	0.07	0.07	0.09	0.09	0.12	0.10	0.12
N	3788	2970	3789	2970	3790	2970	3790	2970	3319	2651	3323	2654	3330	2660	3342	2672

Table 10: Predicting the equity premium in- and out-of-sample

Adjusted R^2 values

		1960 - 1980			1980 - 2000			2000-2013		
		Total R^2 of Δ (bank credit/gdp) plus five controls	**Additional R^2** of Δ (bank credit/gdp) over D/P	**Additional R^2** of Δ (bank credit/gdp) over five controls	**Total R^2** of Δ (bank credit/gdp) plus five controls	**Additional R^2** of Δ (bank credit/gdp) over D/P	**Additional R^2** of Δ (bank credit/gdp) over five controls	**Total R^2** of Δ (bank credit/gdp) plus five controls	**Additional R^2** of Δ (bank credit/gdp) over D/P	**Additional R^2** of Δ (bank credit/gdp) over five controls
broad stock index:										
4-quarter ahead forecast	in-sample	0.08	-0.02	0.00	0.07	0.01	0.01	0.15	0.02	0.04
	out-of-sample	0.06	0.01	0.02	0.01	0.00	0.01	0.11	0.02	0.03
8-quarter ahead forecast	in-sample	0.13	-0.02	0.04	0.13	0.04	0.02	0.32	0.05	0.04
	out-of-sample	0.08	0.05	0.01	0.03	0.01	0.03	0.20	0.04	0.04
12-quarter ahead forecast	in-sample	0.09	-0.02	0.01	0.22	0.05	0.03	0.36	0.06	0.06
	out-of-sample	0.07	0.05	0.04	0.07	0.00	0.01	0.21	0.04	0.05
bank stock index:										
4-quarter ahead forecast	in-sample	0.07	0.02	0.02	0.09	0.03	0.02	0.15	0.03	0.04
	out-of-sample	0.05	0.03	0.05	0.01	0.01	0.01	0.07	0.00	0.02
8-quarter ahead forecast	in-sample	0.07	0.05	0.04	0.15	0.09	0.06	0.27	0.09	0.01
	out-of-sample	0.02	0.04	0.02	0.04	0.02	0.03	0.11	0.03	0.05
12-quarter ahead forecast	in-sample	0.09	0.06	0.04	0.24	0.16	0.12	0.30	0.13	0.06
	out-of-sample	0.00	-0.03	-0.02	0.07	0.03	0.06	0.11	0.03	0.09

Note: Out-of-sample predictions for year t use information from 1950 to year (t-i), where i is the forecast horizon

Table A1 - data and sample period

Country	stock_price_index	exchange_rate	three_mo_tbill	govt_10yr	D_P	book_market	i_k	housing_i_k	inflation	currentaccount_gdp	extdebtliab_gdp	c_a	real_gdp_growth	central_govt_debt gdp	totalcredit_gdp	bankcredit_gdp	HHdebt_totalassets	totalcreditHH_gdp	HHhousingassets growth	NFCequity_totalliab	totalcreditNFC_gdp	BANKassets_gdp	BANKequity_assets
Argentina	1966	1920	1978		1988	1986			1920	1976	1970		1920	1920	1940	1940							2002
Australia	1920	1920	1928	1920	1920	1980	1960	1960	1920	1960	1970	1960	1920	1920	1954	1920	1978	1977	1961	1981	1977	1920	1983
Austria	1922	1920	1960	1923	1925	1980	1960	1960	1920	1960	1970		1949	1924	1949	1949		1995		1993	1995	1987	1987
Belgium	1920	1920	1948	1920	1927	1980	1960	1960	1921	1960	1970		1935	1920	1970	1970		1980		1981	1980	1981	1981
Brazil	1968	1920	1965	1999	1988	1986			1920	1975	1970		1920	1920	1993	1993							1998
Canada	1920	1920	1934	1920	1934	1980	1960	1960	1920	1961	1970	1961	1920	1920	1954	1920	1970	1969	1971	1981	1969	1920	1981
Chile	1920	1920	1920	2004	1983	1986			1920	1975	1970		1920	1920								1990	1990
China	1990	1948	1980	2007	1995	1993			1979	1982	1981		1995	1982	1985	1985		2006			2006		
Denmark	1920	1920	1921	1920	1969	1980	1960	1960	1920	1960	1970		1922	1920	1951	1951		1994		1981	1994	1920	1979
Finland	1920	1920	1978	1987	1962	1988	1960	1960	1921	1960	1970		1927	1920	1970	1974		1970		2000	1970	1979	1979
France	1920	1920	1922	1920	1920	1980	1960	1960	1920	1960	1970	1960	1921	1920	1969	1920	1970	1977	1971	1981	1977	1950	1988
Germany	1924	1920	1920	1920	1920	1980	1960	1960	1920	1960	1970	1970	1926	1925	1950	1925	1950	1970	1951	1981	1970	1925	1979
Greece	1952	1920	1971	1981	1977	1986	1960	1960	1923	1960	1970		1928	1920	1960	1960		1994		1988	1994		1998
Hong Kong	1964	1920	1982	1994	1972	1980			1948		1979		1961		1978	1978		1990		1993	1990		1993
India	1920	1920	1931	1920	1988	1986			1920	1975	1970		1922	1920	1951	1951		2007		1993	2007		2002
Indonesia	1977	1920	1978	2009	1990	1989			1949	1981	1970		1959	1920	1976	1976		2001		1993	2001		
Ireland	1934	1946	1960	1928	1973	1981	1960	1960	1923	1960	1970		1949	1924	1971	1971		2002		1982	2002	1995	1985
Israel	1949	1920	1983	1998	1993	1993			1923	1995	1970		1951		1999	1999		1999		1993	1999	2000	1997
Italy	1920	1920	1922	1920	1925	1981	1960	1960	1920	1960	1970	1980	1920	1920	1950	1920	1966	1950	1967	1982	1950	1920	1983
Japan	1920	1920	1920	1920	1921	1980	1960	1960	1920	1960	1970	1980	1920	1920	1964	1963	1970	1964	1971	1980	1964	1953	1980
Korea	1962	1920	1969	1973	1963	1986			1949	1970	1971		1954	1920	1962	1960		1962		1987	1962	1990	1990
Malaysia	1973	1920	1961	1961	1972	1986			1949	1974	1970		1956	1949	1964	1964				1993			1990
Mexico	1930	1920	1978	1995	1988	1986			1920	1960	1970		1920	1920	1980	1980		1994		1993	1994	2000	1999
Netherlands	1920	1920	1920	1920	1969	1980	1960	1960	1920	1960	1970		1949	1920	1961	1920		1990		1981	1990	1920	1979
New Zealand	1926	1920	1965	1925	1984	1991	1960	1960	1920	1960	1970		1947	1920								1990	
Norway	1920	1920	1924	1920	1969	1984	1960	1960	1920	1960	1970		1920	1920	1953	1920		1975		1981	1975	1920	1979
Philippines	1952	1920	1976	1994	1982	1987			1920	1977	1970		1947	1948						1989			1996
Portugal	1931	1920	1981	1920	1988	1986	1960		1931	1960	1972		1954	1920	1947	1947		1979		1990	1979		1996
Singapore	1965	1920	1972	1998	1972	1980			1949		1970		1958	1969	1991	1991		1991		1993	1991		1982
South Africa	1920	1920	1936	1920	1954	1980			1920	1962	1970		1920	1920	1965	1965		2009		1993	2009		1991
Spain	1920	1920	1924	1920	1920	1990	1960	1960	1920	1960	1970		1920	1920	1970	1970		1980		1993	1980	1920	1979
Sweden	1920	1920	1920	1920	1920	1982	1960	1960	1920	1960	1970		1920	1920	1961	1920		1981		1982	1981	1920	1979
Switzerland	1920	1920	1920	1920	1920	1980	1960	1960	1920	1960	1970		1930	1924	1975	1975		1999		1993	1999	1920	1979
Taiwan	1967	1920	1974	1995	1988	1986			1920		1977		1920										1997
Thailand	1975	1920	1977	1979	1975	1986			1949	1975	1970		1949	1920	1957	1957		1991			1991		1989
Turkey	1986	1920	1985	2012	1986	1988			1923	1960	1970		1951	1925	1986	1986		1986			1986		2002
UK	1920	1920	1920	1920	1923	1980	1960	1960	1920	1960	1970	1960	1920	1920	1962	1920	1971	1962	1972	1981	1976	1920	1981
US	1920	1920	1920	1920	1920	1980	1960	1960	1920	1960	1970	1960	1920	1920	1952	1920	1946	1952	1947	1952	1952	1920	1980

Table A2: other types of credit variables: the equity premium and skewness

Univariate regressions, 4-quarter ahead forecast horizon

All stocks

	Mean	Median	Difference	Negative Skew	R^2
Δ (bank credit / gdp)	-1.303***	-1.016***	-.287*	1.042*	.025
D/P	1.934***	1.366***	.567**	-2.299**	.022
Δ (totalcredit / gdp)	-.651**	-.475**	-.176*	.785*	.015
Δ (totalcredit HH / gdp)	-.882*	.117	-.999***	2.57***	.007
Δ (totalcredit NFC / gdp)	-1.003**	-1.13***	.127	.064	.021
Δ (BANKassets / gdp)	-.354*	-.114	-.24***	.473**	.011
Δ (HH housing assets)	-.518***	-.321	-.197*	.692*	.017
HH debt / assets	.521*	.572*	-.051	-1.141	0
NFC equity / assets	-.523**	-.198	-.325*	1.628**	.006
Bank equity / assets	-2.557**	-1.728*	-.829	3.149	.007
Δ (U.S. broker-dealer leverage)	-.196*	-.219***	.023	-.197*	.015
Δ (govt debt / gdp)	.325**	.265**	.06	-.117	.006
current acct deficit / gdp	-.479*	-.884***	.404***	-1.368***	.008
Δ (external debt / gdp)	-.334*	.01	-.344***	1.091***	.013

Univariate regressions, 4-quarter ahead forecast horizon

Bank stocks

	Mean	Median	Difference	Negative Skew	R^2
Δ (bank credit / gdp)	-2.007***	-1.087***	-.92***	2.385***	.041
D/P	1.101	.574	.527**	-1.986*	.009
Δ (totalcredit / gdp)	-1.338***	-.844***	-.495***	1.408***	.04
Δ (totalcredit HH / gdp)	-1.652*	-.298	-1.355***	4.374***	.053
Δ (totalcredit NFC / gdp)	-1.776***	-2.132***	.356	-.511	.075
Δ (BANKassets / gdp)	-.806**	-.249	-.557***	1.235***	.033
Δ (HH housing assets)	-.494**	-.264	-.231*	1.323***	.012
HH debt / assets	.118	.071	.047	.538	.002
NFC equity / assets	-.016	-.394	.378	.387	.004
Bank equity / assets	.906	.432	.474	.738	.004
Δ (U.S. broker-dealer leverage)	-.297*	-.233***	-.064*	.12	.017
Δ (govt debt / gdp)	.12	.013	.107	-.508*	.007
current acct deficit / gdp	-.939***	-1.064***	.125	-.161	.015
Δ (external debt / gdp)	-.826*	-.111	-.714***	2.013***	.038