Credit Expansion and Neglected Crash Risk*

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PRELIMINARY DRAFT

Abstract

This paper analyzes the causes and consequences of credit expansions through the lens of equity prices. In a set of 24 developed countries over the years 1920-2012, we find that bank credit expansion predicts not only a significantly increased crash risk in the returns of the bank equity index and equity market index but also lower mean returns of these indices in the subsequent one to eight quarters. Conditional on bank credit expansion of a country exceeding a modest threshold of 1.5 standard deviations, the predicted excess return for the bank equity index in the subsequent eight quarters is significantly negative, with a magnitude of -19.3%. This joint presence of increased crash risk and negative mean returns presents a challenge to the views that credit expansions are simply caused by either banks acting against the will of shareholders or by elevated risk appetite of shareholders, and instead suggests a need to account for the role of over-optimism or neglect of crash risk by bankers and shareholders.

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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). 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 frictions. Such acts 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 also reflect largely increased risk appetite of financial intermediaries due to relaxed Value-at-Risk constraints faced by financial intermediaries (Danielsson, Shin and Zigrand, 2012; Adrian, Moench and Shin, 2013). This view belongs to a large literature that emphasizes the limited capital of financial intermediaries as an important factor driving financial market dynamics.[1] Lastly, 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. 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, 2009).

In this paper, we empirically examine causes and consequences of credit expansion through the lens of equity prices. Several reasons motivate such an analysis. First, price fluctuations of bank stocks and equity indices, 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 to the financial sector and the overall economy. Second, and perhaps more important, since equity prices aggregate expectations and preferences of equity investors, the joint dynamics of equity prices, especially of bank stocks, with credit expansion provide a

[1] See, for example, Shleifer and Vishny (1997), Xiong (2001), Kyle and Xiong (2001), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), He and Krishnamurthy (2012, 2013), and Brunnermeier and Sannikov (2014).

channel to analyze the expectations and preferences of equity investors regarding the financial instability associated with credit expansion.

We focus on three questions regarding credit expansion from the perspectives of equity investors: First, does credit expansion predict an increase in the crash risk of bank stocks and the equity market index in subsequent quarters? This question is motivated by the aforementioned views that credit expansion exposes the financial sector and the economy to instability. Our second question is concerned with whether increased stock crash risk is compensated by a higher equity premium. This question is not only a natural continuation of the first, but also serves as an entry point to evaluate different views about the origin of credit expansion. If credit expansion is simply caused by bankers acting against the will of their shareholders (e.g., active underwriting of poor quality loans), we expect the shareholders to demand a higher equity premium as compensation for the increased crash risk they have to bear. On the other hand, credit expansion may also reflect over-optimism or elevated risk appetite of bankers and their shareholders, in which case there may not be a higher equity premium to accompany the increased crash risk. Finally, we separately measure the equity premium following large credit expansions and contractions. The beliefs view emphasizes the overvaluation of equity during expansions and contrasts with key predictions of the risk-appetite view on the increased equity premium during crises.

Our data set consists of 24 developed economies with data from 1920 to 2012. We measure credit expansion as the three-year change in bank credit to GDP ratio in each country. In contrast to the perception that credit expansions are often global, bank credit expansion actually exhibits only a small cross-country correlation throughout our sample period.

To analyze the first question, we test whether credit expansion predicts a significant increase in the crash risk of future returns of the bank equity index and broad equity market index by estimating a probit panel regression. This estimation shows that credit expansion significantly predicts a higher probability of equity crashes in subsequent quarters. In addition to the probit specification, we also use two alternative measures of negative skewness in stock returns: the distance from the median to the lower tail (5^{th} quantile) minus the distance to the upper tail (95^{th} quantile), and the difference between the mean and median. These alternative measures also confirm the same finding that bank credit expansion predicts a significant increase in the crash risk of subsequent returns of the bank equity index and equity market index. The increase in crash risk is particularly strong for the bank equity index.

Next, we address the second question regarding whether increased crash risk associated with credit expansion is compensated by a higher equity premium. We find that one to eight quarters after bank credit expansions, despite increased crash risk, the mean excess returns of the bank equity index and broad equity index are significantly *lower* rather than higher. One concern is that the lower mean excess returns might be caused by a small number of stock crashes in our sample. Interestingly, bank credit expansion also predicts significantly lower *median* excess returns of the bank equity index and equity market index, which are robust to this small sample concern. The lower median excess return predicted by bank credit expansion suggests that not only there is no premium to compensate for the increased crash risk, the equity premium after credit expansions is lower even in the absence of the occurrence of tail events.

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 a 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, book to market, inflation, the term spread, nonresidential investment to capital, and several other variables, bank credit expansion remains strong in predicting lower mean and median returns of the bank equity index and equity market index.

Taken together, our analysis shows that bank credit expansion predicts increased crash risk in the bank equity index and broad equity index, and the increased crash risk is accompanied by a lower, rather than higher, equity premium. The first part of this finding, while perhaps not surprising, confirms the common theme in the literature of financial instability being associated with bank credit expansion. The second part is more surprising and sheds light on different views about the origin of credit expansion.

To the extent that shareholders do not demand a higher equity premium to compensate them for the increased crash risk, there does not appear to be an outright tension between bankers and shareholders during credit expansions. The lack of such a tension presents a challenge to the narrowly-focused agency view of credit expansion and suggests a need to account for optimism and risk taking by shareholders during credit expansions to fully describe the data.

Furthermore, we find that conditional on credit expansions exceeding a modest threshold of 1.5 standard deviations, the mean excess return for the bank equity index in the subsequent eight quarters is substantially negative at -19.3%. It is difficult to explain this substantially negative equity premium simply based on changes in risk appetite of intermediaries and shareholders. Instead, it points to a need to account for potential over-optimism of bankers and equity investors to fully understand credit expansions in the data.

It is important to note that our findings by no means exclude the presence of distorted incentives of bankers and elevated risk appetite of shareholders in driving credit expansions. To the contrary, it is likely that these factors are jointly present. In particular, in the presence of over-optimism or elevated risk appetite by shareholders, bankers will have even greater incentives to underwrite poor quality loans and seek risk in order to cater or take advantage of their shareholders, e.g., Stein (1996), Bolton, Scheinkman and Xiong (2006) and Cheng, Hong and Scheinkman (2013).

Following Rietz (1998) and Barro (2006), a quickly growing literature, e.g., Gabaix (2012) and Wachter (2013), highlights rare disasters as a compelling resolution of the equity premium puzzle. Gandhi and Lustig (2013) argue that greater exposure of small banks to bank-specific tail risk explains the higher equity premium of small banks. Furthermore, Gandhi (2011) presents evidence that in the U.S. data, aggregate bank credit expansion predicts lower bank returns and argues that this finding is driven by reduced tail risk during credit expansion. In sharp contrast to this argument, by directly examining the equity crash risks subsequent to bank credit expansions in 24 countries, we find increased rather than decreased crash risks. This finding suggests that shareholders do not recognized imminent tail risk during credit expansions. In this regard, our study echoes the notion of Gennaioli, Shleifer and Vishny (2012, 2013) that investors may sometimes neglect tail risk. Our analysis does not contradict the importance of tail risk in driving the equity premium. Instead, it further highlights the importance of accounting for shareholders' subjective beliefs of tail risk, which may or may not be fully consistent with the actual tail risk, in order to systematically understand the equity premium in the data.

Our paper is structured as follows. Section discusses the related literature. Section II presents the empirical hypotheses and empirical methodology used in our analysis. Section III describes the data and presents some summary statistics. We then discuss our empirical results in Section IV and conclude in Section V.

I. Related Literature

The literature has recognized that bank credit expansion can predict banking crises. By using a sample of 34 countries between 1960 and 1999, Borio and Lowe (2002) compare a set of variables, including what they call "gaps" in equity prices, bank credit and investment (periods in which the variables deviate from their historic trends), to predict banking crises and find that the bank credit gap performs the best. Schularick and Taylor (2012) construct a historical data set of bank credit for 14 developed countries over a long sample period of 1870-2008 and confirm that a high growth rate of bank credit predicts banking crises. We expand the data sample of Schularick and Taylor to a larger set of countries and show that the growth rate of bank credit is a powerful predictor of equity crashes. More importantly, our analysis further finds that the increased crash risk is not compensated by a higher equity premium, which helps understand the origin of credit expansions.

Our finding of bank credit expansion predicting an increased equity crash risk reflects reduced credit quality during credit expansions, which is consistent with several recent studies. Greenwood and Hanson (2013) find 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) show 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 showing the poor performance of bank equity returns subsequent to credit expansions, our analysis helps further establish that credit expansions involve not just bankers taking advantage of their bond investors and depositors or implicit guarantees from the governments, which would have also benefited their shareholders, but also entail the presence of optimism or risk taking by their shareholders.

Our study is also related to the growing literature that analyzes 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. Different from these studies, our analysis builds on total quantity of bank credit to GDP rather than intermediary leverage and has a different objective by focusing on the joint dynamics of crash risk and expected returns subsequent to bank credit expansions. Muir (2014) documents that risk premia for stocks and bonds increase substantially during financial crises after financial intermediaries suffer large losses. Different from his focus to highlight reduced intermediary capital as the key driver of the largely increased risk premia during financial crises, our analysis is mostly concerned with the increased crash risk and lower equity premium before crises.

A broader literature investigates real and financial effects of credit expansion from both domestic macroeconomic and international finance perspectives, highlighting various consequences of credit expansion such as bank runs, output losses, capital outflows, and currency crashes.[2] In the aftermath of the recent global financial crisis, this literature has strived to integrate financial instability and systemic risk originating from the financial sector into mainstream macroeconomic models, e.g., Gertler and Kiyotaki (2012), He and Krishnamurthy (2012, 2013), and Brunnermeier and Sannikov (2014). Our paper contributes to this literature by highlighting the need to incorporate the role of beliefs by intermediaries and shareholders leading up to crises subsequent to credit expansions.

By highlighting a possible role of over-optimism and neglect of crash risk in driving credit booms, our analysis echoes some earlier studies regarding the beliefs of financial intermediaries during the housing boom that preceded, and arguably led to, the recent global financial crisis. 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. Cheng, Raina and Xiong (2013) provide direct evidence that employees in the securitization finance industry were more aggressive in buying second homes for their personal accounts than some control groups during the housing bubble and, as a result, performed worse.

[2] Bernanke and Gertler (1989), Kashyap, Stein and Wilcox (1993), Kiyotaki and Moore (1997), and Holmstrom and Tirole (1997) show that credit frictions can have significant and persistent effects on the real economy. Mishkin (1978), Bernanke (1983), and Eichengreen and Mitchener (2003) study the role of credit in the propagation of the Great Depression in the U.S. 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) analyze the role of credit in international financial crises.

II. Empirical Hypotheses and Methodology

This section introduces the empirical hypotheses and regression methodology used in our analysis.

A. Empirical hypotheses

Our analysis focuses on three hypotheses. First, we examine financial instability associated with bank credit expansions by analyzing crash risk in equity prices. When there is a large bank credit expansion in the economy, credit may flow to borrowers with poor credit quality, either households or non-financial firms. Reduced borrower quality exposes banks to increased default risks, which may be realized only after a substantial deterioration in the economy. When default risk becomes imminent, banks' equity prices may crash due to downward spirals that amplify the initial loss.[3] Given the critical role played by banks in channeling credit to the economy, investors' anticipation of the large losses suffered by banks being spilled over to the rest of the economy will also cause the broad equity index to crash along with the bank index.

Motivated by these considerations, we hypothesize that bank credit expansion predicts greater crash risk in the bank equity index and the equity market index, as summarized below.

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

If bank credit expansion is indeed accompanied by an increased equity 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 bank equity index and the equity market index.*

Hypothesis II is motivated by the fact that bank equity prices reflect the aggregate expectations and risk preferences of bank shareholders. If during bank credit expansions

[3] Various channels leading to downward spirals may include capital outflows from financial intermediaries (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, 2012, 2013), margin calls (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009), and reduced collateral capacities (e.g., Geanakoplos, 2010).

shareholders anticipate bankers acting against their will, we expect them to demand a higher equity premium as compensation for the increased crash risk they have to bear. Specifically, option-like compensation contracts incentivize bankers to underwrite poor quality loans and seek risk at the expense of their shareholders and creditors (e.g., Allen and Gale, 2000; Bebchuk, Cohen, and Spamann, 2010). In addition, implicit guarantees from governments create a “too big to fail” problem, leading banks to excessively expand credit to the economy (e.g., Rajan, 2006, 2010; Acharya, et al., 2010). On the other hand, excessive credit expansion induced by implicit government guarantees might even benefit shareholders. Of course, if bankers expand credit to take advantage of implicit government guarantees and if the guarantees provide sufficient protection to equity holders, then there would not be any increased equity crash risk associated with bank credit expansion and equity holders would then earn a reasonable expected return on their equity holdings.

Another view of credit expansion focuses on the role of beliefs. Bank credit expansion may be accompanied by widely spread optimism in the economy, as long emphasized by Minsky (1977) and Kindleberger (1978), which would lead to a lower equity premium or even predictable losses for equity investors. During prolonged economic booms, both bankers and their shareholders may become overly optimistic about the economy due to neglected risk (Gennaioli, Shleifer and Vishny, 2012, 2013), group think (Benabou, 2013), extrapolative expectations (Barberis, 2013), or this-time-is-different syndrome (Reinhart and Rogoff, 2009). Such over-optimism may cause bankers to expand excessive credit to households and non-financial firms and at the same time induce shareholders to ignore increased crash risk.

It is worth mentioning that the agency view and the belief view are not mutually exclusive, as risk-seeking incentives of bankers and over-optimism of shareholders may be jointly present in driving bank credit expansions. In particular, in the presence of overly optimistic shareholders, even rational bankers may underwrite poor quality loans and seek risk to cater or take advantage of their shareholders’ optimism (e.g., Stein, 1996; Bolton, Scheinkman and Xiong, 2006; Cheng, Hong and Scheinkman, 2013).

We next consider a third hypothesis, which explicitly addresses the magnitude of equity premium subsequent to credit expansions.

Hypothesis III: *Predicted equity returns subsequent to credit expansions are negative for both the bank equity index and the equity market index, reflecting the over-optimism of shareholders during credit expansions.*

Hypothesis III serves to differentiate the belief view from another view of credit expansion that highlights the role of risk appetite of the financial sector. According to this view, bank credit expansion can be caused by relaxed risk constraints or an elevated risk appetite of bankers and 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 expand more credit to the economy. In their framework, the elevated risk appetite leads not only to credit expansions but also to a reduced equity premium as financial intermediaries are also the marginal investors in stock markets.

In general, it is challenging to fully separate the effects caused by over-optimism and elevated risk appetite. Hypothesis III explores two dimensions to contrast these views. One is based on how much the equity premium can drop during credit expansions. An elevated risk appetite can reduce the equity premium down to zero but not below zero in standard asset pricing models,[4] while over-optimism can cause equity prices to be substantially overvalued and thus cause the equity premium to be negative. This quantitative difference permits a comparison of these two views.

Generally speaking, theories of the effects of intermediary capital on financial markets, such as those referenced in Footnote 1, typically imply a negative relationship between risk premia in asset prices and intermediary capital and put particular emphasis on the largely increased risk premia after financial intermediaries suffer large losses. In contrast, Hypothesis III is concerned with risk premia during credit expansions, which tend to occur during periods when financial intermediaries are well capitalized.

B. Regression methodology

[4] A caveat is that a sufficiently strong hedging motive by equity holders together with a certain correlation between equity returns and endowment risk faced by equity holders may turn the equity premium to negative.

Our analysis employs three types of panel regressions with fixed effects: the probit regression model to ask whether credit expansion predicts increased crash risk (Hypothesis I), the standard linear panel model to ask whether credit expansion predicts an increased equity premium (Hypothesis II), and a non-linear specification to assess whether large credit expansions predict negative returns in the equity and bank indices (Hypothesis III).

To examine Hypothesis I, we estimate probit regressions with an equity crash indicator as the dependent variable to ask if credit expansion predicts increased likelihood of a market crash. According to Hypothesis I, we expect credit expansion to predict increased tail risk.

Specifically, we estimate the following probit model, which predicts future equity crashes using bank credit expansion and various controls:

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

and compute marginal effects, where Φ is the CDF of the standard normal distribution, and Y is a future crash indicator ($Y = 1_{crash}$), which takes on a value of 1 if there is an equity crash in the next K quarters (K = 1,4, and 8) and 0 otherwise. The crash indicator takes on the value of 1 if the real total return of the underlying equity index or bank equity index is less than -20% in one quarter or less than -30% in two quarters, and 0 otherwise. Given that an increased crash probability may be driven by increased volatility rather than increased negative skewness, we also estimate equation (1) with ($Y = 1_{boom}$), where 1_{boom} is a symmetrically defined positive tail event (with respect to the mean), and compute the difference in the marginal effects between the two probit regressions (probability of a crash minus probability of a boom).

The second regression model is the standard panel regression with fixed effects. OLS with country dummies is used to estimate the following model:

$$E\left[r_{i,t+K} - r_{i,t+K}^{f} \mid (predictor\ variables)_{i,t}\right]_{BLP} =$$

$$\alpha_i + \beta^{'}(predictor\ variables)_{i,t} \qquad (2)$$

For Hypothesis II, we test whether β_{mean}, the coefficient of credit expansion in equation (2), is different from zero. Equation (2) is the best linear predictor (BLP) of the equity premium (excess return of either the bank equity index or market index) conditional on the predictor variables. By using a fixed effects model, we test Hypothesis II by focusing on the time series dimension within countries: the predictor variables come from different sources for different countries, so direct comparisons across countries are not feasible.

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, 1999) and time-varying long-run consumption risk (Bansal and Yaron, 2004). A host of variables are known to predict the time variation in the equity premium, such as dividend yield, inflation, the book to market, the term spread, investment to capital, the corporate yield spread, 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 associated with bank credit expansion.

To examine Hypothesis III, we estimate a non-linear model of the predicted equity excess return subsequent to a significant credit expansion:

$$r_{i,t+K} = \alpha_i + \beta \cdot 1_{\{credit\ expansion > x\}} + k \cdot controls + \epsilon_{i,t}, \tag{3}$$

where $x > 0$ is a threshold for credit expansion, expressed in standard deviations from each country's mean. In the absence of controls, this model is equivalent to computing a simple average conditional on credit expansion exceeding the given threshold x. The advantage of this formal estimation technique over simple averaging is that it allows us both to add control variables and also to compute dually-clustered standard errors for hypothesis testing, since the error term $\epsilon_{i,t}$ is possibly correlated both across time and across countries. This model specification is non-linear with respect to credit expansion and thus also serves to ensure that our analysis is robust to the linear regression model in equation (2). After estimating this model, we report a t-statistic to test whether the predicted equity premium $E[r_{i,t+K} \mid \cdot\,]$ is significantly different from zero.

Furthermore, to determine whether the predicted equity excess return is symmetrical with respect to credit expansions and contractions, we also estimate a similar model by conditioning on credit contraction, i.e., credit expansion lower than a negative threshold $y < 0$:

$$r_{i,t+K} = \alpha_i + \beta \cdot 1_{\{credit\ expansion<y\}} + k \cdot controls + \epsilon_{i,t}. \tag{4}$$

We also employ several other specifications as robustness checks. Returning to Hypothesis I, to assess the robustness of crash risk coefficients estimated from probit regressions, we adopt two alternative approaches. One of the alternatives is to estimate crash risk in returns using a quantile-based approach, which studies crash risk without relying on a particular choice of thresholds for crash indicator variables. Specifically, the quantile-based approach estimates the best linear predictor (BLP) of the qth quantile of future equity excess returns conditional on the predictor variables:

$$Quantile_q\left[r_{i,t+K} - r^f_{i,t+K} \mid (predictor\ variables)_{i,t}\right]_{BLP}$$

$$= \alpha_{i,q} + \beta_q^{'}(predictor\ variables)_{i,t} \tag{5}$$

This quantile regression allows one to study how predictor variables relate to the entire shape of the distribution of future returns, not just the mean of the distribution. For example, if credit expansion increases the likelihood or severity of a market crash, we should see this effect by looking at the lower tail of returns, for example the 5th quantile.[5] Thus, as an alternative robustness check to test Hypothesis I, we employ jointly estimated quantile regressions to compute the following negative skewness statistic to ask whether credit expansion predicts increased tail risk:

$$\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}) \tag{6}$$

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. As with the probit regressions, we do not measure just $(\beta_{q=50} - \beta_{q=5})$, the distance between the median and the

[5] Quantile regression estimates have a slightly different interpretation from those of crash indicator probits: indicator probits analyze the frequency of tail events, while quantile movements indicate the severity of tail events. It is possible, for example, for the frequency of crash events to stay constant, while the severity of such events to increase.

left tail, because a larger number could simply be indicative of increased conditional variance. Instead, we measure the asymmetry of the returns distribution, the increase in the lower tail minus the increase in the upper tail.[6]

The second alternative measure of the impact of credit expansion on negative skewness of subsequent equity returns is (β_{median} - β_{mean}), the difference between the coefficient from a median regression (50th quantile regression) and the coefficient from the mean regression.

Special care must be taken to estimate these aforementioned predictive return regressions in a financial panel data setting. An important concern is that both outcome variables (e.g. non-overlapping n-quarter-ahead excess returns, n = 1, 4, and 8) and explanatory variables (e.g. bank credit expansion and controls) are correlated across countries (due to common global shocks) and over time (due to persistent country-specific shocks). If these concerns are not appropriately accounted for, the standard errors of the regression coefficients can be biased downward. Therefore, we estimate standard errors that are dually clustered on time and country, following Thompson (2011), to account both for correlations across countries and over time.

We also take a deliberately conservative approach by using non-overlapping returns. That is, in calculating 4- or 8-quarter ahead returns, we drop the intervening observations from our data set. As a result, we can assume that auto-correlation in the dependent variables (excess returns) is likely to be minimal. Using non-overlapping returns thus makes our estimation robust to many potential econometric issues involved in estimating standard errors of overlapping returns.

For the panel linear and probit regression models with fixed effects, Thompson's dually-clustered standard errors are implemented in Stata using White standard errors adjusted for clustering on time and country separately, and then combined into a single standard error estimate using the formula derived in Thompson (2011). For quantile regressions (including median regressions), we estimate dually-clustered standard errors by block bootstrapping, drawing blocks that preserve the correlation structure both across time and country. In the case of

[6] In the statistics literature, this measure is called the quantile-based measure of skewness. We use the 5th and 95th quantiles to represent tail events. While looking at more extreme events (i.e. the 1st and 99th 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 increasingly rarer with smaller quantiles. Using the 5th and 95th quantiles is a good compromise to obtain high statistical power, allowing the sample of rare events to be large enough while also being indicative of large negative movements in prices.

testing linear restrictions of coefficients, multiple regressions are estimated simultaneously to account for correlations in the joint estimates of the coefficients. For example, in testing the null H_0: $\beta_{negative\ skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}) = 0$, standard errors are generated by block bootstrapping *simultaneous* estimates of the q=5, 50, and 95 quantile regression. Similarly, the difference between the mean and median coefficients, H_0: $\beta_{mean\text{-}median} = 0$, is tested by *simultaneously* bootstrapping mean and median coefficients; the resulting Wald statistic is then used to compute a p-value.

III. Data and Summary Statistics

We construct a panel data set of 24 countries from 1920 to the present using quarterly data. The main outcome variables in our dataset are excess returns of the bank equity index and equity market index. The main predictor variable is three year change in bank credit to GDP. In addition, we employ a host of financial and macroeconomic variables, which are known to predict the equity premium and serve as controls.

The data set is complete for most countries from around 1960 onwards, and for a third of the countries from around 1920 onwards. The sample length of each variable for each country can be found in Table A1 in the appendix.

A. Key variables

Our main predictor variable is the three year change in *bank credit to GDP*. *Bank credit* refers to credit extended from banks to domestic households and private non-financial corporations. It excludes interbank lending and thus only includes non-public end users of credit.[7] 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 extend back over a century but only for 14 countries.

[7] We use bank credit to GDP rather than a measure of bank leverage (such as bank book equity to assets) for a practical reason. Measures of bank leverage are available for most countries only after 1980. As we will show later, bank credit to GDP is highly correlated with bank leverage measures.

Throughout the paper, we refer to the three-year change in bank credit to GDP as "bank credit expansion" (or "contraction" when the change is negative). We look at three year changes, rather than levels, for the following reasons. First, as shown later on in Figure 2, bank credit is rising during booms and falling during crises, while the level may still be high *after* the crisis or crash. Thus, the change of credit, not the level, is more indicative of economy-wide expansion and contraction and separates before versus after the start of banking crises. Second, credit as a percentage of GDP exhibits long-term trends presumably related to structural and regulatory factors. Differencing bank credit removes the secular trend and allows us to focus on cyclical movements corresponding to credit expansions and contractions.[8] When estimating regressions, we normalize the three year change in bank credit to GDP by its mean and standard deviation within each country.

The main outcome variable is future excess returns for both the equity market index and the bank equity index for each country. Our main source for the price series of both indices is Global Financial Data (GFD), and we choose well-known broadly-focused, market-cap-weighted indices for each country. We construct *bank equity excess returns* and *equity excess returns* for all countries by subtracting the *short-term interest rate* from the equity returns. Total returns are constructed by adding *dividend yield*: the dividend yield of the equity index is taken mainly from GFD, and a dividend yield for the bank index for each country was constructed from individual banks' dividend yields using Compustat, Datastream and hand-collected data from Moody's Bank and Finance Manuals.[9] For forecasting purposes, we construct one-quarter-ahead excess returns by applying a lead operator to the excess returns. We also construct 4-, and 8-quarter-ahead excess returns in a non-overlapping fashion.[10]

We also employ several financial and macroeconomic variables known to predict the equity premium as controls. The main control variables are *dividend yield, book-to-market, inflation,*

[8] 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.

[9] See the Appendix for details on constructing the price and dividend yield indices for bank stocks in each country Due to the difficulty in obtaining historical data, the bank dividend yield index for each country does not necessarily contain exactly the same banks as the bank price index.

[10] Throughout the 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. Inflation over 30% rarely occurs in developed countries in the post-war period.

non-residential investment to capital, and the *term spread*. The variables *corporate yield spread* and *household consumption to wealth* are only reliably available for several countries and, while used in some of our analysis, are generally not included as the main control variables due to limited data availability. We also employ various other measures of aggregate credit and leverage of the household, corporate and financial sectors, and measures of international credit. Further information on data sources and variable construction for all variables can be found in the Appendix.

Finally, we also define a *crash indicator*, which takes on the value of 1 if the real return of the underlying equity index is less than -20% in one quarter or less than -30% in two quarters, and 0 otherwise.

B. Summary Statistics

Table 1 presents summary statistics for equity index returns, bank equity index returns and credit growth. Observations in Table 1 are pooled across all time periods and countries. Table 1 reports summary statistics for: equity excess returns, equity total excess returns (excess index returns + dividends), equity real total returns (index returns + dividends - inflation), and bank equity excess returns, excess total returns, and real total returns (defined as above but for the bank equity index). The returns and standard deviations are all expressed as annualized log returns. The label Δ (bank credit / GDP) is the annualized three-year change in bank credit to GDP.

As can be seen in Table 1, the mean equity excess return is 7.1% (3.4% without including dividends). The mean equity real return is 8.8%. Bank stocks have slightly lower mean excess returns (6.7% with dividends, 3.7% excluding dividends, and 7.9% real returns). We also report the median returns for all variables. The standard deviations of returns are around 20-30% for equity index returns, with higher numbers for bank stock returns.

Given that we define crash indicator variables and negative skewness statistics from quantile regressions based on 5th percentile events, it is useful to get a sense of what magnitude drops these percentiles correspond to. A 5th percentile drop, which occurs on average once every 5 years, corresponds to a -65.7% annualized real return, which translates to a -16.4% quarterly real return. On this basis, the crash indicator defined earlier, based on the real return of the equity index being less than -20% in one quarter or less than -30% in two quarters, corresponds to an event that occurs 3.6% of quarters, or once every 7 years on average.

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 terms of the variability of credit expansion, bank credit expansion grew as rapidly as 12.0% of GDP per year (99th percentile) and contracted as rapidly as -6.7% of GDP per year (1st percentile).

The variability of bank and total credit expansion can be seen visually in Figure 1, which plots Δ (bank credit / GDP) over time. The time series for all countries appear mean-reverting and cyclical, with periods of rapid credit expansion often followed by periods of credit contraction.

Table 2 provides additional characteristics of bank credit expansions. Panel A summarizes several variables that predict future credit expansion based on an OLS panel regression with fixed effects for the three-year change of bank credit to GDP (normalized within each country) against the three-year lagged value of each of the following variables: daily equity market volatility, real GDP growth, the corporate spread, and the sovereign yield spread. Consistent with our expectations, bank credit expansions tend to follow good economic states. More specifically, low daily equity market volatility, high real GDP growth, smaller corporate yield spreads, and lower sovereign yield spreads in the past three years tend to precede larger bank credit expansions in the subsequent three years.

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 to GDP, and growth of household housing assets), leverage (of the household, corporate, and banking sectors), and with change in international credit (current account deficits to GDP and change in gross external liabilities to GDP). All variables here are normalized within each country. In particular, R^2 is high for the total credit, household and corporate credit, bank assets, change in gross external liabilities, and household and corporate leverage, demonstrating the tight correlation between different measures of credit.

In Figure 2, we see that historical banking crises, based on data from Reinhart and Rogoff (2009), are accompanied by large drops in equity markets, and especially in bank stocks. On average, the equity market drop starts roughly one year before the start of the banking crisis and continues until two to three years after the start of the crisis. The fact that equity prices drop before the actual banking crises confirms a common wisdom that equity prices tend to anticipate future events that might affect the firms and the economy. In addition, credit peaks at the start of the crisis, with credit gradually contracting during the subsequent two years.[11]

Table 3 presents cross-country correlations of a set of variables. To economize on space, Table 3 only presents the cross-country correlations of other countries with the U.S. In general, quarterly equity excess returns are moderately correlated across countries (average correlation = 0.49) and bank equity excess returns are even less so (0.35). Bank credit expansions have historically been relatively idiosyncratic in nature (average correlation = 0.06), which is surprising, considering that the two most prominent credit expansions, those leading up to the Great Recession 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 may be attributed directly to local credit expansions and not indirectly through spillover from crises in other countries.

IV. Empirical Results

In this section, we report our empirical findings. We first demonstrate that credit expansion predicts an increased equity crash risk in subsequent quarters and then that credit expansion predicts a decrease in mean equity excess returns. Next, we report mean equity excess returns, conditional on bank credit expansion either exceeding a positive threshold or falling below a negative threshold. Finally, we provide a set of robustness checks of our results.

A. Predicting crash risk

To test Hypothesis I, we estimate the probit regression model specified in equation (1) to examine whether bank credit expansion (normalized within each country) predicts an increased probability of equity crashes, both in the bank equity index and the market index, in subsequent 1, 4, and 8 quarters. Table 4 reports marginal effects estimated from the probit model, with the

[11] The gradual contraction process is likely due to credit lines pre-committed by banks, which, as documented by Ivashina and Scharfstein (2010), prevented banks from quickly reducing outstanding bank loans during the recent financial crisis.

dependent variable being the crash indicator ($Y = 1_{crash}$), which as defined in Section III takes on a value of 1 if there is a future equity crash in the next K quarters (K = 1, 4, and 8) and 0 otherwise. Given that an increased crash probability may be driven by increased volatility rather than increased negative skewness, we also estimate equation (1) with ($Y = 1_{boom}$) as the dependent variable, where 1_{boom} is a symmetrically defined positive tail event and then compute and test the difference in the marginal effects between the two probit regressions (i.e. we calculate the increased probability of a crash minus the increased probability of a boom).

Table 4 reports the marginal effects corresponding to crashes in the bank index (panel A) and in the equity index (panel B) conditional on a one standard deviation increase in bank credit expansion. Regressions are estimated with and without the five standard controls. The blocks of columns in Table 4 correspond to 1-, 4-, and 8- quarter-ahead excess returns. Each regression is estimated with three sets of controls: the first block of rows (rows 1-3) reports marginal effects conditional on credit expansion with no controls, the second block of rows (rows 4-10) adding two of the strongest controls, dividend yield and inflation, and the third block of rows (rows 11-23) uses all five main control variables.

Table 4 demonstrates that bank credit expansion predicts an increased probability of negative tail events. The interpretation of the reported marginal effects is as follows: using the estimates for 1-, 4-, and 8-quarter horizons without controls, a one standard deviation rise in Δ (bank credit / GDP) is associated with a subsequent increase in the probability of a crash in the bank equity index by 2.4%, 4.8%, and 6.0%, respectively, and a crash in the market equity index by 2.1%, 4.4%, and 6.8%, respectively, all statistically significant at the 5% level. The marginal effects are slightly reduced but still significant after adding controls: after adding in all five controls, a one standard deviation rise in Δ (bank credit / GDP) is associated with a subsequent increase in the probability of a crash in the bank equity index by 1.5% (not significant), 3.9%, and 5.2%, (for 1-, 4-, and 8-quarter horizons, respectively), and a crash in the market equity index by 1.4%, 4.0%, and 6.3%, respectively, all but one statistically significant at the 5% level. In fact, the control variables are often statistically significant too: lower dividend yield, lower term spread, lower book to market, and higher investment to capital all predict increased negative tail risk.

To distinguish increased crash risk from the possibility of increased volatility of returns conditional on credit expansion, we subtract out the marginal effects estimated for a symmetrically defined positive tail event (i.e. using $Y = 1_{boom}$ as the dependent variable). After doing so, the marginal effects stay about the same or actually increase slightly: the probability of a boom conditional on credit expansion tends to decrease, while the probability of a crash increases, suggesting that the probability of an equity crash subsequent to credit expansion is driven primarily by increased negative skewness rather than increased volatility of returns.

In summary, consistent with Hypothesis I, we find that bank credit expansion predicts an increase in the crash risk of returns of the bank equity index and equity market index in the subsequent 1 to 8 quarters. This predictability is particularly strong for the bank equity index. This result expands the findings of Borio and Lowe (2002) and Schularick and Taylor (2012) by showing that bank credit expansion not only predicts banking crises but also equity crashes, and especially crashes of bank stocks, which tend to precede banking crises.

B. Predicting the equity premium

We now turn to testing Hypothesis II. Table 5 estimates the panel regression model specified in equation (2) of Section II.B (the standard OLS fixed effects model), which predicts future equity excess returns conditional on a one standard deviation increase in credit expansion.

Various columns in Table 5 report estimates of regressions on credit expansion without controls, with two controls, with all five main controls (dividend yield, book to market, term spread, investment to capital, and inflation), and with two additional controls (consumption to wealth, corporate yield spread) for which there is limited data availability. The main reason for including subsets of controls is to evaluate whether bank credit expansion predicts the equity premium because it is closely related to any 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 mostly unchanged in the presence of the controls. Our criterion for adding subsets of controls is to start with controls that are most statistically significant and for which there is most availability of data. We save corporate yield spread and consumption-to-wealth until the end, due to relatively limited data availability, which cuts the sample size for these regressions by almost two-thirds and thus precludes the use of these two additional variables as standard controls in the rest of the paper.

Panel A reports coefficients for the bank equity index as the dependent variable, and panel B reports coefficients for the equity market index. Groups of columns correspond to 1- 4-, and 8-quarter-ahead excess returns. Coefficients and t-statistics are reported, along with the (within-country) adjusted R^2 for the mean regressions.

The coefficients from the mean regression measures the change in the equity premium associated with normalized credit expansion. For the bank equity index, a one standard deviation increase in bank credit expansion predicts a change in excess returns by -0.011, -0.049, and -0.083 for the subsequent 1-, 4-, and 8-quarter, respectively (all significant at the 5% level). The adjusted R^2 ranges from less than 1% for 1-quarter horizons to 3% for 8-quarter horizons. When the controls are included, the coefficients generally are slightly lower and have similar statistical significance, and the adjusted R^2 is increased across all horizons, and in particular with five controls, from 1.0% for the 1-quarter horizon to 4% for the 8-quarter horizon.

For the equity market index, the coefficients are smaller: -0.009, -0.039, and -0.055 (all significant at the 5% level) for 1-, 4-, and 8-quarter-ahead excess returns, respectively.[12] Coefficient estimates remain similar in magnitudes after including the controls.

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

Finally, looking at the controls in Table 5, we see that higher dividend yield, book to market, the term spread, corporate yield spread, and consumption to wealth are all associated with a higher equity premium, while higher inflation and investment to capital are both associated with a lower equity premium. The signs of the coefficients are in line with prior work on equity premium predictability. Most importantly, the coefficient for bank credit expansion remains

[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); 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 similar coefficients when regressed on bank credit expansion.

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

approximately the same magnitude and significance, despite the controls that are added.[14] Thus, bank credit expansion adds new predictive power beyond these other variables and is not simply proxying for another predictor of the equity premium.

Taken together, our analysis so far shows that bank credit expansions are followed by increased crash risk in returns of the bank equity index and equity market index, and that despite the increased crash risk, the predicted equity excess return falls rather than increases.[15] It is important to note that bank credit expansions are directly observable to the public. Thus, it is rather surprising that bank shareholders and stock investors do not demand a higher equity premium from their stock holdings to compensate them for the increased crash risk. This finding challenges the narrowly-focused agency view that bank credit expansions are simply caused by bankers acting against the will of shareholders. Instead, our finding suggests the presence of either over-optimism or elevated risk appetite of stock investors during the periods of bank credit expansions.

C. Excess returns subsequent to credit expansions and contractions

In this subsection, we test Hypothesis III by examining the magnitude of equity excess returns subsequent to credit expansions and contractions by estimating the non-linear regression models (3) and (4) discussed in Section II.B. These regressions robustly test whether the predicted excess return is negative subsequent to a credit expansion and positive subsequent to a credit contraction. We also compare the magnitude of the predicted excess return conditional on a credit expansion and contraction of the same size to examine whether the effects are symmetrical.

Recall equations (3) and (4) from Section II.B. We regress 4-, 8-, and 12-quarter-ahead excess returns on either an indicator for credit expansion exceeding a positive threshold or an indicator for credit contraction falling below a negative threshold, along with the five standard

[14] The exception are the regressions with the corporate yield spread and consumption to wealth as controls. However, the t-statistics corresponding to the coefficient for Δ(bank credit / GDP) are still high but just below the 1.97 cut-off to be significant, and the lack of significance is primarily due to the sharply reduced sample size, which results from adding these two controls to the regression.

[15] Gandhi (2011) shows that in the U.S. data aggregate bank credit expansion negatively predicts the mean return of bank stocks. However, he does not examine the joint presence of increased crash risk subsequent to bank credit expansions.

control variables. This non-linear specification allows us to compute the predicted excess return conditional on a substantial credit expansion or contraction without relying on the linear specifications used in our earlier analysis.

Figure 3 plots the predicted 8-quarter-ahead excess returns for the positive threshold varying from 0 to 2 standard deviations and the negative threshold from 0 to 2 standard deviations. Panel A is for the bank equity index, and panel B is for the equity market index. The black lines are estimates without control variables, and the blue lines are estimates with controls. A 95% confidence interval is shown for each point. The point estimates and corresponding t-statistics are also reported in Table 6, along with number of historical episodes (defined either as separate countries or separate historical periods within one country) meeting the credit expansion threshold to verify that the results are not being driven by a small number of observations.

Figure 3 and Table 6, together, show that the predicted excess returns subsequent to large credit expansion are robustly negative. When credit expansion exceeds 1.5 standard deviations (a substantial but reasonably frequent event), the predicted excess return in the subsequent 8 quarters is -19.3% for the bank index (significant at the 1% level). As there are 23 historical episodes (defined as separated times in history) satisfying this criterion, this substantially negative return is not just driven by a few observations. By varying the credit expansion threshold, the predicted excess returns for both the bank equity index and the equity market index are decreasing with the threshold, and remain negative across the thresholds.

The large and significantly negative excess return predicted by credit expansion confirms Hypothesis III and presents a challenge for models that, as referenced in the introduction, use only elevated risk appetite to explain the joint presence of increased crash risk and decreased mean return subsequent to credit expansion. We are not aware of any existing model in this literature that captures this. Instead, our findings are consistent with shareholders being overly optimistic and neglecting the subsequent crash risk during credit expansions.

Furthermore, Figure 3 and Table 6 also show that subsequent to credit contractions, the excess return is positive. When credit contraction is greater than 1.5 standard deviations, the predicted excess return in the subsequent 8 quarters is 22.9% for the bank index, both significant at the less than 5% level. As bank credit tends to contract after a banking crisis, the positive equity premium subsequent to a credit contraction is consistent with the findings of Muir (2014) that risk premia tend to be large during financial crises.

D. Robustness

In this subsection, we perform several robustness checks. First, we adopt alternative measures of crash risk and the equity premium. Next, we examine subsamples of countries and periods. Finally, we verify that small-sample bias is not a concern.

D.1 Quantile regression-based measures

To assess the robustness of our main results on increased crash risk and lower equity premium subsequent to credit expansions, we adopt alternative measures of crash risk and equity premium based on quantile regressions.

First, as an alternative to probit regressions, we employ two alternative measures of crash risk by using quantile regressions. Recall the quantile regression model specified in equation (5) of Section II.B, which examines the predictability of bank credit expansion (normalized within each country) for the full distribution of subsequent equity returns. This quantile regression-based approach allows one to study crash risk without relying on a particular choice of thresholds for crash indicator variables. Table 7 reports estimates from the quantile regressions. The columns correspond to 1-, 4-, and 8- quarter-ahead excess returns, first for the bank equity index and then for the equity market index. The top portion reports estimates for quantile regressions on credit expansion with no controls, the bottom portion reports estimates on credit expansion with the standard set of five controls (dividend yield, inflation, book to market, term spread, and investment to capital). The coefficients and t-statistics for credit expansion are reported for the three quantile regressions, $\beta_{q=5}$, $\beta_{q=50}$, and $\beta_{q=95}$, followed by the first alternative crash risk measure — the conditional negative skewness coefficient $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$ — and its associated t-statistic. To save space, coefficients on control variables are not reported in Table 7.

For bank equity index returns without control variables, the coefficients for negative skewness, $\beta_{\text{negative skew}}$, are estimated to be 0.027, 0.078, and 0.129 (all significant at the 5% level) for 1-, 4- and 8-quarter horizons, respectively. Similar but less pronounced patterns are observed for the equity market index. The interpretation of the conditional skewness coefficient is as follows: using the estimate for 4-quarter horizon for the bank equity index, a one standard deviation rise in Δ (bank credit / GDP) is associated with a 7.8% increased drop for a left tail event relative to a right tail event. In other words, left tail events become increasingly severe following credit expansion.

Once the controls are included, the coefficient for the 1- quarter horizon remains roughly the same and significant at the 5% level, while for the 4- and 8-quarter horizons become smaller and insignificant. As one would expect, tail risk for equity market index returns has a smaller association with bank credit expansion because the tail risk in the equity market index originates indirectly from the financial instability of banks. These results in general reinforce the conclusion from examining crash risk from probit regressions in Table 4

The second alternative measure of the impact of credit expansion on negative skewness of subsequent equity returns is (β_{median} - β_{mean}), the difference between the coefficient from a median regression (50th quantile regression) and the coefficient from the mean regression. Table 7 reports the difference between mean and median coefficients, β_{mean} - β_{median}, along with an associated p-value. The estimates are 0.005, 0.023, and 0.06 for the bank equity index and 0.004, 0.013 and 0.018 (not significant), for the equity market index at the 1-, 4- and 8- quarter horizons, respectively; all significant at the 5% level or less except for the one marked. After including the controls, the estimates remain at similar values, though less statistically significant. As β_{mean} - β_{median} provides an alternative measure of the negative skew in equity returns, this result again confirms the finding in Table 4 that bank credit expansion predicts a significant increase in the negative skew of the subsequent returns of the bank equity index and equity market index.

In addition to providing an alternative estimate of negative skewness in subsequent equity returns, β_{median} is also useful as a robustness check for the mean regression specified in equation (2) for predicting the equity premium. Due to the increased crash risk associated with credit expansion, one might argue that the lower mean returns might be strongly influenced by a small number of crashes in the sample period. To address this concern, we also examine the estimate of β_{median} with a quantile regression with similar specification, which provides an upper bound on β_{mean}.We interpret β_{median} as measuring 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.

Table 7 reports estimates for median coefficients to be -0.006, -0.026, and -0.048 (not significant) for the bank equity index and -0.005, -0.024, and -0.056 for the equity market index (1-, 4- and 8- quarter horizons, respectively). All coefficient estimates except the one marked are significant at the 5% level. After including the controls, the estimates remain at similar values. In general, the median coefficients are about 1/2 to 2/3 the level of corresponding mean coefficients, which imply that about 1/3 to 1/2 of the decrease in the mean equity return is driven by an increase in the severity or frequency of negative tail events. The lower median excess return predicted by bank credit expansion suggests that the equity premium during credit expansions is lower even in the absence of the occurrence of tail events.

D.2 Robustness in subsamples

Table 8 reports mean and probit coefficients for Δ (bank credit / GDP) on future equity excess returns for various subsets of countries and time periods. Using a 4-quarter forecasting horizon, the regressions are the same as those reported in Tables 4 and 5. In Panel A, the data is subdivided into geographical regions, and separate regressions are run for each of the regions. In Panel B, we change the time period: one set of regressions is run on the full sample (1920-2013), another is run excluding the most recent crisis (1920-2005), and a third is run excluding both the recent crisis and the Great Depression (1950-2005).

In Panel A, for both the bank equity index and the equity market index, we see that the coefficients for the mean and probits are similar 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 (South Europe, Western Europe, Scandinavia, Asia) and slightly lower for other regions (and the U.S. and English-speaking countries). The statistical power is reduced for several regions, though that is probably due to the smaller sample size in these subsets. The probit coefficients for both the bank equity index and equity market index are similar across regions, and with somewhat less statistical power due to the smaller sample size.

Panel B shows the estimated mean and probit coefficients of Δ (bank credit / GDP) on future excess returns for different sample periods. In general, the coefficients have almost the same magnitude and statistical significance regardless of the sample period we use.

D.3 Test for small-sample bias

It is well known that conventional tests of predictability in equity returns may produce biased estimates of coefficients and standard errors in small samples when a predictor variable is persistent and its innovations are highly correlated with returns, e.g., Stambaugh (1999). The reason is that conventional statistical inference relies on asymptotic distribution theory to ensure unbiased estimators in the limit as $N \rightarrow \infty$, so standard estimators may be substantially biased in a finite-sample in certain situations, such as when a predictor variable is persistent and its innovations are highly correlated with returns. Small-sample bias could potentially pose a problem for estimating coefficients in this paper, because the main predictor variable, three-year change in bank credit, is highly persistent on a quarterly level, both because quarterly change in bank credit is persistent due to fundamental reasons and because taking three year changes adds additional autocorrelation across three year periods.

In this section, we test for the possibility of small-sample bias using the methodology of Campbell and Yogo (2006) and find that small-sample bias is most likely not a concern for our estimates. The idea behind the methodology of Campbell and Yogo (2006) is that three conditions need to be jointly met for small-sample bias to be a concern: 1) the predictor variable needs to be persistent, which is observed in our data; 2) innovations need to be highly correlated with returns, which is only minimally true in our data, and 3) the sample size needs to be small, whereas our international data set is large compared to most single-country tests of return predictability. Campbell and Yogo (2006) present Monte Carlo evidence — demonstrating when small-sample bias is and is not likely a concern, as a function of the parameter values corresponding to the sample size, persistence of the regressor, and the correlation of its innovations with returns.[16] We show that our data correspond to parameter values well outside the region for which small-sample bias is likely to be a concern.

[16] Specifically, the Monte Carlo simulations report regions of the parameter space for which the actual size of the nominal 5% t-statistic (generated when testing the estimated β against the true β_0 with null hypothesis $\beta = \beta_0$ and alternative $\beta > \beta_0$) is greater than 7.5%.

Following the Campbell and Yogo (2006) methodology, we estimate the following regressions:

$$r_{i,t+K} = \alpha_i + \beta \cdot credit\_expansion_{i,t} + u_{i,t} \quad (7)$$

$$credit\_expansion_{i,t+K} = \gamma_i + \rho \cdot credit\_expansion_{i,t} + \epsilon_{i,t} \quad (8)$$

Table 9 reports parameter values corresponding to the sample size (N), persistence of the main predictor variable, bank credit expansion (ρ and c = N*(ρ-1)), and the correlation of its innovations with returns (δ = corr($u_{i,t}$, $\epsilon_{i,t}$)). In addition, to test for small-sample bias in multivariate regressions that use the five standard control variables, we estimate the following additional regression:

$$r_{i,t+K} = \alpha_i + k \cdot controls_{i,t} + z_{i,t} \quad (9)$$

and replace the left-hand side variable in equation (7) with the residual, $z_{i,t}$, taken from equation (9). Parameters obtained in the presence of control variables are also reported in Table 9.

From Table 9, we can see that all the values of δ are less than 0.125 (meaning there is minimal correlation between innovations in credit expansion with equity returns), the critical threshold reported in Campbell and Yogo (2006) for which small-sample bias is likely not to be a problem regardless of the value of c. In addition, because of the large sample size of our data, c = N*(δ-1) is universally larger than the threshold for which small-sample bias is likely not to be a problem regardless of the value of δ. Thus, our data correspond to parameter values well outside the region for which small-sample bias may be a concern. Because our data set is a panel and because fixed effects may also cause biased estimates in small samples, as an extra and overly-conservative robustness check, we also obtain tables of parameter estimates for each of the 24 countries individually (results not reported) and find that individual countries' parameters, with only rare exceptions, also fall into the region for which small-sample bias is not likely to be a concern.[17]

[17] Cases in which parameters fall into the region for which small-sample bias may be a concern: Finland (1, 4, 8-quarters, both bank and equity index returns), Ireland (4, 8-quarters, bank returns), Portugal (8-quarters, equity index returns), and Spain (1-quarter, both bank and equity Index returns). However, all these cases had very small sample sizes (N < 20).

V. Conclusion

In a set of developed economies, we find that bank credit expansion predicts significantly increased crash risk in the returns of the bank equity index and equity market index in subsequent one 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. The predicted equity premium of the bank equity index in the eight quarters after credit expansion in a country exceeding 1.5 standard deviations is significantly negative with a magnitude of over -28%. It is difficult to explain the joint appearance of increased crash risk and decreased excess return subsequent to credit expansions simply by bankers acting against the will of shareholders or by elevated risk appetite of bankers and intermediaries. Instead, our findings suggest a need to account for the role of over-optimism or neglect of crash risk by shareholders.

Appendix

This appendix contains additional information related to data sources and variable construction. The sample length for each country and variable is reported in Table A1. All older historical data was extensively examined country-by-country for each variable to ensure accuracy and was compared across multiple sources whenever possible.

Bank credit expansion. The main explanatory variable is bank credit to GDP. As explained in Section III, bank credit refers to credit extended from banks to private end users of credit: domestic households and private non-financial corporations. The data for this variable are derived from two sources: “bank credit” from the BIS's “long series on credit to private non-financial sectors” and from the data of Schularick and Taylor (2012) on “bank loans.” In merging the two series, we scale the level of "bank loans" to avoid breaks in the series. Still, there are slight discrepancies between the two data sources, most likely coming from differing types of institutions defined as banks, differing types of credit instruments considered “credit,” and differing original sources used to compile the data. Fortunately, the BIS and Schularick-Taylor data match qualitatively, as their overlap is highly correlated.

Market and bank index excess total returns. We chose well-known broadly-focused, market cap weighted indices for each country. Our main data source for equity returns was Global Financial Data (GFD), though in a few cases we took data directly from stock exchanges' websites. In countries with several internationally-known equity indices (for example, the S&P 500, DJIA and NASDAQ in the U.S.), we favor the index 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, an index of the financial sector (see Table A2, Panel A in the Online Appendix for details on bank price index construction). Total returns are constructed by adding dividend yield: To get total returns, the dividend yield of the equity index is taken from GFD (occasionally supplemented by Compustat and Datastream), and a dividend yield for the bank index for each country was constructed from individual bank’s dividend yields using Compustat and Datastream (1973 onwards) and from hand-collected price and dividend data (1920–1978) of the largest publicly-listed banks in each country from Moody’s Bank and Finance Manuals (see Table A2, Panel B in the Online Appendix for details on bank dividend yield index construction). Due to the difficulty in obtaining historical data, the bank dividend yield index for each country does not necessarily contain exactly the same banks as the bank price index

Controls. Dividend yield comes from GFD, supplemented by data from Thompson Reuters Datastream. *Book-to-market* comes from Datastream. *Inflation* is calculated from CPI data 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 short-term interest rate. The *term spread* is the long-term interest rate minus the short-term interest rate.

Household *consumption to wealth* is private consumption expenditure from national accounts taken from GFD divided by aggregate financial assets held by the household sector from Piketty and Zucman (2014). *Investment to capital* is private non-residential fixed investment divided by the outstanding private non-residential fixed capital stock, which comes from the Kiel Institute's database on investment and capital stock. *Daily stock volatility* is computed for each country and quarter as the standard deviation of daily returns by using daily stock returns from GFD of the equity market index. 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. The *sovereign spread* is the yield on the 10-year government bond minus the yield on the U.S. 10-year Treasury. *Real GDP growth* (year-over-year) is calculated from nominal GDP and the GDP deflator taken from GFD.

Other measures of credit and leverage. The data on bank credit is compared with several other measures of credit: *total credit* refers to credit extended from all sources to domestic households and private non-financial corporations. The variables *total credit to households* and *total credit to nonfinancial corporations* are the same as *total credit* but decomposed into household and corporate components. All variables are normalized by GDP. Like bank credit, these credit aggregates are taken from the BIS's "long series on credit to private non-financial sectors" and cover credit extended to end users (domestic households and/or private non-financial corporations) and excludes interbank lending.

Other indirect measures of credit: *bank assets to GDP*, which comes mainly from Schularick and Taylor (2012), and *household housing asset growth*, which is the real growth in housing assets owned by the household sector, from Piketty and Zucman (2014). 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 (2014)) and *non-financial equity to assets* and *bank equity to assets* (using book values taken from Thompson Reuters Datastream). Lastly, we also examined international credit flows and aggregates using *current account to GDP* (gathered from the IMF's external debt database and OECD) 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).

Backfilling/forward-filling. This paper performs all analysis on quarterly data. When data comes only in annual time series, as some of the older historical data does, the annual data (assuming it is an explanatory variable, not an outcome variable) is filled forward for the three subsequent quarters. We fill explanatory variables *forward* to avoid look-ahead bias in forecasting, since forward filled information for each quarter would already be known.

References

Acharya, Viral, Thomas Cooley, Matt Richardson and Ingo Walter (2010), Manufacturing tail risk: A perspective on the financial crisis of 2007-09, *Foundations and Trends in Finance* 4, 247-325.

Adrian, Tobias, Erkko Etula, and Tyler Muir (2013), Financial intermediaries and the cross-section of asset returns, *Journal of Finance*, forthcoming.

Adrian, Tobias, Emanuel Moench, and Hyun Song Shin (2013), Leverage asset pricing, Working paper, Princeton University.

Allen, Franklin and Douglas Gale (2000), Bubbles and crises, *Economic Journal* 110, 236-255.

Bansal, Ravi and Amir Yaron (2004), Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481-1509.

Barberis, Nicholas (2012), Psychology and the financial crisis of 2007-2008, in *Financial Innovation and Crisis*, M. Haliassos ed., MIT Press.

Barro, Robert (2006), Rare disasters and asset markets in the twentieth century, *Quarterly Journal of Economics* 121, 823-866.

Bebchuk, Lucian, Alma Cohen and Holger Spamann (2010), The wages of failure: Executive compensation at Bear Stearns and Lehman 2000-2008, *Yale Journal on Regulation* 27, 257-282.

Benabou, Roland (2013), Groupthink: Collective delusions in organizations and markets, *Review of Economic Studies 80*, 429-462.

Bernanke, Ben S (1983), Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression. *American Economic Review* 73(3): 257–76.

Bernanke, Ben and Mark Gertler (1989), Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14-31.

Bolton, Patrick, Jose Scheinkman and Wei Xiong (2006), Executive compensation and short-termist behavior in speculative markets, *Review of Economic Studies* 73, 577-610.

Borio, Claudio and Philip Lowe (2002), Asset prices, financial and monetary stability: exploring the nexus, Working paper, Bank for International Settlements.

Brunnermeier, Markus and Lasse Heje Pedersen (2009), Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201-2238.

Brunnermeier, Markus and Yuliy Sannikov (2014), A Macroeconomic Model with a Financial Sector, *American Economic Review* 104, 379-421.

Campbell, John and John Cochrane (1999), By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

Campbell, John and Motohiro Yogo (2006), Efficient tests of stock return predictability, *Journal of financial economics* 81, 27-60.

Cheng, Ing-Haw, Harrison Hong and Jose Scheinkman (2013), Yesterday's heroes: compensation and creative risk-taking, *Journal of Finance*, forthcoming.

Cheng, Ing-Haw, Sahil Raina and Wei Xiong (2013), Wall Street and the housing bubble, *American Economic Review*, forthcoming.

Danielsson, Jon, Hyun Song Shin and Jean-Pierre Zigrand (2012), Procyclical leverage and endogenous risk, Working paper, Princeton University.

Demirgüç-Kunt, Asli, and Enrica Detragiache (1998). The Determinants of Banking Crises in Developing and Developed Countries. IMF Staff Papers 45(1): 81–109. 38

Eichengreen, Barry, and Carlos Arteta (2002). Banking Crises in Emerging Markets: Presumptions and Evidence. In *Financial Policies in Emerging Markets* edited by Mario Blejer and Marko Škreb. Cambridge, Mass.: MIT Press, pp. 47–94.

Eichengreen, Barry, and Kris J. Mitchener (2003). The Great Depression as a Credit Boom Gone Wrong. BIS Working Paper No. 137, September.

Fisher, Irving (1933), The debt-deflation theory of great depressions, *Econometrica* 1, 337-357.

Foote, Christopher, Kristopher Gerardi and Paul Willen (2012), Why did so many people make so many ex-post bad decisions? The causes of the foreclosure crisis, Working paper, Federal Reserve Bank of Boston.

Gabaix, Xavier (2012), Variable rare disasters: An exactly solved framework for ten puzzles in

Macro-finance, *Quarterly Journal of Economics* 127, 645-700.

Gandhi, Priyank (2011), The relationship between credit growth and the expected returns of bank stocks, Working paper, UCLA.

Gandhi, Priyank, and Hanno Lustig (2013), Size anomalies in US bank stock returns, *Journal of Finance,* forthcoming.

Geanakoplos, John (2010), The leverage cycle, *NBER Macroeconomics Annual 2009*, 24, 1-65.

Gennaioli, Nicola, Andrei Shleifer and Robert Vishny (2012), Neglected risks, financial innovation, and financial fragility, *Journal of Financial Economics 104,* 452-468.

Gennaioli, Nicola, Andrei Shleifer and Robert Vishny (2013), A model of shadow banking, *Journal of Finance*, forthcoming.

Gertler, Mark and Nobuhiro Kiyotaki (2012), Banking, Liquidity and Bank Runs in an Infinite Horizon Economy, NBER Working Paper No. 19129

Goyal, Amit and Ivo Welch (2008), A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455-1508.

Greenwood, Robin and Samuel G. Hanson (2013), Issuer quality and corporate bond returns, *Review of Financial Studies* 26, 1483-1525.

Gromb, Denis and Dimitri Vayanos (2002), Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361-407.

He, Zhiguo and Arvind Krishnamurthy (2012), A Model of Capital and Crises, *Review of Economic Studies* 79, 735-777.

He, Zhiguo and Arvind Krishnamurthy (2013), Intermediary Asset Pricing, *American Economic Review* 103, 732-70.

Holmstrom, Bengt and Jean Tirole (1997), Financial intermediation, loanable funds and the real sector, *Quarterly Journal of Economics* 112, 663-91.

Ivashina, Victoria and David Scharfstein (2010), Bank lending during the financial crisis of 2008, *Journal of Financial economics* 97, 319-338.

Kaminsky, Graciela L. and Carmen M. Reinhart (1999). The twin crises: The causes of banking and balance of payments problems, *American Economic Review* 89, 473-500.

Kashyap, Anil, Jeremy Stein, and David Wilcox (1993), Monetary policy and credit conditions: Evidence from the composition of external finance, *American Economic Review* 83:78-98.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru and Vikrant Vig (2010), Did securitization lead to lax screening? Evidence from subprime loans, *Quarterly Journal of Economics* 125, 307-362.

Kindleberger, Charles (1978), *Manias, Panics, and Crashes: A History of Financial Crises*, New York: Basic Books.

Kiyotaki, Nobu and John Moore (1997), Credit cycles, *Journal of Political Economy* 105, 211-48.

Kyle, Albert and Wei Xiong (2001), Contagion as a wealth effect, *Journal of Finance* 56, 1401-1440.

Laeven, Luc, and Fabian Valencia (2008), Systemic banking crises: A new database, Working paper, International Monetary Fund.

Lane, Philip R. and Gian Maria Milesi-Ferretti (2007), The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004, *Journal of International Economics* 73, 223-250.

Lettau, Martin and Sydney Ludvigson (2010), Measuring and Modeling Variation in the Risk-Return Tradeoff, *Handbook of Financial Econometrics*, edited by Yacine Ait-Sahalia and Lars-Peter Hansen, 617-690.

Mendoza, Enrique and Marco Terrones (2008), An anatomy of credit booms: Evidence from macro aggregates and micro data, NBER Working Paper #14049.

Mian, Atif and Amir Sufi (2009), The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis, *Quarterly Journal of Economics* 124, 1449-1496.

Minsky, Hyman (1977), The financial instability hypothesis: An interpretation of Keynes and an alternative to 'standard' theory, *Nebraska Journal of Economics and Business* 16, 5-16.

Mishkin, Frederic (1978), The household balance sheet and the Great Depression, *Journal of Economic History* 38, 918-937.

Muir, Tyler (2014), Financial crises and risk premia, Working paper, Yale University.

Piketty, Thomas and Gabriel Zucman (2014), Capital is back: Wealth-income ratios in rich countries, 1700-2010, *Quarterly Journal of Economics*, forthcoming

Rajan, Raghuram (2006), Has finance made the world riskier?, *European Financial Management* 12, 499-533.

Rajan, Raghuram (2010), *Fault Lines*, Princeton University Press.

Reinhart, Carmen and Kenneth Rogoff (2009), *This Time Is Different: Eight Centuries of Financial Folly*, Princeton University Press, Princeton, NJ.

Rietz, Thomas (1988), The equity risk premium: A solution, *Journal of Monetary Economics* 22, 117-131.

Schularick, Moritz and Alan Taylor (2012), Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870–2008, *American Economic Review* 102, 1029-1061.

Shleifer, Andrei and Robert Vishny (1997), The Limits of Arbitrage, *Journal of Finance* 52, 35-55.

Stambaugh, Robert (1999), Predictive regressions, *Journal of Financial Economics* 54, 375-421.

Stein, Jeremy (1996), Rational capital budgeting in an irrational world, *Journal of Business* 69, 429-455.

Thompson, Samuel B. (2011), Simple formulas for standard errors that cluster by both firm and time, *Journal of Financial Economics* 99, 1-10.

Wachter, Jessica (2013), Can time-varying risk of rare disasters explain aggregate stock market volatility?, *Journal of Finance* 68, 987-1035.

Xiong, Wei (2001), Convergence trading with wealth effects: An amplification mechanism in financial markets, *Journal of Financial Economics* 62, 247-292.

Figure 1: Three-year change in bank credit to GDP

The three-year change of bank credit to GDP is plotted over time for all 24 countries in the sample. Bank credit refers to credit issued by banks to private domestic end-users of credit (households and non-financial corporations).

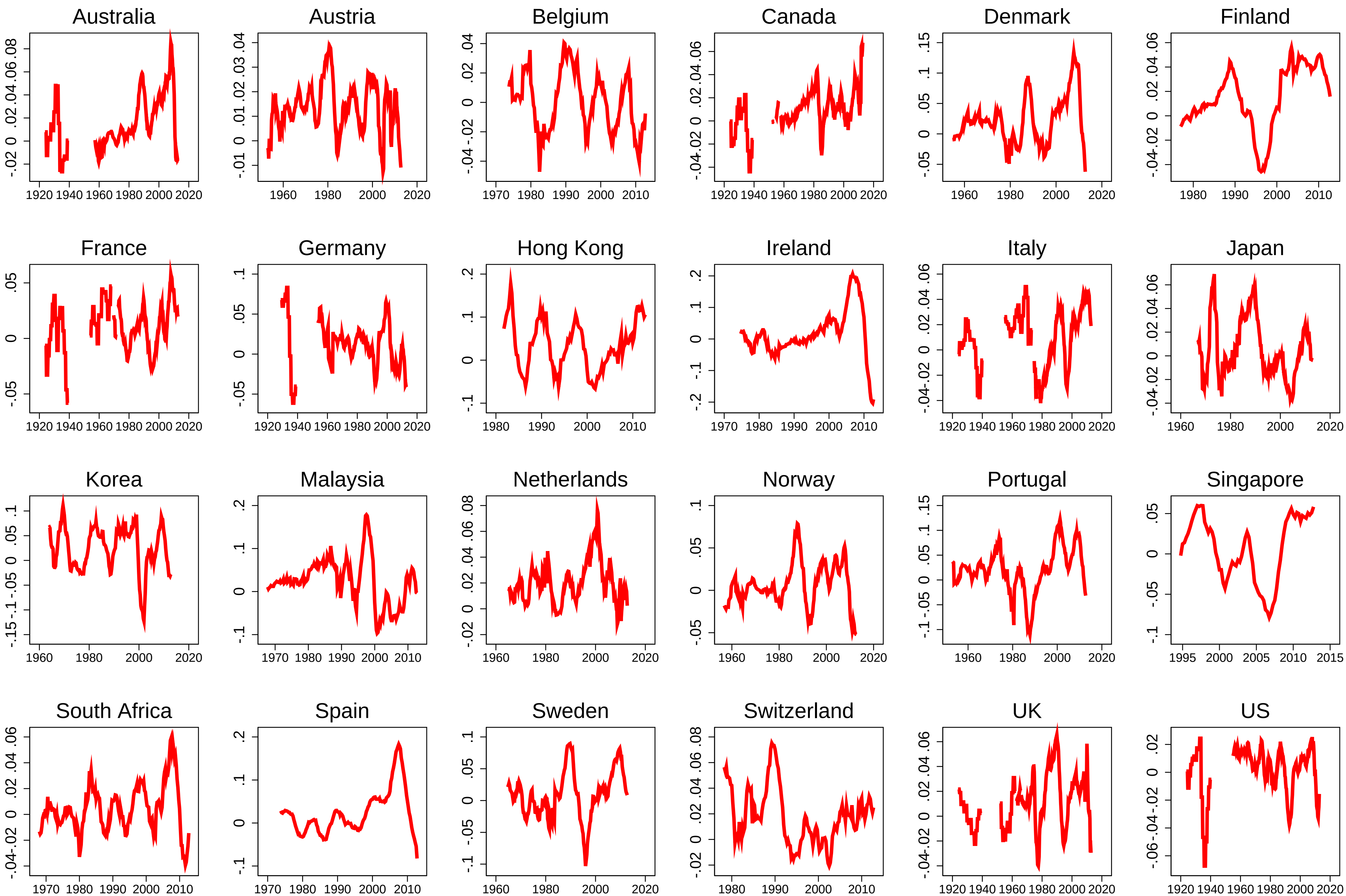


Figure 2: Credit and equity prices before and after banking crises

Bank credit to GDP (relative to each country's historical mean) and the bank equity and equity market price indices (relative to their pre-crisis peaks) are plotted over time before and after the start of banking crises. The plot shows that historical banking crises, based on data from Reinhart and Rogoff (2009), are accompanied by large drops in equity markets and especially in bank stocks. In addition, credit peaks at the start of the crisis, with credit starting to contract within the first year of the start of the crisis. Bank credit to GDP and the two equity price indices plotted are simple averages across time and countries, conditional on the given number of years before or after the start of a banking crisis.

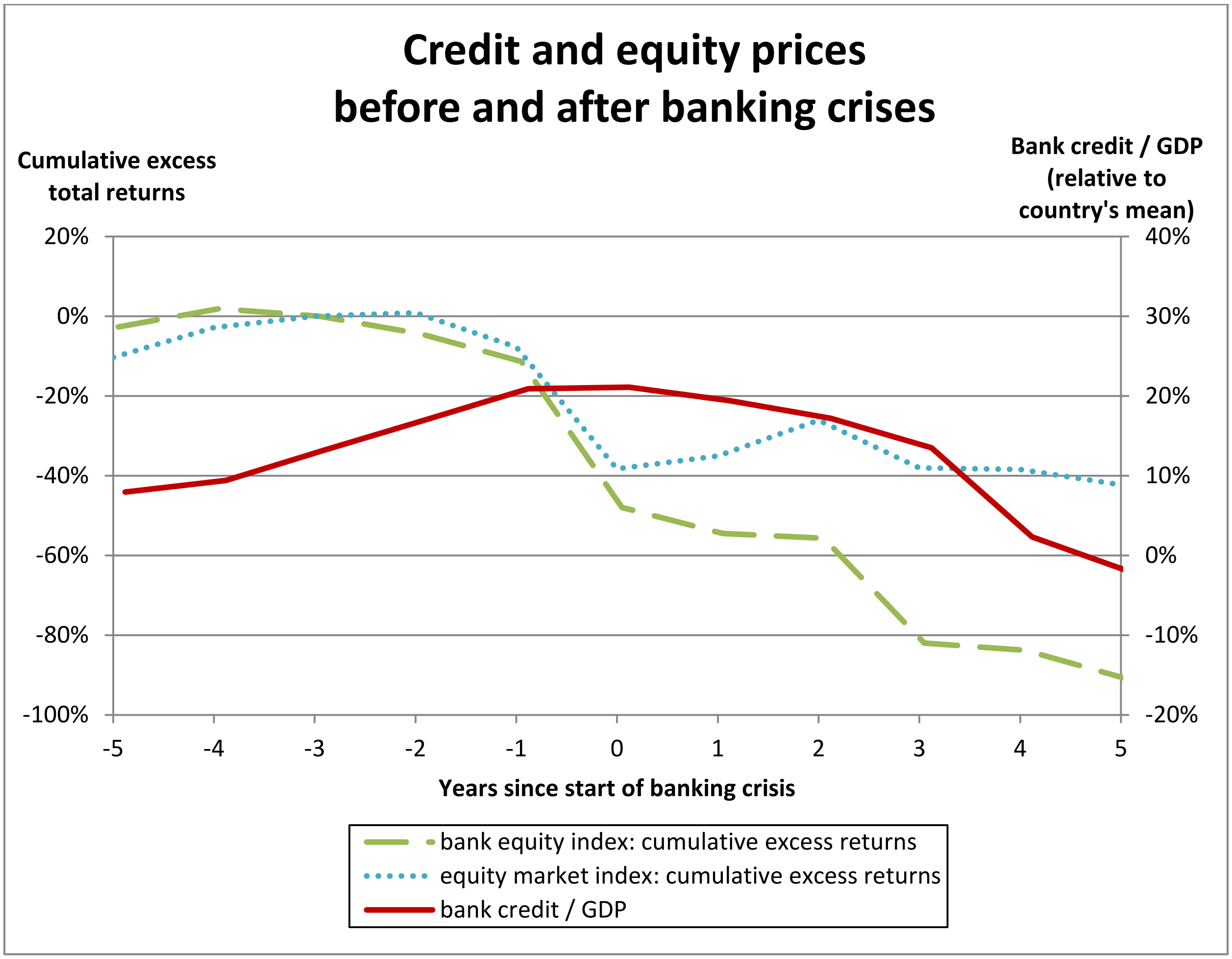
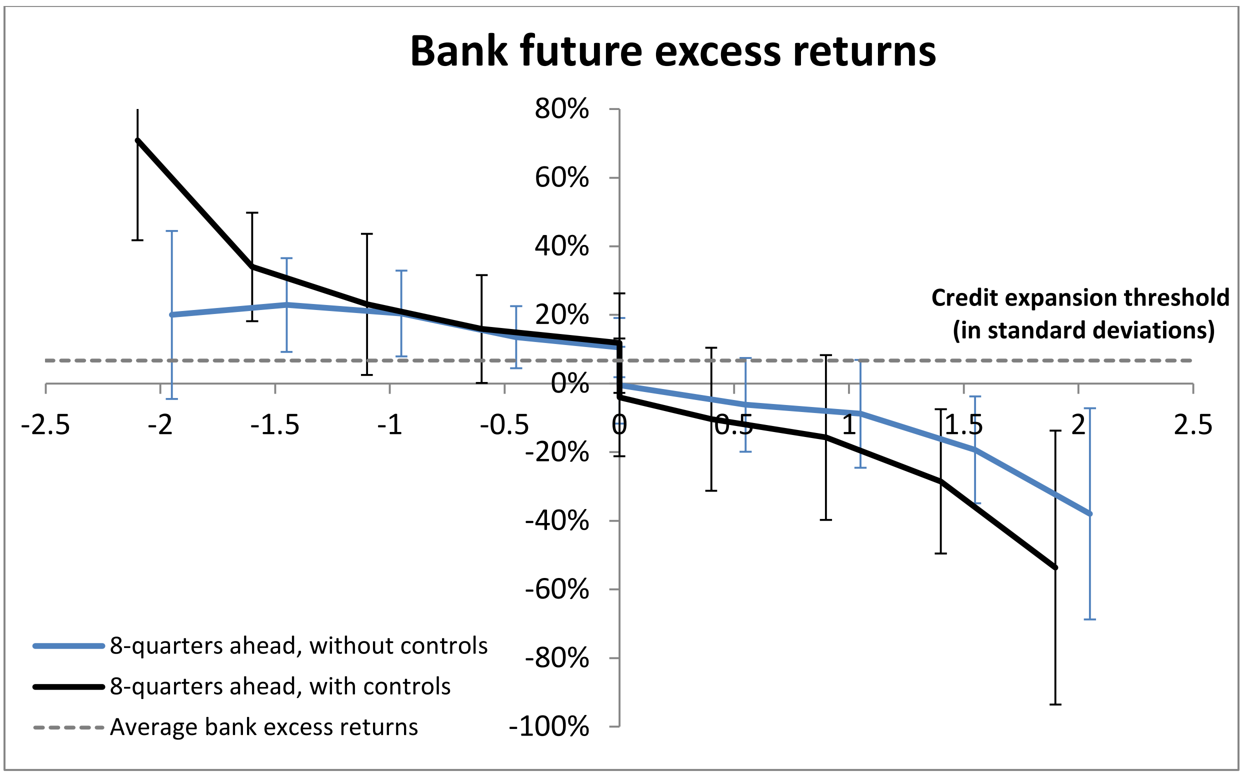


Figure 3: Negative predicted returns subsequent to large credit expansions

Panel A (for bank index returns) and Panel B (for equity market index returns) plot estimates and confidence intervals reported in Table 6 and show that predicted excess returns subsequent to large credit expansions are robustly negative. Specifically, the figures plot the magnitude of equity excess returns 8-quarters subsequent to large credit expansions exceeding a given positive threshold, in addition to the average equity excess returns subsequent to credit contraction (ie. negative credit expansion) below a given negative threshold. The methodology to produce these estimates and confidence intervals, which relies on non-linear regression models (3) and (4), is described in detail both in the caption of Table 6, to which this figure corresponds, and in the text. In the absence of controls, the methodology for constructing these figures is equivalent to computing a simple average conditional on credit expansion exceeding the given positive threshold (or below a negative threshold) x.

Panel A: Bank index returns



Panel B: Equity index returns

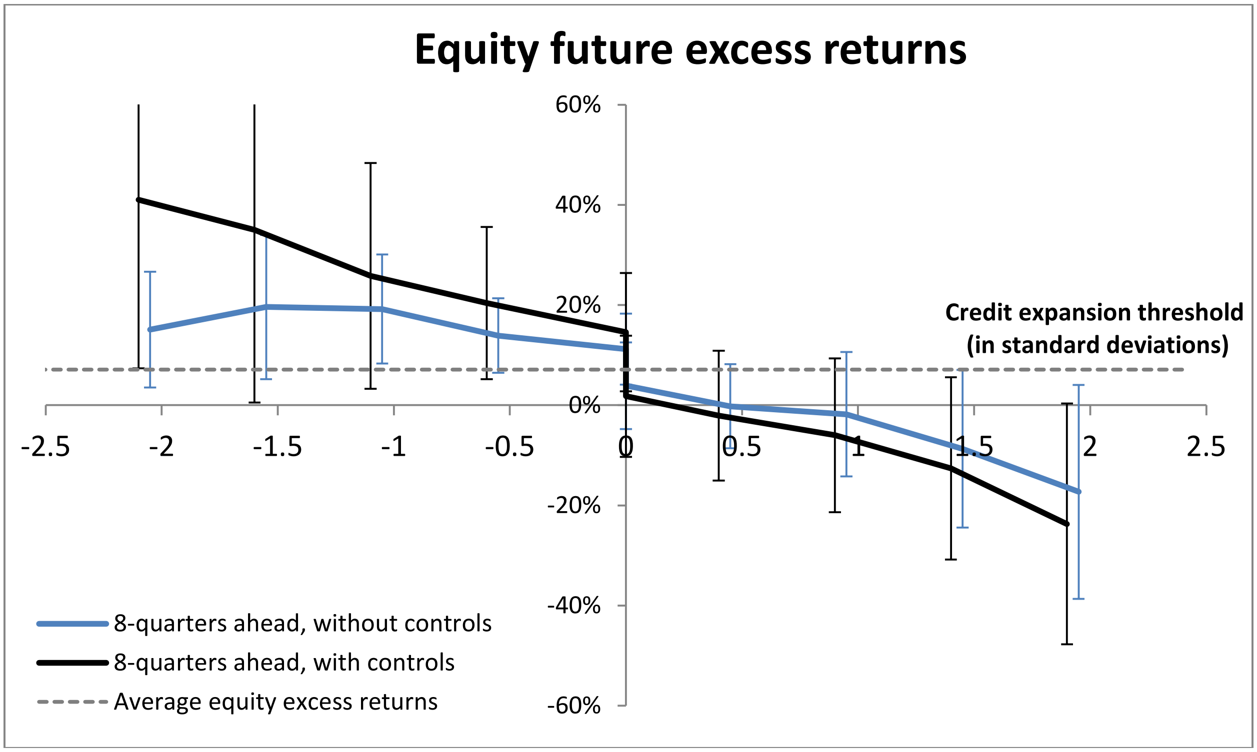


Table 1: Summary statistics

Summary statistics are reported for excess equity returns (with and without dividends) and real returns for both the bank equity and equity market indices. Summary statistics are also reported for the three-year change in bank credit to GDP (credit issued by banks to private domestic households and non-financial corporations) and three-year change in total credit to GDP (credit issued by all sources to private domestic households and non-financial corporations). All statistics are pooled across countries and time.

	N	Mean	Median	Stdev.	1%	5%	10%	90%	95%	99%
Quarterly log returns, annualized										
Equity excess returns (w/out dividends)	5841	3.4%	3.6%	23.0%	-111.8%	-68.6%	-48.1%	51.2%	72.0%	133.2%
Equity excess returns (incl. dividends)	5373	7.1%	7.7%	22.9%	-109.5%	-65.7%	-45.8%	55.7%	76.2%	134.7%
Equity real returns (incl. dividends)	5746	8.8%	9.1%	29.4%	-109.5%	-62.7%	-43.6%	56.8%	77.2%	137.3%
Bank stocks excess returns (w/out dividends)	5087	3.7%	1.8%	29.6%	-141.0%	-78.8%	-54.0%	59.1%	85.2%	178.8%
Bank stocks excess returns (incl. dividends)	4824	6.7%	5.3%	28.4%	-137.6%	-75.1%	-50.1%	61.4%	86.8%	170.0%
Bank stocks real returns (incl. dividends)	5088	7.9%	6.3%	27.8%	-135.5%	-71.9%	-47.6%	62.6%	87.9%	166.7%
Credit to private households and non-financial corporations, 3 year change										
Δ (Bank credit / GDP)	5077	1.3%	1.1%	3.4%	-6.7%	-3.5%	-2.3%	5.1%	6.8%	12.0%
Δ (Total credit / GDP)	4519	2.3%	2.1%	5.0%	-9.0%	-4.8%	-2.9%	8.2%	10.4%	17.2%

Table 2: Time series correlations

Panel A presents evidence that bank credit expansions tend to follow good economic states. Estimates are reported for OLS panel regressions with fixed effects with the dependent variable being three-year change of bank credit to GDP (normalized within each country) regressed on the three-year lagged value of predictor variables. Panel A shows that low daily equity market volatility, high real GDP growth, smaller corporate yield spreads, and lower sovereign yield spreads in the past three years tend to precede larger bank credit expansions in the subsequent three years. Panel B presents evidence that bank credit expansion is positively correlated to changes in other similar credit measures, including aggregate credit variables, leverage (of the household, corporate, and banking sectors), and changes in international credit. Estimates are reported for OLS panel regressions with fixed effects of these credit variables regressed on contemporaneous three-year change of bank credit to GDP. All variables are normalized within each country.

Panel A: Variables that predict future credit expansion

		RHS variable:			
LHS variable:		Daily volatility	Real GDP growth	Corporate yield spread	Sovereign yield spread
Future 3-year change in (bank credit / GDP)	β	-.129**	.176*	-.196**	-.196*
	R^2	0.07	0.03	0.11	0.05
	N	303	424	198	391

Panel B: Contemporaneous variation with other credit variables

						RHS variable:					
LHS variable:		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
Current 3-year change in (bank credit / GDP)	β	.773***	.651***	.63***	.609***	0.228*	0.174*	-0.208*	-0.124*	.318**	.167*
	R^2	0.74	0.45	0.52	0.34	0.19	0.13	0.12	0.09	0.13	0.03
	N	385	240	236	281	124	115	211	216	269	354

Table 3: Cross-country correlations

The table presents cross-country correlations of several variables between other countries and the U.S. In particular, the table demonstrates that bank credit expansions have historically been relatively idiosyncratic in nature (average correlation = 0.06).

Correlation with U.S., 1950-2005

	Selected countries	**Quarterly equity excess total returns**	**Quarterly bank equity excess total returns**	**Equity Crash indicator**	**Bank Equity Crash indicator**	**Δ (Bank credit / GDP)**	**D/P**	**Inflation**	**Term Spread**	**Book / Market**	**I/K**	**C/W**
	US	1	1	1	1	1	1	1	1	1	1	1
Commonwealth	Australia	0.53	0.38	0.60	0.35	0.00	0.59	0.60	0.34	0.91	0.73	0.02
	Canada	0.82	0.61	0.35	0.22	-0.34	0.92	0.87	0.44	0.87	0.66	0.75
	South Africa	0.29	0.28	0.39	0.51	-0.07	0.54	0.52	-0.21	0.08		
	UK	0.60	0.48	0.61	0.34	0.17	0.74	0.78	0.26	0.95	0.79	0.71
W. Europe	Austria	0.29	0.29	-0.02	0.76	-0.12	0.66	0.41	-0.36	0.36	0.55	
	Belgium	0.57	0.43	0.66	0.28	-0.24	0.75	0.72	0.11	0.14	0.43	
	France	0.51	0.39	0.47	0.45	0.46	0.68	0.67	0.02	0.80	0.45	0.61
	Germany	0.53	0.38	0.32	0.36	0.31	0.22	0.56	-0.06	0.82	0.43	0.39
	Ireland	0.52	0.46	0.45	0.38	0.27	0.87	0.74	0.02	0.85	0.67	
	Netherlands	0.73	0.50	0.50	0.26	0.15	0.91	0.53	0.08	0.91	0.64	
	Switzerland	0.61	0.50	0.76	0.61	0.18	0.88	0.54	-0.07	0.90	0.25	
Scandinavia	Denmark	0.38	0.25	0.28	0.18	0.48	0.65	0.70	-0.23	0.58	0.64	
	Finland	0.46	0.28	0.10	0.21	0.29	0.60	0.26	0.06	0.64	0.18	
	Norway	0.40	0.19	0.53	0.44	0.35	0.64	0.62	0.24	-0.25	0.10	
	Sweden	0.53	0.29	0.25	0.21	0.15	0.68	0.70	-0.11	0.75	0.64	
S. Europe	Italy	0.40	0.26	0.47	0.17	0.04	0.51	0.79	-0.25	0.51	0.46	0.39
	Portugal	0.37	0.37	0.22	0.13	0.04	0.05	0.68	-0.16	0.04	0.70	
	Spain	0.56	0.40	0.39	0.16	0.17	0.61	0.64	0.18	0.79	0.17	
Asia	Hong Kong	0.46	0.41	0.17	0.13	-0.13	0.55	0.59	0.90	0.38		
	Japan	0.37	0.11	-0.03	0.12	0.18	0.54	0.54	0.18	-0.05	-0.24	0.12
	Korea	0.34	0.18	0.05	0.06	-0.39	0.59	0.45	-0.19	-0.43		
	Malaysia	0.45	0.22	0.39	0.24	-0.08	0.17	0.60	-0.02	0.02		
	Singapore	0.58	0.30	0.34	0.35	-0.52	0.45	0.62	0.19	0.47		
	Average	0.49	0.35	0.36	0.30	0.06	0.60	0.61	0.06	0.48	0.46	0.43

Table 4: Predictive probit regressions using crash indicators.

This table reports estimates from the probit regression model specified in equation (1) and shows that bank credit expansion (normalized within each country) predicts an increased probability of equity crashes, both in the bank equity index (Panel A) and the market index (Panel B), in subsequent 1, 4, and 8 quarters. The dependent variable is the crash indicator ($Y = 1_{crash}$), which as defined in Section III takes on a value of 1 if there is a future equity crash in the next K quarters (K = 1, 4, and 8) and 0 otherwise. All reported coefficients are marginal effects. Given that an increased crash probability may be driven by increased volatility rather than increased negative skewness, we also estimate equation (1) with ($Y = 1_{boom}$) as the dependent variable, where 1_{boom} is a symmetrically defined positive tail event and then compute and test the difference in the marginal effects between the two probit regressions (probability of a crash minus probability of a boom).

Panel A: Crash in bank index

		1			4			8		
		Crash	Boom	Difference	Crash	Boom	Difference	Crash	Boom	Difference
No controls	Δ (bank credit / GDP)	0.024**	0.001	0.023*	0.048**	-0.007	0.055*	0.060***	-0.011	0.071**
		(2.93)	(0.23)	(2.36)	(2.73)	(-0.70)	(2.24)	(3.48)	(-1.06)	(2.82)
	N	4412	4412	4412	1116	1116	1116	567	567	567
With two controls	Δ (bank credit / GDP)	0.024**	0.000	0.023*	0.047**	-0.008	0.056*	0.054**	-0.007	0.061*
		(2.77)	(0.03)	(2.32)	(2.74)	(-0.87)	(2.33)	(2.97)	(-0.65)	(2.24)
	D/P	-0.975*	0.549	-1.525*	-2.427*	1.247	-3.673**	-3.513**	0.711	-4.224*
		(-2.00)	(1.21)	(-2.29)	(-2.50)	(1.59)	(-2.84)	(-2.83)	(0.94)	(-2.20)
	inflation	0.189	-0.258	0.448	0.315	-0.237	0.552	0.600	0.014	0.586
		(0.83)	(-1.22)	(1.65)	(0.86)	(-0.68)	(1.22)	(1.39)	(0.04)	(0.87)
	N	4196	4196	4196	1060	1060	1060	538	538	538
With all controls	Δ (bank credit / GDP)	0.015	-0.004	0.019*	0.039*	-0.013	0.052*	0.052*	-0.013	0.065
		(1.90)	(-0.66)	(2.13)	(2.40)	(-1.20)	(2.33)	(2.04)	(-0.90)	(1.73)
	D/P	-0.330	0.930*	-1.260	-2.004	1.994*	-3.998*	-3.478**	1.606**	-5.084***
		(-0.47)	(2.11)	(-1.38)	(-1.53)	(2.34)	(-2.53)	(-3.06)	(3.29)	(-4.47)
	inflation	0.038	-0.283	0.321	0.043	-0.344	0.387	0.337	-0.089	0.427
		(0.18)	(-1.41)	(1.36)	(0.10)	(-1.00)	(0.75)	(0.66)	(-0.26)	(0.58)
	term spread	0.216	-0.079	0.295	-0.074	-0.313	0.238	-0.630	-0.666	0.036
		(0.31)	(-0.19)	(0.35)	(-0.06)	(-0.47)	(0.13)	(-0.34)	(-0.78)	(0.01)
	book / market	-0.003	0.017	-0.019	-0.010	0.012	-0.022	-0.091	-0.001	-0.091
		(-0.06)	(1.02)	(-0.48)	(-0.17)	(0.38)	(-0.30)	(-1.66)	(-0.01)	(-1.09)
	i / k	1.129	0.219	0.910	1.415	-0.061	1.476	1.198	0.228	0.970
		(1.79)	(0.46)	(1.08)	(1.38)	(-0.06)	(0.92)	(1.61)	(0.26)	(0.76)
	N	3499	3499	3499	879	879	879	443	443	443

Panel B: Crash in equity index

		1			4			8		
		Crash	Boom	Difference	Crash	Boom	Difference	Crash	Boom	Difference
No controls	Δ (bank credit / GDP)	0.021***	-0.005	0.026***	0.044**	-0.010	0.054**	0.068***	-0.016	0.083***
		(4.13)	(-1.27)	(4.30)	(3.27)	(.)	(3.13)	(3.88)	(-1.61)	(3.88)
	N	4933	4933	4933	1243	1243	1243	629	629	629
With two controls	Δ (bank credit / GDP)	0.022***	-0.002	0.024***	0.046***	-0.008	0.055**	0.067***	-0.011	0.078***
		(4.12)	(-0.72)	(3.90)	(3.53)	(-1.17)	(3.21)	(7.12)	(-1.81)	(3.85)
	D/P	-0.494	0.153	-0.647	-2.298	0.538	-2.836	-3.653*	0.820**	-4.473*
		(-1.47)	(0.79)	(-1.65)	(-1.73)	(1.41)	(-1.80)	(-2.12)	(3.00)	(-2.12)
	inflation	0.202	-0.003	0.205	0.546	0.011	0.536	0.794	0.033	0.761
		(1.15)	(-0.03)	(1.13)	(1.35)	(0.06)	(1.30)	(1.80)	(0.19)	(1.51)
	N	4562	4562	4562	1148	1148	1148	581	581	581
With all controls	Δ (bank credit / GDP)	0.014**	-0.002	0.016**	0.040**	-0.008	0.048**	0.063***	-0.010	0.073**
		(2.72)	(-0.40)	(3.21)	(3.03)	(-0.65)	(2.93)	(4.17)	(-1.08)	(3.12)
	D/P	-0.032	0.275	-0.307	-3.307*	0.835	-4.142**	-4.474**	0.899	-5.372***
		(-0.07)	(0.41)	(-0.72)	(-2.33)	(0.73)	(-2.88)	(-2.97)	(1.23)	(-3.44)
	inflation	0.131	-0.022	0.153	0.182	-0.054	0.236	0.492	-0.035	0.527
		(0.75)	(-0.18)	(1.32)	(0.39)	(-0.28)	(0.50)	(0.79)	(-0.24)	(0.84)
	term spread	-0.337	0.005	-0.342	-1.629*	-0.195	-1.434	-1.860*	-0.373	-1.487
		(-1.39)	(0.04)	(-1.32)	(-2.03)	(-0.47)	(-1.52)	(-2.45)	(-1.05)	(-1.83)
	book / market	-0.065*	-0.001	-0.064**	-0.076	-0.006	-0.070	-0.136*	-0.005	-0.132
		(-2.11)	(-0.09)	(-2.91)	(-1.72)	(-0.23)	(-1.43)	(-2.26)	(-0.82)	(-1.94)
	i / k	0.704	-0.490	1.193	0.680	-1.508	2.188	1.486	-1.424	2.910*
		(1.29)	(-0.45)	(1.79)	(0.53)	(-0.87)	(1.55)	(0.91)	(-1.12)	(2.16)
	N	3776	3776	3776	945	945	945	475	475	475

Table 5: Equity premium predictability regressions

This table reports estimates from the panel regression model specified in equation (2) and shows that credit expansion, despite being associated with subsequent increased crash risk, predicts lower, rather than higher, excess returns both in the bank equity index (Panel A) and the market equity index (Panel B), in subsequent 1, 4, and 8 quarters. The dependent variable is the total excess return, which is regressed on credit expansion (three-year change in bank credit to GDP, normalized within each country) and several subsets of control variables known to predict the equity premium.

Panel A: Bank index

	1 quarter horizon				4 quarter horizon				8 quarter horizon			
Δ (bank credit / GDP)	-0.011*	-0.010*	-0.009*	-0.008	-0.049*	-0.047*	-0.051*	-0.043	-0.083**	-0.078*	-0.092**	-0.065
	(-2.558)	(-2.337)	(-2.234)	(-0.954)	(-2.121)	(-2.063)	(-2.405)	(-1.384)	(-2.666)	(-2.500)	(-2.690)	(-0.997)
D/P		0.591	0.337	0.823		3.475*	3.000	6.029*		3.110	1.716	-1.273
		(1.345)	(0.732)	(1.162)		(2.193)	(1.763)	(2.350)		(1.341)	(0.764)	(-0.421)
Inflation		-0.191	-0.112	-0.396		-0.694	-0.557	-1.661*		-0.312	-0.282	-1.464
		(-1.423)	(-0.896)	(-1.916)		(-1.612)	(-1.170)	(-2.071)		(-0.391)	(-0.382)	(-1.348)
Term spread			0.472	0.132			1.551	0.808			1.976	0.112
			(1.202)	(0.244)			(0.957)	(0.433)			(0.971)	(0.041)
Book / market			0.009	-0.003			-0.003	-0.129			0.117	0.373*
			(0.395)	(-0.083)			(-0.027)	(-1.199)			(1.275)	(2.292)
Invest. / Capital			0.019	-0.201			0.476	-0.327			0.543	0.254
			(0.044)	(-0.525)			(0.274)	(-0.188)			(0.320)	(0.114)
Corporate yield spread				0.043				0.415				0.608
				(0.043)				(0.169)				(0.383)
Consumption / wealth				0.284**				1.015*				1.220
				(3.149)				(2.140)				(1.507)
Adj. R^2	0.00	0.01	0.01	0.02	0.01	0.03	0.03	0.08	0.03	0.03	0.04	0.05
N	4201	4088	3535	1193	1053	1024	884	298	528	515	446	146

Panel B: Equity index

	1 quarter horizon				4 quarter horizon				8 quarter horizon			
Δ (bank credit / GDP)	-0.009**	-0.009**	-0.007*	-0.006	-0.037*	-0.039**	-0.038**	-0.033	-0.055*	-0.055*	-0.062*	-0.052
	(-3.267)	(-3.261)	(-2.341)	(-1.132)	(-2.405)	(-2.584)	(-2.612)	(-1.458)	(-2.465)	(-2.442)	(-2.401)	(-1.310)
D/P		0.580**	0.364	0.849		2.618**	2.423*	5.294*		3.838*	2.516	-1.268
		(2.885)	(1.328)	(1.303)		(2.915)	(2.073)	(2.324)		(2.546)	(1.277)	(-0.431)
Inflation		-0.261**	-0.205*	-0.440**		-0.784*	-0.720	-1.674**		-0.948	-1.004*	-1.366*
		(-2.646)	(-2.235)	(-2.642)		(-2.102)	(-1.864)	(-3.004)		(-1.961)	(-2.227)	(-2.034)
Term spread			0.450*	0.005			1.386	0.006			1.605	-0.053
			(2.213)	(0.012)			(1.584)	(0.004)			(1.237)	(-0.028)
Book / market			0.020	0.017			0.052	-0.064			0.155**	0.404**
			(1.942)	(0.542)			(1.423)	(-0.620)			(3.125)	(2.787)
Invest. / Capital			-0.214	-0.118			-0.550	-0.352			-1.199	0.437
			(-0.703)	(-0.354)			(-0.452)	(-0.259)			(-1.005)	(0.332)
Corporate yield spread				-0.154				0.408				0.627
				(-0.227)				(0.182)				(0.143)
Consumption / wealth				0.301***				1.230***				1.794***
				(4.118)				(3.557)				(4.004)
Adj. R^2	0.00	0.01	0.02	0.04	0.01	0.05	0.07	0.14	0.00	0.05	0.09	0.17
N	4502	4496	3775	1193	1129	1127	945	298	567	566	475	146

Table 6: Negative predicted returns subsequent to large credit expansion

This table reports the magnitude of equity excess returns subsequent to large credit expansions exceeding a given positive threshold and shows that the average excess return subsequent to large credit expansions is robustly negative. The table also reports estimates of equity excess returns subsequent to credit contraction (ie. negative credit expansion) below a given negative threshold. Average returns subsequent to large credit expansions and large credit contractions, along with associated t-statistics, are estimated using non-linear regression models (3) and (4). In the absence of controls, estimating these regressions is equivalent to computing a simple average conditional on credit expansion exceeding the given threshold x (or below a negative threshold y), though the formal regression estimation technique allows one both to add control variables and also to compute dually-clustered standard errors for hypothesis testing. The model specifications in Equation (3) and (4) are non-linear with respect to credit expansion and thus also serve to ensure that our analysis is robust to the linear regression model in equation (2).

Panel A: Bank index

		Threshold in S.D.'s:	**-2**	**-1.5**	**-1**	**-0.5**	**0**	**0**	**0.5**	**1**	**1.5**	**2**
4-quarter ahead returns	no controls	E[r]	16.0%	10.4%	9.0%	7.5%	5.7%	-0.4%	-3.8%	-6.4%	-10.9%	-23.9%
		(t-stat)	(3.425)	(2.218)	(2.244)	(2.471)	(2.004)	(-0.113)	(-0.755)	(-0.895)	(-1.061)	(-1.421)
		N	25	71	159	293	541	518	323	179	80	27
	with controls	E[r]	33.0%	12.5%	8.8%	8.8%	6.8%	-2.8%	-5.5%	-9.5%	-13.5%	-29.8%
		(t-stat)	(4.906)	(2.12)	(1.418)	(1.718)	(1.397)	(-0.497)	(-0.816)	(-0.964)	(-1.112)	(-1.622)
		N	8	34	77	138	256	306	214	124	63	22
8-quarter ahead returns	no controls	E[r]	20.0%	22.9%	20.4%	13.5%	10.5%	-0.5%	-6.2%	-8.8%	-19.3%	-38.0%
		(t-stat)	(1.609)	(3.31)	(3.218)	(2.949)	(2.402)	(-0.088)	(-0.892)	(-1.105)	(-2.439)	(-2.433)
		N	11	31	80	137	263	269	169	90	41	13
	with controls	E[r]	70.9%	34.0%	23.1%	15.9%	11.8%	-4.0%	-10.4%	-15.7%	-28.5%	-53.6%
		(t-stat)	(4.788)	(4.231)	(2.215)	(1.99)	(1.607)	(-0.459)	(-0.984)	(-1.289)	(-2.665)	(-2.645)
		N	3	13	40	64	124	159	114	61	33	11
12-quarter ahead returns	no controls	E[r]	18.6%	34.0%	29.4%	26.1%	17.8%	-4.9%	-15.4%	-20.3%	-46.6%	-62.6%
		(t-stat)	(2.451)	(3.745)	(3.696)	(4.524)	(3.213)	(-0.634)	(-1.621)	(-2.61)	(-4.021)	(-1.978)
		N	8	27	49	90	177	173	114	63	24	8
	with controls	E[r]	49.3%	43.1%	37.2%	35.6%	25.4%	-11.3%	-23.6%	-34.1%	-68.8%	-83.7%
		(t-stat)	()	(4.519)	(2.818)	(4.312)	(2.496)	(-1.011)	(-1.698)	(-3.173)	(-5.601)	(-2.442)
		N	1	13	25	41	79	101	74	41	18	7

Panel B: Equity index

		Threshold in S.D.'s:	-2	-1.5	-1	-0.5	0	0	0.5	1	1.5	2
4-quarter ahead returns	no controls	E[r]	9.4%	9.3%	9.5%	8.1%	6.8%	0.9%	-1.4%	-2.3%	-5.4%	-12.4%
		(t-stat)	(2.493)	(3.14)	(3.717)	(3.472)	(3.055)	(0.302)	(-0.373)	(-0.444)	(-0.752)	(-1.205)
		N	28	74	170	310	569	566	356	191	87	28
	with controls	E[r]	23.0%	15.3%	11.3%	11.4%	8.5%	-0.4%	-2.2%	-4.6%	-6.4%	-14.8%
		(t-stat)	(4.322)	(3.524)	(2.941)	(2.862)	(2.422)	(-0.102)	(-0.444)	(-0.675)	(-0.772)	(-1.448)
		N	8	34	79	141	260	310	217	126	65	23
8-quarter ahead returns	no controls	E[r]	15.1%	19.6%	19.2%	13.9%	11.2%	3.9%	-0.2%	-1.8%	-8.7%	-17.3%
		(t-stat)	(2.577)	(2.681)	(3.471)	(3.678)	(3.114)	(0.886)	(-0.047)	(-0.286)	(-1.089)	(-1.596)
		N	13	33	86	145	278	293	184	97	44	13
	with controls	E[r]	41.0%	35.0%	25.8%	20.4%	14.6%	1.8%	-2.1%	-6.0%	-12.6%	-23.7%
		(t-stat)	(2.4)	(2.001)	(2.255)	(2.645)	(2.434)	(0.293)	(-0.319)	(-0.77)	(-1.363)	(-1.943)
		N	3	13	41	66	126	160	115	62	34	11
12-quarter ahead returns	no controls	E[r]	12.4%	28.8%	25.6%	23.8%	18.9%	3.9%	-2.8%	-6.0%	-20.9%	-30.1%
		(t-stat)	(1.561)	(3.54)	(3.151)	(4.409)	(4.286)	(0.618)	(-0.407)	(-0.928)	(-2.574)	(-1.882)
		N	9	28	52	95	184	188	124	66	25	8
	with controls	E[r]	46.2%	46.4%	39.9%	34.7%	26.4%	1.2%	-3.8%	-10.8%	-25.1%	-41.5%
		(t-stat)	()	(3.402)	(3.284)	(4.462)	(4.077)	(0.157)	(-0.49)	(-1.706)	(-4.233)	(-2.725)
		N	1	13	25	42	80	102	74	41	18	7

Table 7: Robustness of crash predictability

To assess the robustness of crash risk coefficients estimated from probit regressions, we employ two alternative approaches to measure crash risk and negative skewness of returns. The first approach uses the quantile regression model specified in equation (5) to examine the predictability of bank credit expansion for negative skewness, $\beta_{negative\ skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$, of subsequent equity returns. The second approach uses the difference ($\beta_{median} - \beta_{mean}$) between the coefficients from a median regression (50th quantile regression) and mean regression as an alternative measure of the negative skew in equity returns. β_{median} is also useful as a robustness check for the mean regression specified in equation (2) for predicting the equity premium, as it shows that the equity premium after credit expansions is lower even in the absence of the occurrence of tail events. The dependent variable throughout is subsequent excess returns of the bank equity index or the market equity index, which is regressed on credit expansion (three-year change in bank credit to GDP, normalized within each country) and other controls. The coefficients and t-statistics are reported for the three quantile regressions, $\beta_{q=5}$, $\beta_{q=50}$, and $\beta_{q=95}$, followed by the conditional negative skewness coefficient $\beta_{negative\ skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$, the difference between the median and mean coefficients ($\beta_{median} - \beta_{mean}$), and their associated t-statistics or p-values.

		Bank index			Equity index		
Explanatory variables:		1	4	8	1	4	8
Δ (bank credit / GDP)	Q5	-.033***	-.102***	-.153**	-.022***	-.096***	-.113***
	(t stat)	(-5.19)	(-3.73)	(-2.73)	(-5.55)	(-5.9)	(-5.91)
	Q50 (median)	-.006**	-.026**	-.048	-.005***	-.024*	-.056*
	(t stat)	(-2.89)	(-2.98)	(-1.44)	(-3.58)	(-2.22)	(-2.17)
	Q95	-.005	-.028	-.072*	-.001	-.02	-.056
	(t stat)	(-1.11)	(-1.27)	(-2.58)	(-.42)	(-1.64)	(-1.81)
	negative skew	**.027*** **	**.078***	**.129***	**.012** **	**.068** **	**.056**
	(t stat)	**(3.5)**	**(2.08)**	**(2.02)**	**(2.6)**	**(2.88)**	**(1.09)**
	mean	-.011*	-.049*	-.108**	-.009**	-.037*	-.074**
	(t stat)	(-2.56)	(-2.12)	(-2.7)	(-3.27)	(-2.41)	(-2.68)
	median	-.006**	-.026**	-.048	-.005***	-.024*	-.056*
	(t stat)	(-2.89)	(-2.98)	(-1.44)	(-3.58)	(-2.22)	(-2.17)
	difference	**.005** **	**.023** **	**.06** **	**.004** **	**.013***	**.018**
	(p-value)	**(.002)**	**(.006)**	**(.002)**	**(.004)**	**(.021)**	**(.07)**
	N	4201	1053	525	4502	1129	562
Δ (bank credit / GDP), with D/P, inflation, book to market, term spread, and i/k as controls (coefficients on controls not shown)	Q5	-.03***	-.096***	-.123**	-.021***	-.079***	-.098***
	(t stat)	(-5.08)	(-3.79)	(-2.77)	(-3.74)	(-3.51)	(-3.84)
	Q50 (median)	-.004	-.026*	-.056	-.005**	-.032**	-.072**
	(t stat)	(-1.37)	(-1.98)	(-1.87)	(-3.07)	(-3.02)	(-3.06)
	Q95	-.001	-.047**	-.096*	-.003	-.015	-.036
	(t stat)	(-.21)	(-2.87)	(-2.31)	(-.75)	(-1.88)	(-1.02)
	negative skew	**.024** **	**.091*** **	**.107**	**.013***	**.03**	**-.011**
	(t stat)	**(2.87)**	**(3.43)**	**(1.31)**	**(2.32)**	**(.9)**	**(-.17)**
	mean	-.009	-.049	-.109*	-.008*	-.041*	-.078**
	(t stat)	(-1.74)	(-1.82)	(-2.42)	(-2.47)	(-2.32)	(-2.64)
	median	-.004	-.026*	-.056	-.005**	-.032**	-.072**
	(t stat)	(-1.37)	(-1.98)	(-1.87)	(-3.07)	(-3.02)	(-3.06)
	difference	**.005***	**.023**	**.053**	**.003**	**.009**	**.006**
	(p-value)	**(.032)**	**(.072)**	**(.058)**	**(.079)**	**(.316)**	**(.594)**
	N	3535	884	438	3775	945	470

Table 8: Robustness in geographical and time subsamples

This table demonstrates that the estimates reported in Tables 4 and 5 for the mean and probit regression models are robust to various choices of geographical and time subsets. For Panel A, the data is subdivided into geographical regions, and separate regressions are estimated for each region, while in Panel B, we change the time period: one set of regressions is run on the full sample (1920-2013), another is run excluding the most recent crisis (1920-2005), and a third is run excluding both the recent crisis and the Great Depression (1950-2005). This table reports estimates of mean and probit coefficients (using the same methodology as in Tables 4 and 5) of 4-quarter-ahead future equity excess returns regressed on credit expansion (three-year change in bank credit to GDP, normalized by country), with or without the five standard controls, for various subsets of countries and time periods. Coefficients reported are always on Δ (bank credit / GDP); coefficients on control variables are omitted.

Panel A: Robustness by geographical region (4 quarter forecast horizon)

			All	Largest Eight	U.S.	English speaking	W. Europe	S. Europe	Scandinavia	Asia
Bank Index	**probit - without controls**	Δ (bank credit / GDP)	0.055*	0.058*	0.027	0.039	0.081**	0.192***	0.052	0.008
		(t-stat)	(2.24)	(2.14)	(0.41)	(1.42)	(2.81)	(5.46)	(1.23)	(0.40)
		N	1116	522	74	295	687	120	166	176
	probit - with controls	Δ (bank credit / GDP)	0.052*	0.058*	0.071	0.045*	0.062**	0.202**	0.063	0.009
		(t-stat)	(2.33)	(2.48)	(1.09)	(2.22)	(2.68)	(2.94)	(1.30)	(0.32)
		N	879	534	74	284	698	129	158	46
	mean - without controls	Δ (bank credit / GDP)	-0.049*	-0.037*	-0.045	-0.024	-0.069*	-0.100*	-0.070	-0.010
		(t-stat)	(-2.121)	(-2.058)	(-1.472)	(-1.460)	(-2.278)	(-2.282)	(-1.895)	(-0.322)
		N	1053	495	69	271	680	96	188	145
	mean - with controls	Δ (bank credit / GDP)	-0.051*	-0.034	-0.039	-0.022	-0.067**	-0.189**	-0.063***	-0.002
		(t-stat)	(-2.405)	(-1.655)	(-1.274)	(-1.460)	(-2.755)	(-3.168)	(-7.265)	(-0.029)
		N	884	495	69	271	642	96	155	46
Equity Index	**probit - without controls**	Δ (bank credit / GDP)	0.054**	0.063***	0.049	0.060**	0.071**	0.119*	0.084*	-0.021
		(t-stat)	(3.13)	(3.80)	(0.70)	-3.2	-3.27	(2.35)	(2.13)	(-1.00)
		N	1243	557	74	324	796	166	197	183
	probit - with controls	Δ (bank credit / GDP)	0.048**	0.055**	0.044	0.044	0.047*	0.126*	0.048	-0.049
		(t-stat)	(2.93)	(3.28)	(0.64)	(0.40)	(2.39)	(2.23)	(1.44)	(-1.16)
		N	945	534	74	276	698	129	158	156
	mean - without controls	Δ (bank credit / GDP)	-0.037*	-0.034*	-0.024	-0.021	-0.052**	-0.042	-0.044	-0.006
		(t-stat)	(-2.405)	(-2.501)	(-0.806)	(-1.484)	(-2.702)	(-1.422)	(-1.129)	(-0.236)
		N	1129	535	74	276	709	131	167	175
	mean - with controls	Δ (bank credit / GDP)	-0.038**	-0.032	-0.022	-0.015	-0.050**	-0.087**	-0.014	0.006
		(t-stat)	(-2.612)	(-1.964)	(-0.723)	(-0.974)	(-3.283)	(-3.768)	(-0.526)	(0.143)
		N	945	534	74	276	698	129	158	46

Panel B: Robustness by time period (4 quarter forecast horizon)

			1920-2012	1920-2005	1950-2005
Bank Index	**probit - without controls**	Δ (bank credit / GDP)	0.055*	0.050**	0.055**
		(t-stat)	(2.24)	(3.27)	(3.19)
		N	1116	978	886
	probit - with controls	Δ (bank credit / GDP)	0.052*	0.042**	0.045*
		(t-stat)	(2.33)	(2.60)	(2.23)
		N	879	837	748
	mean - without controls	Δ (bank credit / GDP)	-0.049*	-0.036*	-0.039*
		(t-stat)	(-2.121)	(-2.514)	(-2.358)
		N	1053	916	847
	mean - with controls	Δ (bank credit / GDP)	-0.051*	-0.038*	-0.046*
		(t-stat)	(-2.405)	(-2.302)	(-2.455)
		N	884	776	707
Equity Index	**probit - without controls**	Δ (bank credit / GDP)	0.054**	0.048***	0.051**
		(t-stat)	(3.13)	(3.47)	(3.00)
		N	1243	1105	996
	probit - with controls	Δ (bank credit / GDP)	0.048**	0.043**	0.045*
		(t-stat)	(2.93)	(2.96)	(2.36)
		N	945	837	748
	mean - without controls	Δ (bank credit / GDP)	-0.037*	-0.033*	-0.033*
		(t-stat)	(-2.405)	(-2.530)	(-2.242)
		N	1129	991	901
	mean - with controls	Δ (bank credit / GDP)	-.038**	-0.034*	-0.039*
		(t-stat)	(-2.612)	(-2.369)	(-2.221)
		N	945	837	748

Table 9: Test for possible small-sample bias

This table tests for the possibility of small-sample bias using the methodology of Campbell and Yogo (2006) and finds that small-sample bias is most likely not a concern for our estimates. Equations 8 and 9 are estimated, and parameter values corresponding to the sample size (N), persistence of bank credit expansion (ρ), and the correlation of its innovations with returns ($\delta = corr(u_{i,t}, \epsilon_{i,t})$) are reported. All parameter estimates of δ are less than 0.125, the critical threshold reported in Campbell and Yogo (2006) for which small-sample bias is likely not a concern.

Panel A: Bank stock returns

Quarters ahead	Controls?	ρ	δ	N	N * (ρ - 1)
1	N	0.971	0.025	4172	-122.657
1	Y	0.971	0.045	3509	-103.165
4	N	0.802	0.049	1024	-202.650
4	Y	0.802	0.068	862	-170.590
8	N	0.488	0.049	494	-253.175
8	Y	0.488	0.032	418	-214.225

Panel B: Index returns

Quarters ahead	Controls?	ρ	δ	N	N * (ρ - 1)
1	N	0.971	0.015	4472	-131.477
1	Y	0.971	0.040	3747	-110.162
4	N	0.802	0.019	1096	-216.898
4	Y	0.802	0.052	920	-182.068
8	N	0.488	0.009	532	-272.650
8	Y	0.488	0.008	447	-229.088

Table A1 - Data and sample length

This table reports the sample length for each variable by showing the first year of data of each variable in each country.

Country	bankcredit_gdp	equity_return	bank_equity_return	D_P	bank_d_p	banking_crisis_firstyear	exchange_rate	cpi	three_mo_tbill	govt_10yr	corpbond_longterm_yield	E_P	stock_daily_volatility	book_market	i_k	currentaccount_gdp	extdebtliab_gdp	c_fa	real_gdp_growth	central_govt_debt_gdp	totalcredit_gdp	HHdebt_totalassets	totalcreditHH_gdp	HHhousingassets_growth	NFCequity_totalliab	totalcreditNFC_gdp	BANKequity_assets
Australia	1920	1920	1920	1920	1924	1920	1920	1920	1928	1920	1983	1973	1958	1980	1960	1960	1970	1978	1920	1920	1954	1978	1977	1961	1981	1977	1983
Austria	1950	1950	1986	1969	1986	1950	1950	1950	1960	1950	1970	1973	1975	1980	1960	1960	1970		1950	1950	1950		1995		1993	1995	1987
Belgium	1970	1950	1950	1951	1965	1950	1950	1950	1950	1950	1970	1969	1973	1980	1960	1960	1970		1950	1950	1970		1980		1981	1980	1981
Canada	1920	1920	1920	1934	1923	1920	1920	1920	1934	1920	1970	1956	1973	1980	1960	1961	1970	1970	1920	1920	1954	1970	1969	1971	1981	1969	1981
Denmark	1951	1950	1950	1969	1952	1950	1950	1950	1950	1950	1994	1969	1979	1980	1960	1960	1970		1950	1950	1951		1994		1981	1994	1979
Finland	1974	1950	1950	1962	1975	1950	1950	1950	1978	1987		1988	1987	1988	1960	1960	1970		1950	1950	1970		1970		2000	1970	1979
France	1920	1920	1920	1920	1924	1920	1920	1920	1922	1920	1970	1971	1968	1980	1960	1960	1970	1970	1921	1920	1969	1970	1977	1971	1981	1977	1988
Germany	1925	1924	1928	1924	1928	1924	1924	1924	1924	1924	1970	1969	1970	1980	1960	1960	1970	1970	1926	1925	1950	1950	1970	1951	1981	1970	1979
Hong Kong	1978	1964	1973	1972	1973		1950	1950	1982	1994		1972	1969	1980			1979		1961		1978		1990		1993	1990	1993
Ireland	1971	1950	1973	1973	1973	1950	1950	1950	1960	1950		1973	1973	1981	1960	1960	1970		1950	1950	1971		2002		1982	2002	1985
Italy	1920	1920	1973	1925	1973	1920	1920	1920	1922	1920	1970	1984	1957	1981	1960	1960	1970	1980	1920	1920	1950	1966	1950	1967	1982	1950	1983
Japan	1963	1920	1946	1921	1958	1920	1920	1920	1920	1920	1970	1956	1948	1980	1960	1960	1970	1980	1920	1920	1964	1970	1964	1971	1980	1964	1980
Korea	1960	1962	1975	1963	1987	1950	1950	1950	1969	1973	1972	1988	1962	1986		1970	1971		1954	1970	1962		1962		1987	1962	1990
Malaysia	1964	1974	1970	1972	1986	1950	1950	1950	1961	1961		1972	1980	1986		1974	1970		1956	1950	1964				1993		1990
Netherlands	1961	1950	1950	1969	1951	1950	1950	1950	1950	1950	1970	1969	1973	1980	1960	1960	1970		1950	1950	1961		1990		1981	1990	1979
Norway	1953	1950	1988	1969	1986	1950	1950	1950	1959	1950	1970	1969	1980	1984	1960	1960	1970		1950	1950	1953		1975		1981	1975	1979
Portugal	1950	1950	1950	1988	1989	1950	1950	1950	1981	1950		1988	1986	1986	1960	1960	1972		1954	1950	1950		1979		1990	1979	1996
Singapore	1991	1965	1970	1972	1986	1950	1950	1950	1972	1998		1972	1965	1980			1970		1958	1969	1991		1991		1993	1991	1982
South Africa	1965	1950	1980	1954	1981	1950	1950	1950	1950	1950		1960	1986	1980		1962	1970		1950	1950	1965		2009		1993	2009	1991
Spain	1970	1950	1950	1950	1966	1950	1950	1950	1972	1950		1979	1971	1990	1960	1960	1970		1950	1950	1970		1980		1993	1980	1979
Sweden	1961	1950	1950	1950	1953	1950	1950	1950	1950	1950	1974	1969	1980	1982	1960	1960	1970		1950	1950	1961		1981		1982	1981	1979
Switzerland	1975	1950	1950	1966	1950	1950	1950	1950	1950	1950	2000	1969	1969	1980	1960	1960	1970		1950	1950	1975		1999		1993	1999	1979
UK	1920	1920	1920	1923	1923	1920	1920	1920	1920	1920	1970	1927	1969	1980	1960	1960	1970	1971	1920	1920	1962	1971	1962	1972	1981	1976	1981
US	1920	1920	1920	1920	1929	1920	1920	1920	1920	1920	1920	1920	1928	1980	1960	1960	1970	1960	1920	1920	1952	1946	1952	1947	1952	1952	1980