Credit Expansion and Neglected Crash Risk*

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Abstract

This paper analyzes the causes and consequences of credit expansions through the lens of equity prices. In a set of 20 developed countries over the years 1920-2012, bank credit expansion predicts increased crash risk in the bank equity index and equity market index. However, despite the elevated crash risk, bank credit expansion predicts lower rather than higher mean returns of these indices in the subsequent one to eight quarters. In fact, conditional on bank credit expansion of a country exceeding a 95th percentile threshold, the predicted excess return for the bank equity index in the subsequent eight quarters is -23.0%. 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 regarding financial instability associated with credit expansion. 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 20 developed economies with data from 1920 to 2012. We measure credit expansion as the past 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 outside the two most prominent credit expansions, the boom of the 1920s leading up to the Great Depression and the boom of the 2000s.

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 (2^{nd} quantile) minus the distance to the upper tail (98^{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 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 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 95^{th} percentile threshold, the mean excess return for the bank equity index in the subsequent eight quarters is substantially negative at -23.0%. 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 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, we find increased rather than decreased crash risks subsequent to bank credit expansions in a sample of 20 countries. This finding suggests that shareholders neglect imminent crash risk during credit expansions, as pointed out by Gennaioli, Shleifer and Vishny (2012, 2013). Our analysis does not contradict the importance of tail risk in driving equity premium. Instead, it highlights that shareholders' beliefs regarding tail risk are likely subjective, as suggested by Weitzman (2007), and may or may not be consistent with the actual tail risk. In this regard, our analysis also reinforces the concern expressed by Chen, Dou and Kogan (2013) regarding a common practice of attributing puzzles in asset prices to "dark matter," such as tail risk, that is difficult to measure in the data.

Our paper is structured as follows. Section I 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.

Our finding of bank credit expansion predicting an increased equity crash risk reflects reduced credit quality during credit expansions, which complements several recent studies. 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. Using U.S. data back to 1920, 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. These findings suggest the presence of over-optimism by corporate bondholders during credit booms. By using equity prices across 20 countries, our analysis systematically examines the predictability of bank credit expansion for both equity crash risk and mean equity returns and further confirms the presence of over-optimism by equity shareholders during credit booms.

Our study complements 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. Muir (2014) documents that risk premia for stocks and bonds increase substantially during financial crises after financial intermediaries suffer large losses. Different from these studies, our analysis builds on total quantity of bank credit to GDP rather than intermediary leverage or capital. By examining equity returns subsequent to both bank credit expansions and contractions, our analysis systematically summarizes the time-varying equity premium across credit cycles: the equity premium tends to be largely increased during credit contractions (which are typically crisis periods) and reduced (to even substantially negative levels) during credit expansions.

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, the literature has made an effort 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.

II. Empirical Hypotheses and Methodology

This section introduces three empirical hypotheses that anchor our analysis, together with the regression methodology we use to analyze these hypotheses.

A. Crash risk

We first 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.

[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.

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 spilling 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.*

To examine this hypothesis, we estimate probit regressions with an equity crash indicator as the dependent variable to see if credit expansion predicts increased crash 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. Note that 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. We define an equity crash when the log excess total return of the underlying equity index or bank equity index is less than -20% in one quarter or less than -30% in two consecutive quarters. With this definition, the equity crash indicator takes on the value of 1 every 5.4% of quarters, or one quarter every 4.6 years on average. Given that an increased crash probability may be driven by increased volatility rather than increased crash risk on the down side, 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

[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).

difference in the marginal effects between the two probit regressions (probability of a crash minus probability of a boom).[4]

B. Equity premium

If bank credit expansion is indeed accompanied by increased equity crash risk, the equity premium during credit expansion offers a lens to uncover shareholders' expectations and preferences regarding the increased crash risk. The literature has highlighted that 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). If during bank credit expansions 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.[5]

Another view of credit expansion focuses on the role of beliefs. Bank credit expansion may be accompanied by widespread optimism in the economy, a view 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 excessively expand 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 beliefs 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 the presence of overly optimistic shareholders, even rational bankers may underwrite poor quality loans and seek risk to cater or take advantage of

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[4] Another potential way to measure tail risk (or perception of tail risk) is to use options data. However, such data is limited to recent years in most countries.

[5] The literature has also pointed out that implicit guarantees from governments create a "too big to fail" problem and may lead banks to excessively expand credit to the economy (e.g., Rajan, 2006, 2010; Acharya, et al., 2010). Note that excessive credit expansion induced by implicit government guarantees might even benefit shareholders. 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.

their shareholders' optimism (e.g., Stein, 1996; Bolton, Scheinkman and Xiong, 2006; Cheng, Hong and Scheinkman, 2013). Separately, distorted incentives and group-think among bankers and shareholders may lead them to turn a blind eye to warning signs about potential tail risk they face in credit markets (e.g., Benabou, 2013; Cole, Kanz, and Klapper, 2013).

These different views motivate us to examine the following hypothesis regarding the relationship between the equity premium and credit expansion.

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

To examine Hypothesis II, we use an OLS panel regression with country fixed effects:

$$r_{i,t+K} - r^{f}_{i,t+K} = \alpha_i + \beta^{'}(predictor\ variables)_{i,t} + \epsilon_{i,t} \tag{2}$$

which predicts the K quarter ahead excess return of either the bank equity index or equity market index, conditional on a set of predictor variables including bank credit expansion. We test whether β_{mean}, the coefficient of credit expansion in equation (2), is different from zero. By using a fixed effects model, we test Hypothesis II by focusing on the time series dimension within countries. As the predictor variables come from different sources for different countries, direct comparison of the level of the predictor variables across countries is 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, book to market, the term spread, investment to capital, and consumption to wealth. See Lettau and Ludvigson (2010) for a review of this literature. It is thus important in our analysis to control for these variables to isolate effects associated with bank credit expansion.

Lastly, in estimating coefficients for equation (2), we test for the possible presence of small-sample bias, which 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). In Section IV.D.3, we use the methodology of Campbell and Yogo (2006) to show that small-sample bias is most likely not a concern for our estimates.

C. *Magnitude of equity premium*

Another view of credit expansion 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.

It is challenging to fully separate the effects caused by over-optimism and elevated risk appetite. We explore a quantitative difference between these views. An elevated risk appetite can reduce the equity premium down to zero but not below zero in standard asset pricing models,[6] while over-optimism can cause equity prices to be substantially overvalued and thus cause the equity premium to be negative. This quantitative difference motivates us to examine the magnitude of the equity premium during credit expansions, as stated in the following hypothesis.

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.*

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 a 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

[6] 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.

intermediaries are well capitalized. To examine Hypothesis III, we estimate a non-linear model of the predicted equity excess return subsequent to a large credit expansion:

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

where $x > 0$ is a threshold for credit expansion, expressed in percentiles. In the absence of controls, this model is equivalent to computing a simple average conditional on credit expansion exceeding the given percentile 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. Adding control variables shows that, with the additional information from the controls available to shareholders at the time, the returns subsequent to credit expansions may be even more predictably negative. 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 $E[r_{i,t+K} - r^f_{i,t+K} \mid \cdot]$ is significantly different from zero.

Furthermore, to examine the predicted equity excess return subsequent to large credit contractions, we also estimate a similar model by conditioning on credit contraction, i.e., credit expansion lower than a negative threshold $y < 0$:

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

D. Alternative measures of crash risk

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 of the qth quantile of future equity excess returns conditional on the predictor variables:

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

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

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 in the lower tail of returns, for example in a change to the 2nd quantile.[7] 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:

$$\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=2}) - (\beta_{q=98} - \beta_{q=50}) \quad (6)$$

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 $(\beta_{q=50} - \beta_{q=2})$, the distance between the median and the 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.[8]

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

E. Standard errors

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)

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[7] Quantile regression estimates have a slightly different interpretation from the probit estimates: the probits analyze the likelihood of tail events, while quantile regressions 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.

[8] In the statistics literature, this measure is called the quantile-based measure of skewness. We use the 2nd and 98th quantiles to represent tail events, though the results from the quantile regressions are qualitatively similar for various other quantiles (for example, 1st/99th or 5th/95th quantiles) but with slightly less statistical significance. There is a trade-off with statistical power in using increasingly extreme quantiles, since the number of extreme events gets smaller while the magnitude of the skewness coefficient gets larger.

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, in effect estimating the regressions on annual or biennial data. 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 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 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: $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=2}) - (\beta_{q=98} - \beta_{q=50}) = 0$, standard errors are generated by block bootstrapping *simultaneous* estimates of the q=2, 50, and 98 quantile regression. Similarly, the difference between the mean and median coefficients, H_0: $\beta_{\text{mean-median}} = 0$, 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 20 countries from 1920 to 2012 using quarterly data. The main outcome variables in our data set are excess returns of the bank equity index and equity market index. The main predictor variable is the past three-year change in bank credit to GDP, which we often refer to simply as credit expansion. In addition, we employ a host of financial and macroeconomic variables, which are known to predict the equity premium, to serve as controls.

The data set is mostly complete for most countries from around 1950 onwards, and for half 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

The main predictor variable is the three-year change in *bank credit to GDP*, expressed as an annualized percentage point difference. *Bank credit* refers to credit extended from banks to domestic households and private non-financial corporations. It excludes interbank lending and only includes non-public end users of credit.[9] 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 covers the postwar era, and from the data of Schularick and Taylor (2012) on "bank loans," which extend back over a century but only for a subset of the countries.

Throughout the paper, we refer to the three-year change in bank credit to GDP as credit expansion or credit growth (or credit contraction when the change is negative). We often denote this predictor variable as Δ(bank credit / GDP), which is short-hand for $(\text{bank credit / GDP})_t$ - $(\text{bank credit / GDP})_{t-3}$. We look at changes in bank credit to GDP, rather than levels, for the following reasons. First, as shown later in Figure 2, the *change* in bank credit is positive during booms and falling during crises, while the *level* of bank credit may still be high after the crisis. Thus, the change of credit, not the level, is more indicative of the expansion or contraction phase and separates before versus after the start of banking crises. Second, bank 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 emphasizes the cyclical movements corresponding to credit expansions and contractions.[10] We show that the three-year horizon for

[9] We use bank credit to GDP rather than bank leverage for the practical reason that measures of bank leverage are available for most countries only after 1980. As we show in Table 2, bank credit to GDP is correlated with bank leverage.

[10] As an alternative approach, we repeat our analysis with the detrended level of bank credit, using a one-sided Hodrick-Prescott (HP) filter (λ=100,000) to avoid look-ahead bias; results were qualitatively similar.

differencing bank credit to GDP is roughly consistent with the frequency of credit cycles.[11] Finally, when estimating regressions, we standardize the three year change in bank credit to GDP by its mean and standard deviation within each country.[12]

The main outcome variable is future returns for both the equity market index and the bank equity index for each country. We consistently use log excess total returns as our measure of returns throughout the paper.[13]

Our main source for the price series of both indices is Global Financial Data (GFD). 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 is constructed from individual banks' dividend yields using Compustat, Datastream and hand-collected data from Moody's Bank and Finance Manuals.[14] 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.[15]

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*, *non-residential investment to capital*, and the *term spread*. The variable *household consumption*

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[11] In the online appendix, we provide additional analysis in Table S5 to show the strongest predictive power occurs using the three-year horizon. Specifically, we repeat our main analysis but with decomposing the three-year change into various lags of one-year changes in bank credit to GDP. The greatest predictive power comes from the 2 and 3 year lags, with the magnitude of the coefficients strongly dropping off at longer lags. This suggests that three-year horizons are roughly the frequency of credit cycles.

[12] Standardization is based on the in-sample distribution of each country. In Table S8 of the online appendix, we also show that results are robust to standardizing with past data only.

[13] We also repeat all the main results in the online appendix (Table S6) with arithmetic returns as a robustness check. The results are significant, albeit slightly less in magnitude for the probit and quantile regressions.

[14] See the appendix and online 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.

[15] 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.

to wealth is only reliably available for several countries and, while used in some of the analysis, is 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 log excess return of the underlying equity index is less than -20% in one quarter or less than -30% in two consecutive 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 without and with dividends, equity real total returns (index returns + dividends - inflation), bank equity excess returns without and with dividends, and bank equity 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.

In Table 1, the mean equity log excess return is 6.6% (2.7% without including dividends). The mean equity log real total return is 7.9%. Bank stocks have slightly lower mean excess returns (6.1% with dividends, 2.5% excluding dividends, and 7.4% real total returns). We also report the median returns for all variables. The standard deviations of returns are around 20% for equity index returns, with higher numbers for bank stock returns.

Given that we study crash indicators and negative skewness statistics from quantile regressions based on left tail events, it is useful to get a sense of what magnitude drops these percentiles correspond to. From Table 1, we see that a 5th percentile return, which occurs on average once every 5 years, corresponds to a -65.2% annualized log return, and a 1st percentile return corresponds to an annualized log return of -109.9%. Table 1 also gives a sense of the magnitudes and variability of credit expansion. On average, bank credit to GDP expanded by 1.2% per year. In terms of the variability of credit expansion, bank credit expansion grew as rapidly as 11.4% of GDP per year (99th percentile) and contracted as rapidly as -6.7% of GDP per year (1st percentile). Total credit to GDP, which includes both bank credit and credit from other sources extended to households and non-financial corporations, grew at twice the rate of bank credit on average, 2.4%, and is similarly volatile, with total credit expansion growing as rapidly as 17.5% of GDP per year (99th percentile) and contracting as rapidly as -8.7% of GDP per year (1st percentile). In Table 2, we show that there is a 59% time-series correlation between bank credit growth and total credit growth.

The variability of bank 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, lower daily equity market volatility, higher 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 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, and bank assets and modest for change in gross external liabilities and household and corporate leverage, demonstrating 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 in the year leading up to 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. This also makes it non-trivial for credit expansion to predict equity price crashes. In addition, credit peaks at the start of the crisis, with credit gradually contracting during the subsequent two years.[16]

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 = 0.50) and bank equity excess returns are even less so (0.42). Bank credit expansions have historically been relatively idiosyncratic in nature with an average correlation of 0.26. This is rather modest, considering that the two most prominent credit expansions, those leading up to the Great Depression and the recent crisis, were global in nature. In fact, the average correlations of bank credit expansions in 1950-2005 (outside of these two episodes) is only 0.11. 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 conditions 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

[16] The gradual contraction process may be 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.

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 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 equity index (panel A) and in the equity market index (panel B) conditional on a one standard deviation increase in bank credit expansion. Regressions are estimated with and without the control variables. 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 4-8) adding dividend yield, and the third block of rows (rows 9-21) uses all five main control variables (dividend yield, book to market, term spread, investment to capital, and inflation).

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, 4.4, and 4.8 percentage points, respectively, and a crash in the market equity index by 1.7, 3.4, and 4.3 percentage points, 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 1.6 (not significant), 3.6, and 3.9 percentage points, (for 1-, 4-, and 8-quarter horizons, respectively), and a crash in the market equity index by 1.2, 2.5, and 3.0 percentage points, respectively, all but one statistically significant except the last at the 5% level. In fact, the control variables are often statistically significant too: lower dividend yield, term spread, and book to market all predict increased crash 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. Also, as a robustness check, we adopt two alternative measures of crash risk in Section IV.D.1 using a quantile-regression-based approach, which studies crash risk without relying on a particular choice of thresholds for crash indicator variables.

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 adding dividend yield as a control, with all five main controls (dividend yield, book to market, term spread, investment to capital, and inflation), and with an additional sixth control (consumption to wealth) for which there is limited data availability. The reason for 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.[17]

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) R^2 and adjusted R^2 for the mean regressions.

The coefficients from the mean regression measure 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 1.1, 4.9, and 8.3 percentage point decreases in subsequent returns over the 1-, 4-, and 8-quarter, respectively, all significant at the 5% level. When the controls are included, the coefficients generally are slightly lower but have similar statistical significance. For the equity market index, the coefficients are smaller: a one standard deviation increase in bank credit expansion predicts 0.8, 3.3, and 4.9 percentage point decreases (all significant at the 5% level) for 1-, 4-, and 8-quarter-ahead excess returns, respectively.[18,19]

[17] For all six control variables, missing values are imputed using each country's mean. Since the data set for the five main control variables is mostly complete, mean imputation has minimal effect on the regression results, which we verify. However, for consumption-to-wealth, for which there is limited data availability, mean imputation is necessary to retain a large enough sample size to analyze the coefficients on credit expansion. The robustness checks in Table S7 in the online appendix compare regressions with consumption to wealth with and without imputed missing values, along with regressions without consumption-to-wealth but on the smaller sample size for which there is consumption-to-wealth data, to show that consumption-to-wealth, while a powerful predictor of the equity premium, does not kill off the effect from bank credit expansion.

[18] The predictive power of credit expansion on subsequent returns is due to country-specific effects and not spillover effects from other countries. To disentangle the effects of local versus global credit expansions, we repeat the analysis (see Table S3 in the online appendix) controlling for U.S. credit expansion and U.S. broker-dealer leverage. U.S. credit expansion has no predictive power for equity returns in other country, and while U.S. broker-dealer leverage is a significant pricing factor for foreign equity returns, it does not reduce the predictive power of local credit expansion.

[19] The higher coefficients for the bank equity index are not due to bank stocks having a high market beta, which would simply magnify the effects that credit expansion has on the broad market. We verify both that the bank equity index has a market beta of about 1 and that even after estimating a time-varying beta for the bank stock index, our main results hold also on the idiosyncratic component of bank returns.

In general, 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.[20]

Coefficient estimates remain similar in magnitudes after including the controls. For the equity market index, higher dividend yield, book to market, term 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. These control variables tend to have stronger predictability for the equity market returns than for the bank equity returns. Most importantly, the coefficient for bank credit expansion remains approximately the same magnitude and significance, despite the controls that are added. Thus, bank credit expansion adds new predictive power beyond these other variables and is not simply reflecting another known predictor of the equity premium.[21]

Table 5 also reports R^2 and adjusted R^2 (both adjusted and non-adjusted are variously reported in the equity premium predictability literature). In the univariate framework with just credit expansion as a predictor, the adjusted R^2 ranges from less than 1% for 1-quarter horizons to 3.4% for bank returns and 0.6% for equity index returns. Adding the five standard controls (column 3) increases the adjusted R^2 to 0.9%, 2.8%, 3.3% for bank returns and 2.3%, 6.4%, and 8.7% for equity index returns for 1-, 4-, and 8-quarters ahead, respectively. These values are within the range of values previously reported in the literature for the various control variables.[22]

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

[21] Table S3 in the Online appendix provides various robustness checks to show that the results are not driven by changes in the denominator (GDP) but by changes in the numerator (bank credit) of the main predictor variable. Table S3 also shows that the findings are robust to using log change in credit or log change in credit/GDP as the dependent variable, and also to controlling for change or log change in GDP on the right hand side of the regression.

[22] There is a large range of R^2 and adjusted R^2 values reported in the literature for common predictors of the equity premium in U.S. data. For example, Campbell, Lo, and MacKinlay (1996) report R^2 for dividend yield: 0.015, 0.068, 0.144 (1, 4, 8 quarter overlapping horizons, 1927-1994); Lettau and Ludvigsson (2010) report adjusted R^2 for dividend yield: 0.00, 0.01, 0.02, and for *cay*: 0.08, 0.20, 0.28 (1,4,8 quarter overlapping horizons, respectively, 1952-2000); Cochrane (2012) reports R^2 for dividend yield: 0.10, for *cay* and dividend yield together: 0.16, and for i/k and dividend yield together: 0.11 (for 4 quarter horizons, 1947-2009); Goyal and Welch (2008) report adjusted R^2 of 0.0271, -0.0099, -0.0094, 0.0414, 0.0663, 0.1572 (annual returns, 1927-2005) for dividend yield, inflation, term spread, book to market, i/k, and *cay*, respectively.

As a robustness check, in Section IV.D.2 we re-analyze the probit and mean regressions but on various geographical subsets. In general, the coefficients have similar magnitudes as before regardless of subset of countries analyzed, though the statistical power is reduced due to the smaller sample size in these subsets. We also perform the probit and mean regressions on various subsets in time: excluding the most recent crisis (1920-2005) and excluding both the recent crisis and the Great Depression (1950-2005). The coefficients have almost the same magnitude and statistical significance in these time subsets as when run on the full sample.

Taken together, the results in these two subsections show that despite the increased crash risk associated with bank credit expansion, the predicted equity excess return falls rather than increases.[23] 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 periods of bank credit expansions.

C. Excess returns subsequent to credit expansions and contractions

Next, we test Hypothesis III by examining excess returns subsequent to large credit expansions and contractions. We find that predicted excess returns subsequent to large credit expansion are significantly negative and large in magnitude.

We estimate the magnitude of equity excess returns subsequent to credit expansions and contractions using non-linear regression models (3) and (4) discussed in Section II.C. These regressions estimate 4-, 8-, and 12-quarter-ahead excess returns on an indicator for credit expansion exceeding a high percentile threshold (an event we call a large credit expansion) or falling below a low percentile threshold (a large credit contraction), along with the five standard control variables. These regressions allow us to test whether the predicted excess return is

[23] 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.

negative subsequent to a credit expansion and positive subsequent to a credit contraction without relying on the linear specifications used in our earlier analysis.

The predicted excess returns conditional on credit expansion exceeding or falling below given percentile thresholds are plotted in Figure 3 and reported in Table 6. Specifically, Figure 3 plots the predicted 8- and 12-quarter-ahead excess returns for various credit expansion percentile threshold, varying from >50th percentile to >98th percentile for large credit expansions and from <50th percentile to <2nd percentile for large credit contractions. Panel A is for the bank equity index, and panel B is for the equity market index. A 95% confidence interval is plotted for each of the returns. As one can see in Figure 3, 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 upper percentile thresholds.

Table 6 reports the same information but in tabular form, in particular the average return and corresponding t-statistics conditional on the past three-year credit expansion exceeding some percentile threshold. The predicted negative returns are weaker for the 4-quarter horizon but get increasingly stronger for 8- and 12- quarter horizons. For example, at the 95th percentile threshold, the predicted negative returns are -13.7%, -23.0%, and -42.3% for the 4-, 8-, and 12-quarter ahead horizons without controls, respectively, with t-statistics of -1.065, -2.131, and -2.527, respectively. Panel A further shows that after controlling for the five standard controls, both the magnitude and t-statistic of the predicted negative returns at the 8- and 12-quarter ahead horizons remain similarly strong.

The predicted negative returns for the broad equity market index, while weaker in both magnitude and t-statistic than those for the bank index, are nevertheless substantial. Panel B shows that at the 95th percentile threshold, the predicted returns are -6.6%, -11.4%, and -20.0% for the 4-, 8-, and 12-quarter ahead horizons without controls, with t-statistics of -0.814, -1.598, and -2.262, respectively.

The large and significantly negative excess returns predicted by credit expansion confirm Hypothesis III and present 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. Instead, our findings suggest that shareholders are overly optimistic and neglect crash risk during credit expansions.

Finally, Figure 3 and Table 6 also show that subsequent to credit contractions, the excess returns are positive. When credit contraction is less than the 5th percentile by country, the predicted excess return in the subsequent 8 quarters is 30.1% for the bank index and 20.3% for the equity market index, both significant at the 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.

Various robustness checks are performed in Section IV.D.4. We show that predicted excess returns subsequent to large credit expansions are robustly negative: 1) even after grouping observations of large credit expansions into distinct episodes (clusters) and then averaging across these episodes (addressing the concern that multiple observations of large credit expansions ought to be treated as a single global episode rather than separate local events), and 2) defining the percentile thresholds for each quarter strictly based on past observations for that country.

Figure 3 and Table 6 document a full picture of the dramatic, time-varying equity premium across credit cycles. During large bank credit expansions, the expected excess returns of both the bank equity index and broad equity market index are substantially negative, while during large bank credit contractions the expected excess returns are substantially higher than the long-run level of the equity premium.

D. Further analysis

In this subsection, we perform several robustness checks. First, we adopt alternative measures of crash risk and of the equity premium. Next, we check the robustness of the probit and mean regressions in geographical and time subsamples. We also verify that small-sample bias due to persistent predictor variables in the regressions is not likely to be a cause for concern. Finally, we examine alternative ways to cluster standard errors and classify observations in our analysis of the large negative and positive returns subsequent to large credit expansions and contractions.

D.1 Quantile regression-based measures

To assess the robustness of our main results of increased crash risk and lower equity premium subsequent to credit expansions, we adopt alternative measures of crash risk and the equity premium based on quantile 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 half reports estimates for quantile regressions on credit expansion with no controls, while the bottom half 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, $\beta_{q=2}$, $\beta_{q=50}$, and $\beta_{q=98}$, followed by the first alternative crash risk measure — the conditional negative skewness coefficient $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=2}) - (\beta_{q=98} - \beta_{q=50})$ — 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 0.028, 0.089, and 0.114 (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 8.9 percentage point drop in returns 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 becomes 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 0.004, 0.02, and 0.023 (all but the last significant at the 5% level) for the bank equity index and 0.003, 0.009 and -0.001 (only the first significant), for the equity market index at the 1-, 4- and 8- quarter horizons, respectively. 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 varies "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 -0.007, -0.029, and -0.06 (the last one not significant) for the bank equity index and -0.005, -0.024, and -0.05 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 implies 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.

As a robustness check, we re-estimate the probit and mean regressions but on various geographical subsets (e.g., Western Europe or English-speaking countries) and various subsets in time: excluding the most recent crisis (1920-2005) and excluding both the recent crisis and the Great Depression (1950-2005). In general, the coefficients have similar magnitudes regardless of the subset of countries analyzed, reflecting the fact that our results are not driven predominantly by particular countries or historical time periods.

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 probit regressions are roughly 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, implying that our results are not driven simply by the Great Depression or the recent financial crisis.

D.3 Test for small-sample bias

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 $N \to \infty$, so standard estimators may be substantially biased in finite samples when the 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; 2) innovations need to be highly correlated with returns (which we show 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 or 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.[24]

Section B of the Appendix discusses the methodology in detail to test for small-sample bias along the lines of Campbell and Yogo (2006). Table 9 reports parameter values corresponding to the sample size (N), persistence of bank credit expansion (ρ), and the correlation of its innovations with returns (δ). Table 9 shows that our data correspond to parameter values well outside the region for which small-sample bias is likely to be a concern: see Section B of the Appendix for a discussion of results. To test for small-sample bias in multivariate regressions

[24] 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%.

that use the five standard control variables, the same parameter values are also computed after replacing returns with the returns residual after controlling for the five standard control variables: see Section B of the Appendix for details. 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 20 countries individually (results reported in the online appendix, Table S10) 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.[25]

D.4 Robustness of negative returns subsequent to large credit expansions

Clustering observations by historical episodes. Recall Table 6, which plots future returns of the bank equity index subsequent to large credit expansions and large credit contractions. One might argue that multiple observations of large credit expansions across many countries concurrently might reflect a single global episode rather than various local events. Accordingly, large credit expansions may have correlated effects across countries and over the duration of the expansion in ways not captured by dually-clustered standard errors. Here we demonstrate that the predicted excess returns subsequent to large credit expansions are robustly negative, even after grouping observations of large credit expansions into distinct episodes (clusters) and then averaging across these episodes.

By our count, there are 16 distinct historical episodes of credit expansion encompassed by our data set, which are widely dispersed throughout our sample period. Some of these 16 distinct historical events are well-known (like the Japanese boom of the late 80s, the boom preceding the 1997-8 East Asian Crisis, and the boom preceding the Scandinavian financial crises of the late 80s and early 90s, to name three examples), while other historical episodes are less well-known. This robustness check thus averages large credit expansion observations across multiple countries and years that are part of the same historical episode, and then considers each historical episode (cluster) as a single data point.

[25] The few cases in which parameters fall into the region for which small-sample bias may still be a concern: Ireland (4, 8-quarters only, bank returns only), Portugal (8-quarters only, equity index returns only), and Spain (1-quarter only, both bank and equity index returns), since these countries had unusually large and persistent credit expansions in the 2000s. See Table S9 in the online appendix for details.

Specifically, we do as follows. Since countries undergoing large credit expansions (or contractions) may remain over the 95th (or under the 5th) percentile thresholds for multiple years, to collapse observations across time, we select only the returns subsequent to the *first* year in which credit expansion first crosses the 95th (or 5th) percentile thresholds.[26] Then we group concurrent observations across countries into distinct historical episodes. Finally, returns from the resulting 16 historical episodes in the sample are averaged together to generate Table 10, taking each such historical episode as a single, independent observation.

Even after grouping observations into 16 distinct historical episodes and averaging across these historical episodes, the subsequent returns are robustly negative. Table 10 reports the average returns in the 4, 8, and 12 quarters following the start of historical episodes of large credit expansions (Panel A) and large credit contractions (Panel B). For large credit expansions, subsequent returns 4, 8, and 12-quarters ahead are: -9%, -15%, and -21% (for the bank equity index; t-stats of -1.35, -1.94, and -2.10, respectively) and -7%, -14% and -10% (for the equity market index; t-stats of -1.44, -2.47, and -1.64, respectively). For large credit contractions, subsequent returns 4, 8, and 12-quarters ahead are: 12%, 17%, and 27% (for the bank equity index, t-stats of 1.91, 2.93, and 4.14, respectively) and 19%, 25%, and 36% (for the equity market index, t-stats of 2.25, 2.64, and 3.32, respectively).

Classifying large credit expansions based strictly on past information. One may worry that the percentile thresholds for classifying large credit expansions and contraction use future information, since the percentiles are calculated for each country with the full in-sample distribution of credit expansion. Thus, we repeat the analysis used to predict negative returns conditional on large credit expansions but this time calculate the percentile thresholds for each quarter based only on past observations (percentile thresholds are only calculated when there is at least 5 years of past data for that country). For example, for credit expansion to be above the 95% threshold, credit expansion in that quarter must be greater than 95% of all previous observations for that country.

[26] A list of all large credit expansions (based on the 90th, 95th, or 98th percentile thresholds) and large credit contractions (based on the 2nd, 5th, or 10th percentile thresholds), with their subsequent equity and bank equity returns, grouped together into historical episodes, can be found in Table S1 in the online appendix.

Table 11 demonstrates that predicted excess returns subsequent to large credit expansions are robustly negative, even when conditioning returns strictly on past information. The predicted negative returns are similar to those reported in Table 6 for the 95th and 98th percentiles, though slightly weaker in terms of both magnitude and t-statistics of the coefficients. Thus, the predicted negative returns are robust, even conditioning strictly on only past information.

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 exceeding the 95th percentile for that country is significantly negative with a magnitude of -23.0%. 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

A. Data construction

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. However, 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.

B. Methodology and results for small-sample bias test

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

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

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

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:

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

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.

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Figure 1: Credit expansion

Credit expansion, measured as the past three-year change of bank credit to GDP, is plotted over time for the 20 countries in the sample. Observations are quarterly, 1920-2012. Bank credit refers to credit issued by banks to domestic households and domestic private non-financial corporations.

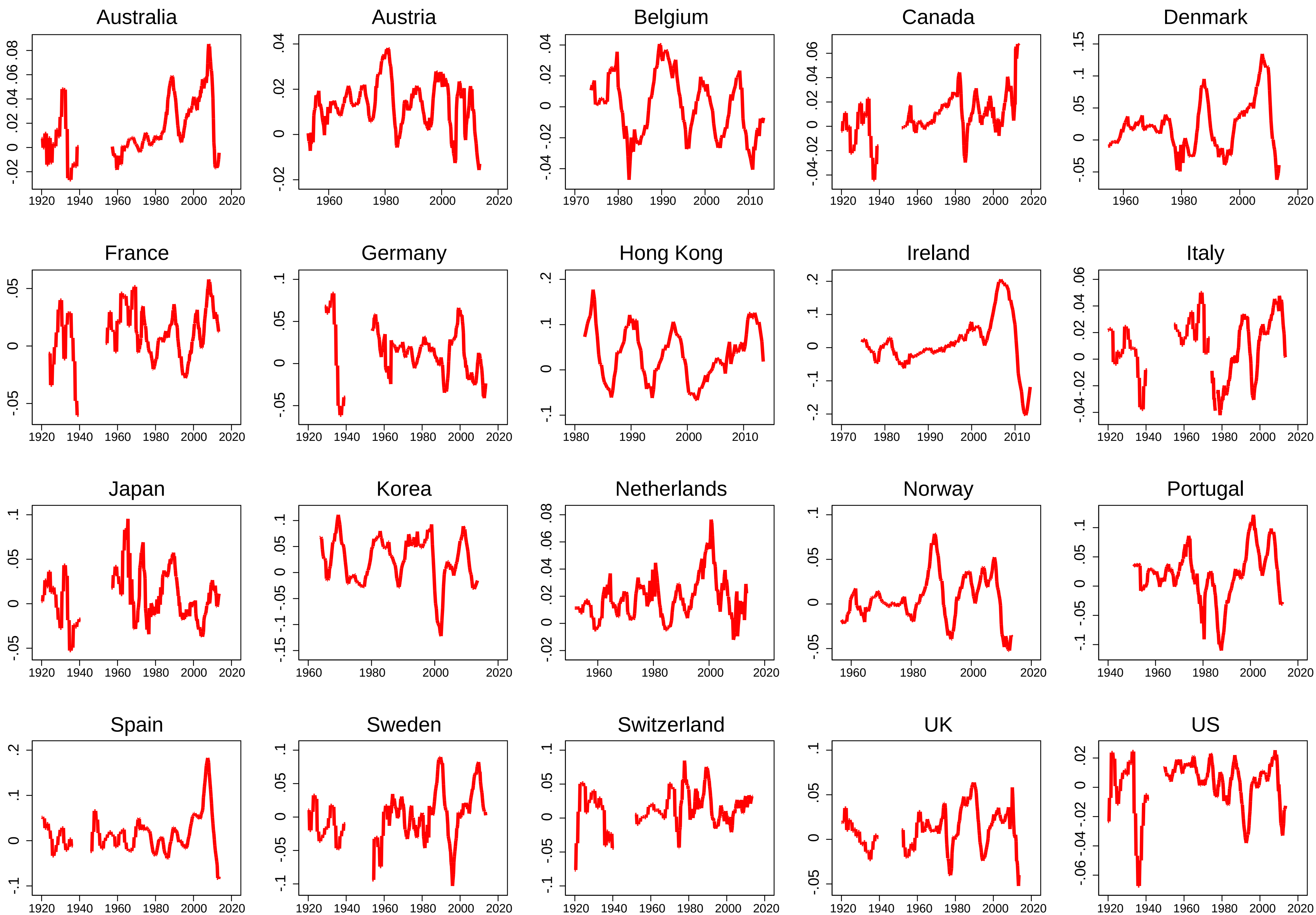


Figure 2: Credit and equity prices before and after banking crises

Bank credit to GDP (relative to each country's historical mean) and the bank equity and equity market cumulative total return indices (relative to their pre-crisis peaks) are plotted over time before and after the start of banking crises, where the start of banking crises is based on data from Reinhart and Rogoff (2009). The plot demonstrates that historical banking crises are accompanied by large drops in equity markets and especially in bank stocks. In addition, bank 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 indices are pooled averages across time and countries, conditional on the given number of years before or after the start of a banking crisis. Data are from 20 countries, 1920-2012.

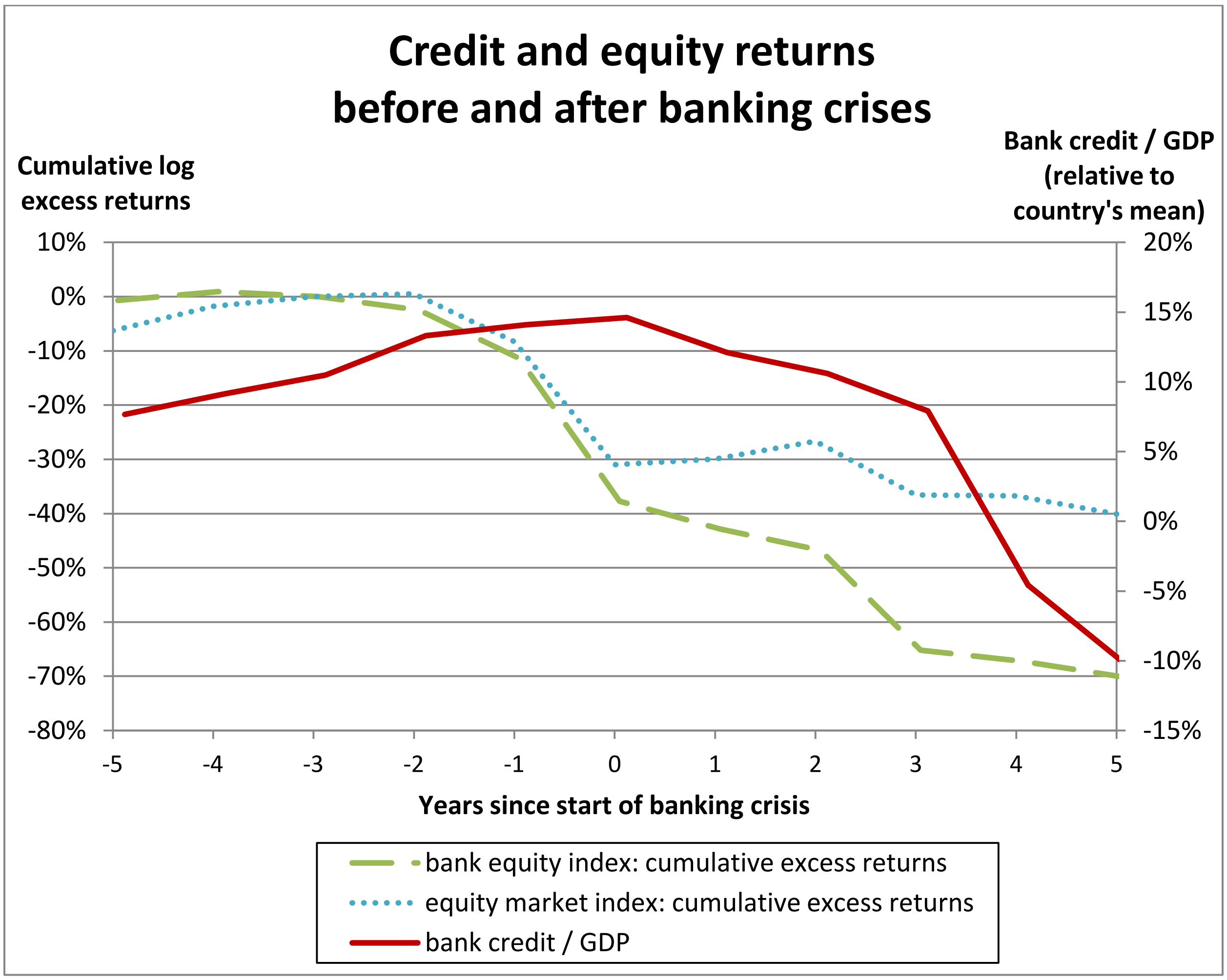
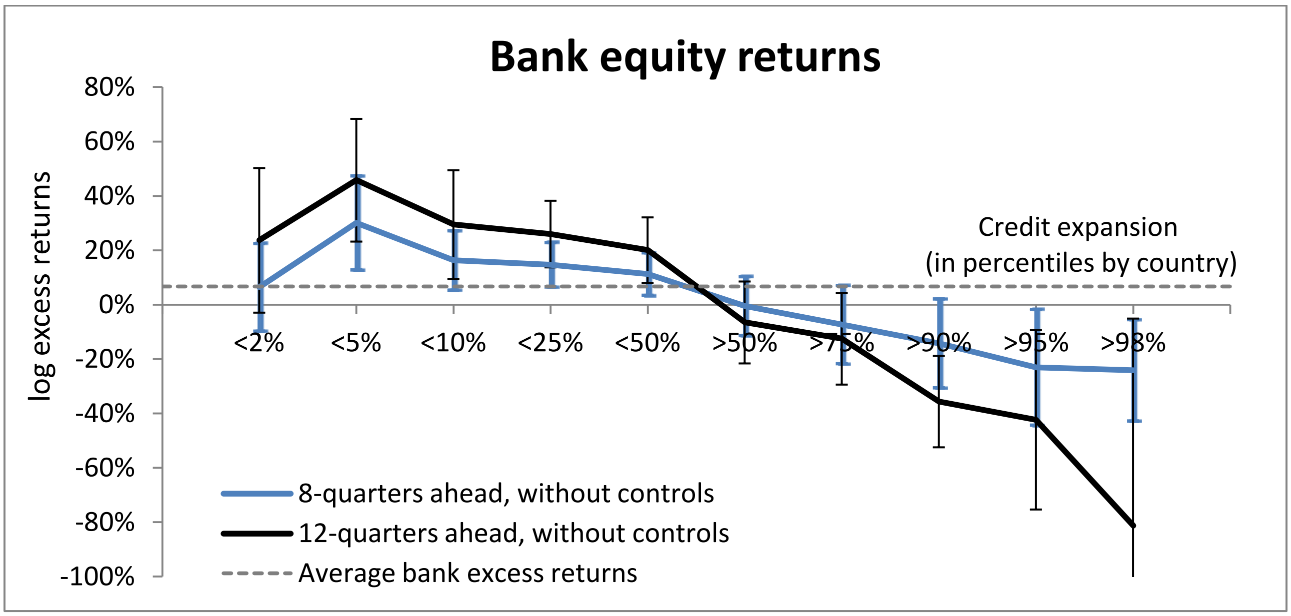


Figure 3: Negative predicted returns subsequent to large credit expansions

Panel A (for bank index returns) and Panel B (for equity market index returns) plot estimates and confidence intervals reported in Table 6, showing that predicted excess returns subsequent to large credit expansions are significantly negative. The plot shows the magnitude of equity excess returns 8- and 12-quarters subsequent to large credit expansions (when credit expansion exceeds a given percentile threshold), in addition to average returns subsequent to large credit contractions (when credit expansion falls below a given percentile threshold). Average returns conditional on the thresholds are computed using regression models (3) and (4) with non-overlapping returns, which in the absence of control variables is equivalent to computing a simple average of returns conditional on credit expansion exceeding or falling below the given threshold. 95% confidence intervals are computed using dually-clustered standard errors estimated with regression equations (3) and (4). Observations for 8- and 12-quarter ahead returns are non-overlapping, from 20 countries from 1920 to 2012.

Panel A: Bank index returns



Panel B: Equity index returns

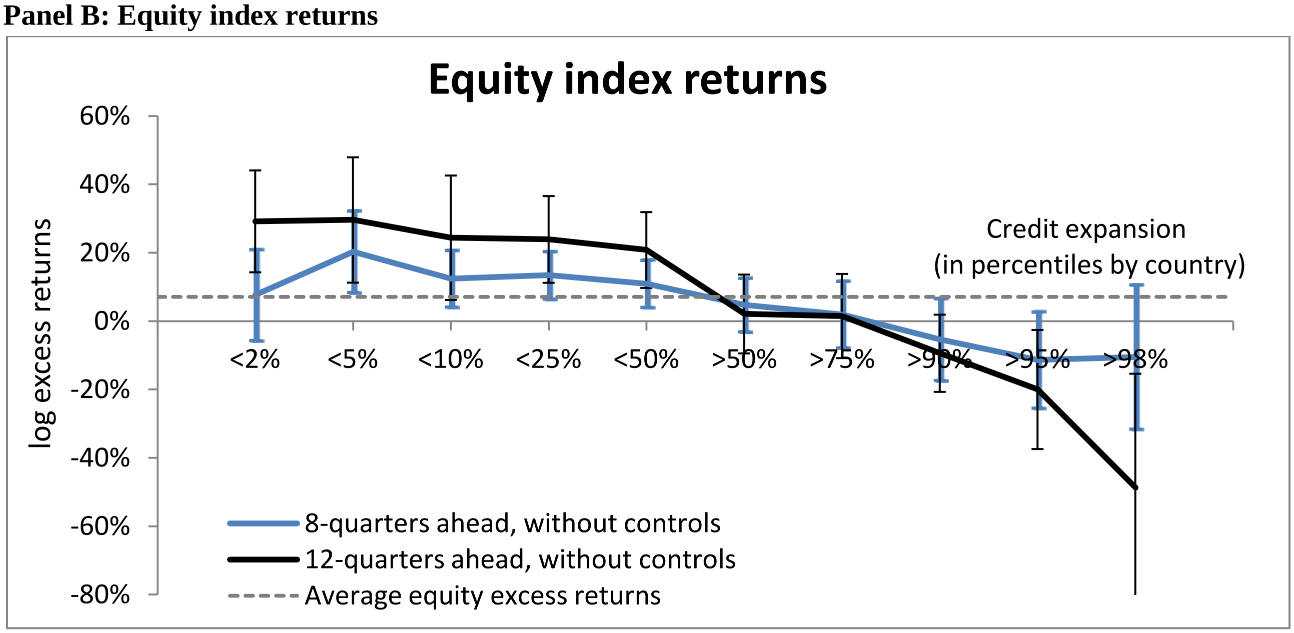


Table 1: Summary statistics

Summary statistics are reported for equity log excess 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 domestic households and domestic private non-financial corporations) and three-year change in total credit to GDP (credit issued by all sources to domestic households and domestic private 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)	5664	0.027	0.029	0.219	-1.099	-0.652	-0.456	0.476	0.677	1.254
Equity excess returns (incl. dividends)	4816	0.066	0.072	0.220	-1.062	-0.642	-0.440	0.532	0.724	1.269
Equity real returns (incl. dividends)	5200	0.079	0.087	0.222	-1.079	-0.615	-0.428	0.548	0.744	1.298
Bank stocks excess returns (w/out dividends)	4890	0.025	0.012	0.273	-1.377	-0.757	-0.512	0.540	0.795	1.685
Bank stocks excess returns (incl. dividends)	4541	0.061	0.050	0.277	-1.362	-0.745	-0.491	0.589	0.839	1.705
Bank stocks real returns (incl. dividends)	4770	0.074	0.059	0.272	-1.334	-0.719	-0.465	0.599	0.848	1.660
Credit to private households and non-financial corporations, 3 year percentage point change										
Δ (Bank credit / GDP)	5333	1.2%	1.1%	3.3%	-6.7%	-3.4%	-2.3%	4.9%	6.5%	11.4%
Δ (Total credit / GDP)	3978	2.4%	2.1%	5.1%	-8.7%	-4.6%	-2.9%	8.4%	10.6%	17.5%

Table 2: Time series correlations

Panel A presents evidence that bank credit expansions tend to follow good economic states. Estimates are reported for panel regressions with fixed effects with the dependent variable being three-year change of bank credit to GDP (standardized within each country) regressed on the three-year contemporaneous or lagged value of predictor variables. Panel A shows that low equity market daily volatility, high real GDP growth, low corporate yield spreads, and low sovereign yield spreads in the past three years tend to precede bank credit expansions in the subsequent three years. Panel B presents evidence that bank credit expansion is positively correlated with changes in other similar credit measures, including other aggregate credit variables (total credit to households (HH) and/or non-financial corporations (NFC), etc.), leverage (of the household, corporate, and banking sectors), and changes in international credit. Estimates are reported from panel regressions with fixed effects on each of the alternative credit measures regressed on contemporaneous three-year change of bank credit to GDP. All variables are standardized 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	-.258***	.148*	-.227**	-.136*
	R^2	0.1	0.02	0.13	0.02
	N	278	430	200	398

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	.754***	.639***	.649***	.626***	.232*	0.19	-0.247	-.237*	.332**	.16*
	R^2	0.59	0.43	0.41	0.37	0.12	0.14	0.12	0.12	0.15	0.05
	N	337	221	217	324	126	117	189	184	232	328

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 = 0.26).

Correlation with U.S.

	Country	**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	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Commonwealth	Australia	0.43	0.33	0.39	0.33	0.40	0.57	0.70	0.37	0.88	0.68	0.13
	Canada	0.79	0.56	0.42	0.21	0.24	0.92	0.87	0.49	0.82	0.72	0.77
	UK	0.50	0.42	0.31	0.32	0.25	0.63	0.66	0.41	0.94	0.82	0.68
W. Europe	Austria	0.39	0.42	0.31	0.60	-0.09	0.68	0.23	-0.22	0.40	0.61	
	Belgium	0.61	0.47	0.66	0.52	-0.03	0.59	0.48	0.26	0.14	0.51	
	France	0.41	0.41	0.39	0.38	0.35	0.33	0.52	0.19	0.80	0.54	0.61
	Germany	0.37	0.34	0.43	0.41	0.49	0.36	0.61	0.15	0.82	0.53	0.41
	Ireland	0.57	0.49	0.61	0.42	0.56	0.88	0.62	0.19	0.54	0.64	
	Netherlands	0.63	0.42	0.48	0.34	0.00	0.90	0.62	0.20	0.91	0.68	
	Switzerland	0.52	0.49	0.24	0.51	0.22	0.71	0.68	0.09	0.85	0.39	
Scandinavia	Denmark	0.37	0.30	0.35	0.39	0.48	0.68	0.50	-0.12	0.56	0.69	
	Norway	0.47	0.28	0.56	0.40	0.47	0.59	0.61	0.26	0.00	0.32	
	Sweden	0.48	0.33	0.24	0.26	0.21	0.67	0.62	0.00	0.73	0.69	
S. Europe	Italy	0.38	0.34	0.29	0.28	0.25	0.32	0.43	-0.03	0.50	0.53	0.41
	Portugal	0.41	0.44	0.53	0.47	0.11	0.10	0.56	0.03	0.16	0.65	
	Spain	0.55	0.44	0.47	0.34	0.24	0.42	0.53	0.23	0.69	0.23	
Asia	Hong Kong	0.53	0.49	0.38	0.17	-0.23	0.58	0.45	0.76	0.40		
	Japan	0.28	0.14	0.12	0.23	0.46	0.61	0.33	0.19	0.05	-0.26	0.19
	Korea	0.38	0.22	0.26	-0.06	-0.25	0.62	0.47	-0.14	-0.30		
	Average	0.50	0.42	0.42	0.38	0.26	0.61	0.58	0.21	0.54	0.55	0.53

Table 4: Predictive probit regressions using crash indicators.

This table reports estimates from the probit regression model specified in equation (1) and demonstrates that bank credit expansion (standardized within each country) predicts an increased likelihood of an equity crash, 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 takes on a value of 1 if there is a future equity crash, as defined in Section III, in the next K quarters (K = 1, 4, and 8) and 0 otherwise, which is regressed on the three-year change in bank credit to GDP (standardized within each country) and several subsets of control variables known to predict the equity premium. All reported estimates are marginal effects, so that a coefficient of 0.024 means that a one-standard deviation increase in Δ(bank credit / GDP) predicts a 2.4 percentage point increase in the likelihood of a future crash. 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 right tail event; we then compute and test the difference in the marginal effects between the two probit regressions (the probability of a crash minus probability of a boom). Standard errors are dually-clustered on country and time. Observations are quarterly over 20 countries from 1920 to 2012.

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**	-0.008	0.031**	0.044**	-0.024	0.068*	0.048***	-0.032	0.079**
		(2.87)	(-1.04)	(2.74)	(2.89)	(-1.50)	(2.44)	(3.55)	(-1.75)	(2.66)
	N	4186	4186	4186	1061	1061	1061	542	542	542
With two controls	Δ (bank credit / GDP)	0.021*	-0.009	0.030*	0.040**	-0.025	0.064*	0.040**	-0.029	0.069*
		(2.40)	(-1.15)	(2.43)	(2.75)	(-1.52)	(2.37)	(2.79)	(-1.44)	(2.10)
	log(d/p)	-0.059*	0.017	-0.075*	-0.113*	0.062	-0.175*	-0.098**	0.034	-0.132
		(-2.15)	(0.72)	(-1.99)	(-2.56)	(1.51)	(-2.57)	(-2.63)	(0.96)	(-1.92)
	N	3880	3880	3880	1000	1000	1000	509	509	509
With all controls	Δ (bank credit / GDP)	0.016	-0.011	0.027*	0.036**	-0.030	0.066*	0.039*	-0.029	0.069
		(1.89)	(-1.47)	(2.19)	(2.59)	(-1.84)	(2.51)	(2.20)	(-1.38)	(1.83)
	log(d/p)	-0.042	-0.003	-0.039	-0.096	0.035	-0.131	-0.071	0.017	-0.089
		(-1.21)	(-0.14)	(-0.94)	(-1.80)	(0.81)	(-1.65)	(-1.64)	(0.41)	(-1.10)
	Inflation	0.014	-0.077	0.091	-0.143	0.268	-0.412	-0.264	0.484	-0.749
		(0.06)	(-0.32)	(0.32)	(-0.41)	(0.67)	(-0.71)	(-0.63)	(1.00)	(-0.88)
	term spread	0.205	0.125	0.080	-0.353	-0.228	-0.125	-0.638	0.144	-0.782
		(0.32)	(0.23)	(0.08)	(-0.31)	(-0.22)	(-0.06)	(-0.49)	(0.12)	(-0.32)
	log(book / market)	-0.015	0.052	-0.067	0.008	0.046	-0.038	-0.023	-0.007	-0.016
		(-0.29)	(1.77)	(-1.18)	(0.14)	(0.77)	(-0.37)	(-0.35)	(-0.10)	(-0.12)
	log(i / k)	0.091	0.097	-0.006	0.087	0.089	-0.002	0.076	0.008	0.068
		(1.12)	(1.38)	(-0.05)	(0.84)	(0.60)	(-0.01)	(0.67)	(0.06)	(0.30)
	N	3659	3659	3659	943	943	943	479	479	479

Panel B: Crash in equity index

		1			4			8		
		Crash	Boom	Difference	Crash	Boom	Difference	Crash	Boom	Difference
No controls	Δ (bank credit / GDP)	0.017**	-0.002	0.019*	0.034*	-0.011	0.045	0.043**	-0.017	0.060*
		(2.95)	(-0.37)	(2.44)	(2.35)	(-0.76)	(1.79)	(2.93)	(-1.19)	(2.29)
	N	4332	4332	4332	1118	1118	1118	569	569	569
With two controls	Δ (bank credit / GDP)	0.017**	-0.001	0.018*	0.031*	-0.009	0.040	0.033*	-0.009	0.042
		(2.84)	(-0.27)	(2.19)	(2.29)	(-0.65)	(1.68)	(2.30)	(-0.57)	(1.52)
	log(d/p)	-0.062**	0.021	-0.082***	-0.155***	0.065	-0.219***	-0.203***	0.096**	-0.299***
		(-3.21)	(1.46)	(-3.63)	(-3.67)	(1.91)	(-3.54)	(-4.25)	(2.67)	(-3.91)
	N	4285	4285	4285	1109	1109	1109	560	560	560
With all controls	Δ (bank credit / GDP)	0.012*	-0.002	0.013	0.025*	-0.007	0.032	0.030	-0.007	0.036
		(2.03)	(-0.30)	(1.70)	(2.06)	(-0.51)	(1.51)	(1.78)	(-0.40)	(1.14)
	log(d/p)	-0.037	0.013	-0.051*	-0.132***	0.034	-0.166**	-0.155**	0.054	-0.209**
		(-1.81)	(0.82)	(-2.26)	(-3.36)	(0.90)	(-2.71)	(-3.23)	(1.37)	(-2.61)
	Inflation	0.220	0.002	0.218	0.189	0.086	0.103	0.318	0.069	0.248
		(1.25)	(0.01)	(1.11)	(0.59)	(0.30)	(0.26)	(1.13)	(0.20)	(0.49)
	term spread	-0.610*	0.440	-1.050*	-2.011**	0.253	-2.264	-1.667*	-0.095	-1.572
		(-2.31)	(1.29)	(-2.39)	(-2.91)	(0.35)	(-1.93)	(-2.30)	(-0.13)	(-1.17)
	log(book / market)	-0.041	0.042	-0.083*	-0.047	0.087	-0.134	-0.074	0.045	-0.119
		(-1.39)	(1.82)	(-2.25)	(-1.23)	(1.53)	(-1.61)	(-1.89)	(0.97)	(-1.48)
	log(i / k)	0.068	0.031	0.038	0.075	-0.005	0.080	0.152	-0.092	0.244
		(0.96)	(0.58)	(0.41)	(0.58)	(-0.04)	(0.35)	(1.28)	(-0.71)	(1.11)
	N	3995	3995	3995	1035	1035	1035	522	522	522

Table 5: Equity premium predictability regressions

This table reports estimates from the panel regression with fixed effects model specified in equation (2) and demonstrates that credit expansion, despite being associated with subsequent increased crash risk, predicts lower, rather than higher, log excess returns both in the bank equity index (Panel A) and the market equity index (Panel B), in subsequent 1, 4, and 8 quarters. Returns are non-overlapping, and standard errors are dually-clustered on country and time. A coefficient of -0.011 means that a one-standard deviation increase in Δ(bank credit / GDP) predicts a 1.1 percentage point decrease in subsequent returns. The dependent variable is log excess total returns, which is regressed on the three-year change in bank credit to GDP (standardized within each country) and several subsets of control variables thought to predict the equity premium. Observations are quarterly over 20 countries from 1920 to 2012.

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*	-0.045*	-0.047*	-0.046*	-0.083**	-0.076**	-0.079**	-0.077**
	(-2.691)	(-2.292)	(-2.308)	(-2.209)	(-2.119)	(-1.982)	(-2.434)	(-2.384)	(-3.086)	(-2.820)	(-2.796)	(-2.769)
log(d/p)		0.016	0.010	0.009		0.098	0.085	0.076		0.105	0.067	0.061
		(1.182)	(0.668)	(0.601)		(1.953)	(1.344)	(1.207)		(1.648)	(0.850)	(0.792)
Inflation			-0.112	-0.116			-0.290	-0.320			-0.121	-0.149
			(-0.992)	(-1.029)			(-0.668)	(-0.739)			(-0.180)	(-0.215)
term spread			0.445	0.403			1.529	1.317			1.777	1.633
			(1.210)	(1.088)			(1.035)	(0.883)			(0.930)	(0.860)
log(book / market)			0.020	0.016			0.035	0.019			0.096	0.082
			(0.729)	(0.576)			(0.324)	(0.177)			(0.604)	(0.520)
log(i / k)			0.016	0.017			0.081	0.082			0.035	0.038
			(0.320)	(0.345)			(0.436)	(0.443)			(0.175)	(0.193)
Consumption / wealth				0.259**				0.984**				0.829
				(3.185)				(2.640)				(1.340)
R^2	0.009	0.011	0.015	0.017	0.034	0.049	0.053	0.059	0.071	0.080	0.081	0.084
Adj. R^2	0.004	0.005	0.009	0.011	0.015	0.028	0.028	0.034	0.034	0.039	0.033	0.034
N	4163	3862	3643	3643	1039	981	927	927	521	493	467	467

Panel B: Equity index

	1 quarter horizon				4 quarter horizon				8 quarter horizon			
Δ (bank credit / GDP)	-0.008**	-0.007**	-0.006*	-0.006*	-0.033*	-0.033*	-0.033*	-0.031*	-0.049*	-0.047*	-0.051*	-0.048*
	(-2.970)	(-2.824)	(-2.218)	(-2.115)	(-2.172)	(-2.225)	(-2.408)	(-2.346)	(-2.343)	(-2.306)	(-2.301)	(-2.239)
log(d/p)		0.014	0.009	0.007		0.079*	0.068*	0.059		0.128*	0.081	0.071
		(1.871)	(1.145)	(1.019)		(2.514)	(2.145)	(1.853)		(2.258)	(1.552)	(1.391)
Inflation			-0.183*	-0.185*			-0.521	-0.537			-0.871*	-0.891*
			(-2.179)	(-2.213)			(-1.456)	(-1.509)			(-2.011)	(-2.039)
term spread			0.453*	0.413*			1.565*	1.357			1.629	1.416
			(2.528)	(2.287)			(1.976)	(1.715)			(1.359)	(1.198)
log(book / market)			0.031*	0.027*			0.078	0.062			0.169*	0.148*
			(2.272)	(1.990)			(1.641)	(1.325)			(2.369)	(2.109)
log(i / k)			-0.006	-0.005			-0.013	-0.012			-0.049	-0.044
			(-0.193)	(-0.156)			(-0.106)	(-0.098)			(-0.420)	(-0.393)
Consumption / wealth				0.255***				1.005***				1.287**
				(4.044)				(3.640)				(3.209)
R^2	0.007	0.011	0.028	0.032	0.027	0.056	0.086	0.098	0.043	0.088	0.130	0.142
Adj. R^2	0.002	0.006	0.023	0.027	0.009	0.037	0.064	0.076	0.006	0.050	0.087	0.098
N	4286	4239	3950	3950	1062	1059	987	987	532	530	494	494

Table 6: Negative predicted returns subsequent to large credit expansion

Panel A (for the bank equity index) and Panel B (for the equity market index) report average log excess returns, including dividends, 4-, 8- and 12-quarters subsequent to large credit expansions (when credit expansion exceeds a given percentile threshold) and subsequent to large credit contractions (when credit expansion falls below a given percentile threshold). This table demonstrates that excess returns subsequent to large credit expansions are predictably negative. Average returns conditional on the thresholds (and corresponding t-statistics and adjusted R^2) are computed using regression models (3) and (4) with non-overlapping 4-, 8-, and 12-quarter ahead returns. Computing average returns using the formal regression estimation technique is, in the absence of control variables, equivalent to computing a simple average of returns conditional on credit expansion exceeding or falling below the given threshold. T-statistics are computed using dually-clustered standard errors. Observations are quarterly over 20 countries from 1920 to 2012.

Panel A: Bank index

	Threshold in percentiles:		**<2%**	**<5%**	**<10%**	**<25%**	**<50%**	**>50%**	**>75%**	**>90%**	**>95%**	**>98%**
4-quarter ahead returns	no controls	E[r]	-0.074	0.140	0.101	0.082	0.059	-0.006	-0.040	-0.081	-0.137	-0.264
		(t-stat)	(-1.168)	(3.319)	(2.185)	(3.134)	(2.565)	(-0.178)	(-0.796)	(-1.006)	(-1.065)	(-2.025)
		Adj. R^2	0.014	0.019	0.018	0.021	0.021	0.022	0.027	0.026	0.028	0.031
		N	21	53	101	247	519	529	279	115	62	24
	with controls	E[r]	-0.034	0.159	0.110	0.083	0.062	-0.010	-0.044	-0.089	-0.138	-0.265
		(t-stat)	(-0.472)	(3.284)	(2.118)	(3.067)	(2.592)	(-0.255)	(-0.87)	(-1.062)	(-1.104)	(-2.141)
		Adj. R^2	0.033	0.051	0.04	0.047	0.051	0.052	0.066	0.059	0.058	0.046
		N	18	47	91	223	451	481	266	109	61	24
8-quarter ahead returns	no controls	E[r]	0.064	0.301	0.163	0.147	0.113	-0.005	-0.073	-0.142	-0.230	-0.241
		(t-stat)	(0.783)	(3.43)	(2.945)	(3.555)	(2.852)	(-0.091)	(-1.001)	(-1.712)	(-2.131)	(-2.548)
		Adj. R^2	0.057	0.085	0.076	0.093	0.11	0.118	0.111	0.132	0.105	0.095
		N	12	26	50	118	255	273	147	59	29	14
	with controls	E[r]	0.095	0.343	0.173	0.153	0.117	-0.009	-0.084	-0.164	-0.247	-0.244
		(t-stat)	(0.906)	(3.229)	(2.753)	(3.397)	(2.852)	(-0.166)	(-1.109)	(-1.822)	(-2.286)	(-2.945)
		Adj. R^2	0.037	0.042	0.04	0.043	0.044	0.042	0.047	0.048	0.05	0.053
		N	9	23	46	109	222	250	140	55	28	14
12-quarter ahead returns	no controls	E[r]	0.237	0.458	0.295	0.260	0.201	-0.065	-0.125	-0.356	-0.423	-0.812
		(t-stat)	(1.756)	(4)	(2.908)	(4.181)	(3.29)	(-0.85)	(-1.462)	(-4.172)	(-2.527)	(-2.101)
		Adj. R^2	0.049	0.068	0.055	0.062	0.064	0.062	0.078	0.075	0.072	0.06
		N	5	18	34	78	169	176	100	37	19	5
	with controls	E[r]	0.282	0.460	0.314	0.273	0.210	-0.073	-0.135	-0.386	-0.416	-0.806
		(t-stat)	(1.867)	(3.229)	(2.712)	(4.603)	(3.514)	(-0.907)	(-1.533)	(-4.948)	(-2.758)	(-2.381)
		Adj. R^2	0.109	0.127	0.121	0.14	0.15	0.15	0.146	0.179	0.151	0.139
		N	5	15	30	71	147	160	95	34	19	5

Panel B: Equity index

		Threshold in percentiles:	<2%	<5%	<10%	<25%	<50%	>50%	>75%	>90%	>95%	>98%
4-quarter ahead returns	no controls	E[r]	0.024	0.106	0.092	0.080	0.063	0.013	0.001	-0.028	-0.066	-0.115
		(t-stat)	(0.44)	(3.163)	(3.138)	(3.815)	(3.119)	(0.482)	(0.033)	(-0.514)	(-0.814)	(-1.165)
		Adj. R^2	0.006	0.009	0.01	0.012	0.011	0.02	0.016	0.016	0.019	0.016
		N	24	55	100	252	516	557	304	128	70	28
	with controls	E[r]	0.092	0.143	0.116	0.081	0.063	0.009	-0.008	-0.041	-0.074	-0.123
		(t-stat)	(1.733)	(4.994)	(4.403)	(4.037)	(3.275)	(0.324)	(-0.21)	(-0.754)	(-0.965)	(-1.354)
		Adj. R^2	0.013	0.02	0.015	0.02	0.018	0.028	0.03	0.038	0.038	0.024
		N	20	49	90	232	472	521	287	120	68	27
8-quarter ahead returns	no controls	E[r]	0.076	0.203	0.124	0.134	0.109	0.047	0.019	-0.054	-0.114	-0.105
		(t-stat)	(1.126)	(3.356)	(2.949)	(3.806)	(3.113)	(1.184)	(0.384)	(-0.889)	(-1.598)	(-0.981)
		Adj. R^2	0.021	0.028	0.027	0.04	0.05	0.084	0.05	0.056	0.056	0.049
		N	14	27	50	122	255	285	159	66	33	16
	with controls	E[r]	0.140	0.248	0.148	0.140	0.110	0.035	-0.001	-0.086	-0.145	-0.133
		(t-stat)	(1.989)	(3.313)	(3.454)	(3.687)	(3.284)	(0.854)	(-0.013)	(-1.431)	(-2.406)	(-1.549)
		Adj. R^2	0.051	0.057	0.056	0.055	0.053	0.06	0.058	0.061	0.062	0.059
		N	10	23	45	112	232	267	150	61	31	15
12-quarter ahead returns	no controls	E[r]	0.292	0.296	0.244	0.239	0.208	0.021	0.015	-0.094	-0.200	-0.487
		(t-stat)	(3.86)	(3.18)	(2.641)	(3.711)	(3.695)	(0.359)	(0.24)	(-1.64)	(-2.262)	(-2.879)
		Adj. R^2	0.08	0.089	0.081	0.085	0.083	0.09	0.092	0.108	0.101	0.088
		N	7	19	33	80	164	185	106	41	20	5
	with controls	E[r]	0.297	0.314	0.293	0.258	0.212	0.000	-0.002	-0.131	-0.203	-0.479
		(t-stat)	(4.808)	(3.479)	(4.043)	(4.835)	(4.489)	(-0.007)	(-0.038)	(-3.574)	(-2.486)	(-4.834)
		Adj. R^2	0.15	0.155	0.157	0.168	0.17	0.197	0.162	0.182	0.18	0.166
		N	7	17	30	73	152	172	100	37	20	5

Table 7: Robustness of crash predictability

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 subsequent negative skewness of equity returns, $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$. The second approach uses the difference ($\beta_{\text{median}} - \beta_{\text{mean}}$) between the coefficients from a median regression (50th quantile regression) and mean regression as an alternative measure of the negative skew. β_{median} is also useful as a robustness check for the mean regression specified in equation (2), 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 is subsequent non-overlapping 4-, 8-, or 12-quarter ahead returns of the bank equity index or the market equity index, which is regressed on credit expansion 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 $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$, the difference between the median and mean coefficients ($\beta_{\text{median}} - \beta_{\text{mean}}$), and their associated t-statistics or p-values. Standard errors are dually-clustered on country and time. Observations are quarterly over 20 countries from 1920 to 2012.

		Bank index			Equity index		
Explanatory variables:		1	4	8	1	4	8
Δ (bank credit / GDP)	Q5	-.048***	-.119***	-.093*	-.033***	-.077**	-.106*
	(t stat)	(-4.07)	(-4.46)	(-2.28)	(-3.51)	(-2.9)	(-2.5)
	Q50 (median)	-.007***	-.029*	-.06	-.005**	-.024***	-.05*
	(t stat)	(-3.32)	(-2.5)	(-1.89)	(-2.7)	(-3.73)	(-2.31)
	Q95	.006*	-.028	-.14***	-.003	-.038*	-.051
	(t stat)	(2.12)	(-.98)	(-3.55)	(-.88)	(-1.97)	(-1.73)
	Negative skew	**.028***	**.089*****	**.114****	**.026***	**.066**	**.057**
	(t stat)	**(2.29)**	**(3.94)**	**(3.05)**	**(2.49)**	**(1.8)**	**(.71)**
	mean	-.011**	-.049*	-.083**	-.008**	-.033*	-.049*
	(t stat)	(-2.69)	(-2.12)	(-3.09)	(-2.97)	(-2.17)	(-2.34)
	median	-.007***	-.029*	-.06	-.005**	-.024***	-.05*
	(t stat)	(-3.32)	(-2.5)	(-1.89)	(-2.7)	(-3.73)	(-2.31)
	difference	**.004***	**.02***	**.023**	**.003***	**.009**	**-.001**
	(p-value)	**(.045)**	**(.036)**	**(.272)**	**(.023)**	**(.092)**	**(.918)**
	N	4163	1039	521	4286	1062	532
Δ (bank credit / GDP), with D/P, inflation, book to market, term spread, and i/k as controls (coefficients on controls not shown)	Q5	-.035**	-.085***	-.03	-.024***	-.047	-.02
	(t stat)	(-2.88)	(-3.71)	(-1.12)	(-3.3)	(-1.44)	(-.49)
	Q50 (median)	-.006*	-.036***	-.036	-.005**	-.031	-.055***
	(t stat)	(-2.19)	(-3.48)	(-1.28)	(-2.58)	(-3.97)	(-3.55)
	Q95	-.004	-.003	-.073	-.002	-.02	-.022
	(t stat)	(-.5)	(-.14)	(-1.9)	(-.39)	(-1.03)	(-.74)
	Negative skew	**.027*****	**.016**	**.032**	**.016***	**.005**	**-.069**
	(t stat)	**(4.09)**	**(.51)**	**(.560)**	**(2.42)**	**(.13)**	**(-1.22)**
	mean	-.009*	-.047*	-.079**	-.006*	-.033*	-.051*
	(t stat)	(-2.31)	(-2.43)	(-2.8)	(-2.22)	(-2.41)	(-2.3)
	median	-.006*	-.036***	-.036	-.005**	-.031***	-.055***
	(t stat)	(-2.19)	(-3.48)	(-1.28)	(-2.58)	(-3.97)	(-3.55)
	difference	**.004***	**.017**	**.042*****	**.002***	**.004**	**-.002**
	(p-value)	**(.047)**	**(.154)**	**(<0.001)**	**(.035)**	**(.556)**	**(.818)**
	N	3643	927	467	3950	987	494

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 within various geographical and time subsets. Panel A analyzes various geographical subsets, while Panel B analyzes various time subsets: 1920-2013 (the full sample), 1920-2005 (excluding the recent crisis), and 1950-2005 (excluding both the recent crisis and the Great Depression). The table reports estimates of mean and probit coefficients (using the same methodology as in Tables 4 and 5) of non-overlapping 4-quarter-ahead log excess returns of either the bank equity index or the equity market index regressed on credit expansion with or without the five standard controls. Coefficients reported in this table are always on Δ (bank credit / GDP); coefficients on control variables are omitted.

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

			All	Largest Eight	U.S.	English speaking	W. Europe	S. Europe	Scandinavia
Bank Index	**probit - without controls**	Δ (bank credit / GDP)	0.044**	0.041**	0.052	0.048**	0.054**	0.098***	0.061*
		(t-stat)	(2.89)	(2.58)	(1.56)	(2.59)	(2.93)	(3.98)	(2.08)
		N	1061	524	76	286	741	100	185
	probit - with controls	Δ (bank credit / GDP)	0.036**	0.035*	0.040	0.046**	0.043*	0.048*	0.048
		(t-stat)	(2.59)	(2.53)	(0.82)	(2.93)	(2.39)	(2.21)	(1.88)
		N	943	587	84	294	752	135	166
	mean - without controls	Δ (bank credit / GDP)	-0.049*	-0.033	-0.037	-0.024	-0.066*	-0.089*	-0.070*
		(t-stat)	(-2.119)	(-1.947)	(-1.464)	(-1.569)	(-2.410)	(-2.246)	(-2.276)
		N	1039	518	76	283	731	100	179
	mean - with controls	Δ (bank credit / GDP)	-0.047*	-0.031	-0.003	-0.010	-0.063**	-0.153*	-0.073***
		(t-stat)	(-2.434)	(-1.601)	(-0.093)	(-0.714)	(-2.678)	(-2.565)	(-3.787)
		N	927	517	76	282	669	98	155
Equity Index	**probit - without controls**	Δ (bank credit / GDP)	0.034*	0.035**	0.017	0.033*	0.042*	0.134*	0.060*
		(t-stat)	(2.35)	(2.68)	(0.45)	(2.57)	(2.38)	(2.57)	(2.00)
		N	1118	522	76	284	681	100	159
	probit - with controls	Δ (bank credit / GDP)	0.025*	0.029*	0.010	0.038*	0.027	0.057	0.020
		(t-stat)	(2.06)	(2.24)	(0.26)	(2.28)	(1.79)	(1.69)	(0.65)
		N	1035	584	84	292	744	133	164
	mean - without controls	Δ (bank credit / GDP)	-0.033*	-0.028*	-0.014	-0.020	-0.048**	-0.039	-0.032
		(t-stat)	(-2.172)	(-2.092)	(-0.679)	(-1.404)	(-2.833)	(-1.651)	(-1.031)
		N	1062	580	84	290	708	135	144
	mean - with controls	Δ (bank credit / GDP)	-0.033*	-0.025	0.004	-0.005	-0.049***	-0.073**	-0.010
		(t-stat)	(-2.408)	(-1.639)	(0.177)	(-0.329)	(-3.472)	(-3.081)	(-0.342)
		N	987	579	84	290	701	131	144

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

			1920-2012	1920-2005	1950-2005
Bank Index	**probit - without controls**	Δ (bank credit / GDP)	0.044**	0.040***	0.040**
		(t-stat)	(2.89)	(3.44)	(3.13)
		N	1061	947	846
	probit - with controls	Δ (bank credit / GDP)	0.036**	0.027*	0.027*
		(t-stat)	(2.59)	(2.28)	(2.00)
		N	943	1004	845
	mean - without controls	Δ (bank credit / GDP)	-0.049*	-0.037**	-0.040**
		(t-stat)	(-2.119)	(-2.898)	(-2.713)
		N	1039	926	830
	mean - with controls	Δ (bank credit / GDP)	-0.047*	-0.035**	-0.045**
		(t-stat)	(-2.434)	(-2.665)	(-2.891)
		N	927	825	730
Equity Index	**probit - without controls**	Δ (bank credit / GDP)	0.034*	0.032**	0.034*
		(t-stat)	(2.35)	(2.77)	(2.45)
		N	1118	841	742
	probit - with controls	Δ (bank credit / GDP)	0.025*	0.018	0.022
		(t-stat)	(2.06)	(1.58)	(1.38)
		N	1035	933	777
	mean - without controls	Δ (bank credit / GDP)	-0.033*	-0.027*	-0.030*
		(t-stat)	(-2.172)	(-2.263)	(-2.196)
		N	1062	948	834
	mean - with controls	Δ (bank credit / GDP)	-0.033*	-0.028*	-0.038*
		(t-stat)	(-2.408)	(-2.197)	(-2.509)
		N	987	885	772

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 ($\delta = \mathrm{corr}(u_{i,t}, \varepsilon_{i,t})$) are reported. Panel A corresponds to bank equity index returns, and Panel B corresponds to equity market index returns. All parameter estimates of δ in both panels 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	0.964	0.026	4130	-148.68
1	Y	0.964	0.037	3614	-130.10
4	N	0.794	0.033	1020	-210.12
4	Y	0.794	0.056	888	-182.93
8	N	0.491	0.012	497	-252.97
8	Y	0.491	0.017	434	-220.91

Panel B: Index returns

Quarters ahead	Controls?	ρ	δ	N	N * (ρ - 1)
1	N	0.964	0.024	4247	-152.89
1	Y	0.964	0.037	3913	-140.87
4	N	0.794	0.018	1036	-213.42
4	Y	0.794	0.049	966	-199.00
8	N	0.491	-0.007	506	-257.55
8	Y	0.491	0.008	472	-240.25

Table 10: Robustness of negative returns: Clustering observations by historical episodes

This table demonstrates that predicted excess returns subsequent to large credit expansions are robustly negative, even after first grouping observations across time and countries into distinct episodes (clusters) and then averaging across these episodes. This analysis addresses the concern that multiple observations of large credit expansions across many countries concurrently might reflect a single global episode rather than various local events. As before, we define a large credit expansion as credit expansion exceeding the 95th percentile and a large credit contraction as falling below the 5th percentile. Since countries undergoing large credit expansions (or contractions) may remain over the 95^{th} (or under the 5^{th}) percentile thresholds for multiple years, to collapse observations across time, we select only the returns subsequent to the *first* year in which credit expansion first crosses the 95^{th} (or 5^{th}) percentile thresholds. Then we group concurrent observations across countries into distinct historical episodes. Finally, returns from the resulting historical episodes in the sample are averaged together, taking each such historical episode as a single, independent observation. Observations are from 20 countries, 1920-2012. A list of all large credit expansions and large credit contractions, grouped together by historical episode, can be found in Table S1 in the online appendix.

Panel A: Returns subsequent to large credit expansions (observations grouped by episodes)

	returns on bank equity			returns on market index		
Quarters ahead:	4	8	12	4	8	12
Average over episodes:	-0.09	-0.15	-0.21	-0.07	-0.14	-0.10
T-STAT	-1.35	-1.94	-2.10	-1.44	-2.47	-1.64
S.E.	0.07	0.08	0.10	0.05	0.06	0.06
N (episodes)	15	15	15	16	16	16

Panel B: Returns subsequent to large credit contractions (observations grouped by episodes)

	returns on bank equity			returns on market index		
Quarters ahead:	4	8	12	4	8	12
Average over episodes:	0.12	0.17	0.27	0.19	0.25	0.36
T-STAT	1.91	2.93	4.14	2.25	2.64	3.32
S.E.	0.06	0.06	0.07	0.08	0.09	0.11
N (episodes)	19	19	19	20	20	20

Table 11: Robustness of negative predicted returns: out-of-sample predictability

This table demonstrates that predicted excess returns subsequent to large credit expansions are robustly negative, even when conditioning returns strictly on past information. This table is similar to Table 6, but the percentile threshold for each quarter is calculated only using previous information for that country (given at least 5 years of past data for that country). For example, for credit growth to be above the >95% threshold, credit growth must be greater than 95% of all previous observations for that country.

Panel A: Bank index

	Threshold in percentiles:		**<2%**	**<5%**	**<10%**	**<25%**	**<50%**	**>50%**	**>75%**	**>90%**	**>95%**	**>98%**
4-quarter ahead returns	no controls	E[r]	5.5%	7.8%	9.1%	7.4%	6.4%	-0.7%	-2.8%	-5.3%	-5.8%	-8.8%
		(t-stat)	(1.438)	(2.302)	(2.705)	(3.048)	(2.844)	(-0.187)	(-0.58)	(-0.809)	(-0.747)	(-1.257)
		Adj. R^2	0.013	0.015	0.019	0.019	0.022	0.023	0.024	0.023	0.02	0.02
		N	89	113	151	262	478	567	334	178	117	67
	with controls	E[r]	6.4%	9.4%	10.0%	7.8%	6.4%	-0.7%	-3.1%	-5.8%	-5.6%	-8.6%
		(t-stat)	(1.162)	(2.045)	(2.445)	(2.884)	(2.651)	(-0.178)	(-0.626)	(-0.853)	(-0.728)	(-1.23)
		Adj. R^2	0.037	0.039	0.045	0.051	0.053	0.058	0.062	0.053	0.059	0.049
		N	61	84	120	226	413	516	312	166	114	66
8-quarter ahead returns	no controls	E[r]	14.2%	14.1%	17.0%	15.5%	12.4%	-1.3%	-5.3%	-8.9%	-16.1%	-15.2%
		(t-stat)	(3.419)	(2.432)	(3.869)	(4.016)	(3.37)	(-0.232)	(-0.777)	(-1.165)	(-1.987)	(-2.197)
		Adj. R^2	0.062	0.07	0.073	0.076	0.102	0.109	0.102	0.106	0.09	0.1
		N	44	57	75	131	236	289	181	87	53	35
	with controls	E[r]	16.9%	15.8%	19.1%	16.3%	12.3%	-1.2%	-5.8%	-9.7%	-15.6%	-14.6%
		(t-stat)	(2.901)	(2.02)	(3.66)	(3.778)	(3.202)	(-0.204)	(-0.812)	(-1.217)	(-2.064)	(-2.289)
		Adj. R^2	0.035	0.037	0.039	0.041	0.042	0.041	0.044	0.045	0.041	0.041
		N	30	43	61	115	203	266	170	81	52	35
12-quarter ahead returns	no controls	E[r]	20.4%	25.2%	24.8%	20.9%	20.9%	-5.1%	-9.9%	-20.7%	-23.7%	-39.3%
		(t-stat)	(3.254)	(4.119)	(3.666)	(3.901)	(3.656)	(-0.635)	(-1.148)	(-1.918)	(-2.165)	(-2.817)
		Adj. R^2	0.052	0.052	0.058	0.064	0.062	0.063	0.071	0.065	0.068	0.061
		N	31	38	47	81	154	190	118	59	34	20
	with controls	E[r]	23.2%	30.4%	28.8%	22.3%	21.1%	-5.2%	-10.6%	-21.6%	-22.2%	-38.1%
		(t-stat)	(2.297)	(3.132)	(3.3)	(3.69)	(3.52)	(-0.598)	(-1.099)	(-1.891)	(-2.36)	(-3.223)
		Adj. R^2	0.112	0.118	0.122	0.123	0.136	0.136	0.138	0.14	0.124	0.138
		N	20	26	35	69	133	173	110	56	33	20

Panel B: Equity index

		Threshold in percentiles:	<2%	<5%	<10%	<25%	<50%	>50%	>75%	>90%	>95%	>98%
4-quarter ahead returns	no controls	E[r]	6.0%	6.7%	8.2%	7.0%	6.6%	1.4%	0.4%	-0.9%	-1.6%	-3.6%
		(t-stat)	(2.048)	(2.624)	(3.53)	(3.72)	(3.282)	(0.488)	(0.113)	(-0.198)	(-0.324)	(-0.76)
		Adj. R^2	0.006	0.007	0.009	0.009	0.011	0.019	0.016	0.014	0.013	0.013
		N	92	114	157	272	484	584	349	192	130	79
	with controls	E[r]	7.0%	7.9%	8.6%	7.2%	6.5%	1.1%	-0.3%	-1.8%	-2.1%	-3.8%
		(t-stat)	(2.088)	(2.9)	(3.47)	(3.854)	(3.245)	(0.39)	(-0.072)	(-0.394)	(-0.441)	(-0.846)
		Adj. R^2	0.013	0.013	0.015	0.022	0.018	0.031	0.034	0.027	0.035	0.032
		N	77	98	138	247	439	550	334	183	129	79
8-quarter ahead returns	no controls	E[r]	8.3%	9.1%	12.3%	14.0%	11.4%	4.3%	1.8%	-0.1%	-5.4%	-7.2%
		(t-stat)	(1.565)	(2.015)	(3.094)	(3.923)	(3.417)	(1.036)	(0.361)	(-0.016)	(-0.775)	(-1.02)
		Adj. R^2	0.019	0.02	0.019	0.023	0.039	0.068	0.056	0.05	0.055	0.063
		N	43	54	76	136	237	299	188	94	60	41
	with controls	E[r]	9.5%	10.0%	13.0%	14.2%	11.2%	3.5%	0.5%	-2.1%	-7.1%	-7.4%
		(t-stat)	(1.425)	(1.864)	(2.943)	(3.693)	(3.222)	(0.834)	(0.11)	(-0.339)	(-1.237)	(-1.236)
		Adj. R^2	0.051	0.051	0.052	0.052	0.053	0.058	0.057	0.058	0.055	0.056
		N	36	47	68	124	214	282	180	89	59	41
12-quarter ahead returns	no controls	E[r]	12.8%	17.9%	16.1%	18.4%	20.2%	3.6%	1.1%	-3.4%	-10.0%	-20.2%
		(t-stat)	(1.171)	(2)	(1.894)	(2.626)	(3.715)	(0.632)	(0.192)	(-0.46)	(-1.311)	(-2.493)
		Adj. R^2	0.08	0.08	0.08	0.085	0.082	0.09	0.093	0.091	0.097	0.095
		N	28	35	44	81	154	193	123	65	40	24
	with controls	E[r]	13.8%	21.0%	18.3%	19.3%	19.2%	2.8%	0.1%	-4.9%	-11.1%	-20.3%
		(t-stat)	(1.155)	(2.159)	(2.378)	(2.95)	(3.601)	(0.525)	(0.022)	(-0.651)	(-1.823)	(-3.65)
		Adj. R^2	0.15	0.15	0.15	0.152	0.155	0.173	0.167	0.163	0.168	0.181
		N	23	29	38	74	140	183	118	62	39	24

Table A1 - Data and sample length

This table shows the sample length for each variable by reporting the first year of data for each variable within each country.

Country	Bank credit / gdp	equity return	bank equity return	D / P	bank D / P	first year of banking crisis	exchange rate	inflation	three mo tbill yield	govt 10yr yield	longterm corpbond yield	E / P	stock daily volatility	book / market	i / k	stock market turnover	currentaccount / gdp	gross external debt / gdp	c / w	real gdp growth	central govt debt / gdp	totalcredit / gdp	Hhdebt / totalassets	totalcreditHH / gdp	growth in housing assets	NFC equity / assets	totalcreditNFC / gdp	BANK equity / assets
Australia	1920	1920	1920	1920	1924	1920	1920	1920	1928	1920	1983	1973	1958	1980	1960	1973	1960	1970	1978	1920	1920	1954	1978	1977	1961	1981	1977	1983
Austria	1949	1922	1986	1925	1986	1920	1920	1920	1960	1923	1970	1973	1975	1980	1960	1989	1960	1970		1949	1924	1949		1995		1993	1995	1987
Belgium	1970	1920	1934	1927	1965	1920	1920	1920	1948	1920	1970	1969	1973	1980	1960	1980	1960	1970		1935	1920	1970		1980		1981	1980	1981
Canada	1920	1920	1920	1934	1923	1920	1920	1920	1934	1920	1970	1956	1973	1980	1960	1995	1961	1970	1970	1920	1920	1954	1970	1969	1971	1981	1969	1981
Denmark	1951	1921	1921	1969	1952	1920	1920	1920	1921	1920	1994	1969	1979	1980	1960	1991	1960	1970		1922	1920	1951		1994		1981	1994	1979
France	1920	1920	1920	1920	1924	1920	1920	1920	1922	1920	1970	1971	1968	1980	1960	1991	1960	1970	1970	1921	1920	1969	1970	1977	1971	1981	1977	1988
Germany	1925	1924	1928	1920	1928	1920	1920	1920	1920	1920	1970	1969	1970	1980	1960	1968	1960	1970	1970	1926	1925	1950	1950	1970	1951	1981	1970	1979
Hong Kong	1978	1964	1973	1972	1973		1920	1947	1982	1994		1972	1969	1980		1988		1979		1961		1978		1990		1993	1990	1993
Ireland	1971	1934	1973	1973	1973	1920	1946	1922	1960	1928		1973	1973	1981	1960	1997	1960	1970		1949	1924	1971		2002		1982	2002	1985
Italy	1920	1920	1973	1925	1973	1920	1920	1920	1922	1920	1970	1984	1957	1981	1960	1993	1960	1970	1980	1920	1920	1950	1966	1950	1967	1982	1950	1983
Japan	1920	1920	1946	1920	1958	1920	1920	1920	1920	1920	1970	1956	1948	1980	1960	1972	1960	1970	1980	1920	1920	1964	1970	1964	1971	1980	1964	1980
Korea	1960	1962	1975	1963	1987	1920	1920	1948	1969	1973	1972	1988	1962	1986		1978	1970	1971		1954	1920	1962		1962		1987	1962	1990
Netherlands	1948	1920	1928	1969	1928	1920	1920	1920	1920	1920	1970	1969	1973	1980	1960	1986	1960	1970		1949	1920	1961		1990		1981	1990	1979
Norway	1953	1950	1988	1969	1986	1950	1950	1950	1959	1950	1970	1969	1980	1984	1960	1987	1960	1970		1950	1950	1953		1975		1981	1975	1979
Portugal	1947	1934	1938	1988	1989	1920	1920	1930	1981	1920		1988	1986	1986	1960	1988	1960	1972		1954	1920	1947		1979		1990	1979	1996
Spain	1920	1920	1940	1920	1966	1920	1920	1920	1924	1920		1979	1971	1990	1960	1990	1960	1970		1920	1920	1970		1980		1993	1980	1979
Sweden	1920	1920	1920	1920	1926	1920	1920	1920	1920	1920	1974	1969	1980	1982	1960	1995	1960	1970		1920	1920	1961		1981		1982	1981	1979
Switzerland	1920	1920	1930	1920	1930	1920	1920	1920	1920	1920	2000	1969	1969	1980	1960	1989	1960	1970		1930	1924	1975		1999		1993	1999	1979
UK	1920	1920	1920	1923	1923	1920	1920	1920	1920	1920	1970	1927	1969	1980	1960	1966	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	1934	1960	1970	1960	1920	1920	1952	1946	1952	1947	1952	1952	1980