Credit Expansion and Neglected Crash Risk*

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Abstract

By analyzing 20 developed countries over 1920–2012, we find the following evidence of overoptimism and neglect of crash risk by bank equity investors during credit expansions: 1) bank credit expansion predicts increased bank equity crash risk, but despite the elevated crash risk, also predicts lower mean bank equity returns in subsequent one to three years; 2) conditional on bank credit expansion of a country exceeding a 95th percentile threshold, the predicted excess return for the bank equity index in subsequent three years is -37.3%; and 3) bank credit expansion is distinct from equity market sentiment captured by dividend yield and yet dividend yield and credit expansion interact with each other to make credit expansion a particularly strong predictor of lower bank equity returns when dividend yield is low.

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The recent financial crisis in 2007–2008 has renewed economists' interest in the causes and consequences of credit expansions. There is now substantial evidence showing that credit expansions can have severe consequences on the real economy as reflected by subsequent banking crises, housing market crashes, and economic recessions, e.g., Borio and Lowe (2002), Mian and Sufi (2009), Schularick and Taylor (2012), and López-Salido, Stein, and Zakrajšek (2015). However, the causes of credit expansion remain elusive. An influential yet controversial view put forth by Minsky (1977) and Kindleberger (1978) emphasizes overoptimism as an important driver of credit expansion. According to this view, prolonged periods of economic booms tend to breed optimism, which in turn leads to credit expansions that can eventually destabilize the financial system and the economy. The recent literature has proposed various mechanisms that can lead to such optimism, such as neglected tail risk (Gennaioli, Shleifer, and Vishny 2012, 2013), extrapolative expectations (Barberis, Shleifer, and Vishny 1998), and this-time-is-different thinking (Reinhart and Rogoff 2009).

Greenwood and Hanson (2013) provide evidence that during credit booms in the U.S. the credit quality of corporate debt issuance deteriorates and this deterioration forecasts lower corporate bond excess returns. While these findings are consistent with debt holders being overly optimistic at the time of credit booms—especially their finding that a deterioration in credit quality predicts negative returns for high-yield debt—the low but, on average, positive forecasted returns for the overall bond markets may also reflect elevated risk appetite of debt holders during credit expansions. The severe consequences of credit expansions on the whole economy also invite another important question of whether agents in the economy, other than debt holders, recognize the financial instability associated with credit expansion at the time of an expansion. While overoptimism might have caused debt holders to neglect credit risk during credit expansions, this may not be true of equity holders—and, in particular, bank shareholders, who often suffer large losses during financial crises and thus should have strong incentives to forecast the possibility of financial crises.[1] On the other hand, a long tradition links large credit expansions with

[1] In contrast, bank depositors and creditors are often protected by explicit and implicit government guarantees during financial crises. Even in the absence of deposit insurance, U.S. depositors in the Great Depression lost only 2.7% of the average amount of deposits in the banking system for the years 1930–1933, despite the fact that 39% of banks failed (Calomiris 2010).

overoptimism in equity markets (Kindleberger 1978), even though it is challenging to find definitive evidence of excessive equity valuations.

In this paper, we address these issues by systematically examining the expectations of equity investors, an important class of participants in financial markets. Specifically, we take advantage of a key property of equity prices—they reveal the knowledge and expectations of investors who trade and hold shares. By examining bank equity returns predicted by credit expansion, we can infer whether bank shareholders anticipate the risk that large credit expansions often lead to financial distress and whether shareholders demand a risk premium as compensation.

Our data set consists of 20 developed economies with data from 1920 to 2012. We focus on the bank lending component of credit expansions and measure bank credit expansion as the past three-year change in the bank-credit-to-GDP ratio in each country, where bank credit is the amount of net new lending from the banking sector to domestic households and non-financial corporations in a given country. We use this measure of credit expansion, which excludes debt securities held outside the banking sector, because data on non-bank credit are historically limited and because previous studies (e.g., Schularick and Taylor 2012) demonstrate that the change in bank credit is a robust predictor of financial crises. Furthermore, the build-up of credit on bank balance sheets (rather than financed by non-bank intermediaries or bond markets) poses the most direct risk to the banking sector itself. Thus, we analyze whether equity investors price in these risks.

Our analysis focuses on four questions regarding credit expansion from the perspective of bank equity holders. First, does credit expansion predict an increase in the crash risk of the bank equity index in subsequent one to three years? As equity prices tend to crash in advance of banking crises, the predictability of credit expansion for banking crises does not necessarily imply predictability for equity crashes. By estimating a probit panel regression as the baseline analysis together with a series of quantile regressions as robustness checks, we find that credit expansion predicts a significantly higher likelihood of bank equity crashes in subsequent years.

Our second question is whether the increased equity crash risk is compensated by higher equity returns on average. Note that the predictability of bank credit expansion for subsequent economic recessions, as documented by Schularick and Taylor (2012), does not necessarily imply that shareholders should earn lower average returns. If shareholders anticipate the increased likelihood of crash risk at the time of a bank credit expansion, they could demand higher expected returns by immediately lowering share prices and thus earn higher future average returns from holding bank stocks. This is a key argument we use to determine whether shareholders anticipate the increased equity crash risk associated with credit expansions.

We find that one to three years after bank credit expansions, despite the increased crash risk, the mean excess return of the bank equity index is significantly *lower* rather than higher. Specifically, a one standard deviation increase in credit expansion predicts an 11.4 percentage point decrease in subsequent 3-year-ahead excess returns. One might argue that the lower returns predicted by bank credit expansion may be caused by a correlation of bank credit expansion with a lower equity premium due to other reasons such as elevated risk appetite. However, even after controlling for a host of variables known to predict the equity premium, including dividend yield, book to market, inflation, term spread, and nonresidential investment to capital, bank credit expansion remains strong in predicting lower mean returns of the bank equity index.

Our third question asks the magnitude of the average bank equity returns during periods of large credit expansions and contractions. We find that conditional on credit expansions exceeding a 95th percentile threshold, the mean excess return in subsequent two and three years is substantially negative at -17.9% (with a *t*-statistic of -2.02) and -37.3% (with a *t*-statistic of -2.52), respectively. Note that for publicly traded banks, there is no commitment of shareholders to hold bank equity through both good and bad times and thus earn the unconditional equity premium. Our analysis thus implies that bank shareholders choose to hold bank equity during large credit booms even when the predicted excess returns are sharply negative. This substantially negative equity premium cannot be explained simply by elevated risk appetite and, instead, points to the presence of overoptimism or neglect of crash risk by equity holders during credit expansions.

Our final question is how the sentiment associated with bank credit expansions differs from and interacts with equity market sentiment captured by dividend yield, which is a robust predictor of mean equity returns and which is sometimes taken as a measure of equity market sentiment. Interestingly, while both bank credit expansion and low dividend yield of the bank equity index strongly predict lower bank equity returns, they have only a small correlation with each other. Furthermore, credit expansion has strong predictive power for bank equity crash risk, while dividend yield has no such predictive power for bank equity crash risk. Consistent with the theoretical insight of Simsek (2013), this contrast indicates two different types of sentiment—credit expansions are associated with neglect of tail risk, while low dividend yield is associated with optimism about the overall distribution of future economic fundamentals. Nevertheless, they are not independent predictors of bank equity returns. The predictive power of credit expansion is minimal when dividend yield is high, but particularly strong when dividend yield is low. This asymmetric pattern indicates that credit expansion and dividend yield amplify each other to give credit expansion even stronger predictability for bank equity returns when equity market sentiment is high.

As our analysis builds on predicting bank equity returns after extreme values of bank credit expansion, we have paid particular attention to verifying the robustness of our results along a number of dimensions. First, we have consistently used past information in constructing and normalizing the predictor variables at each point in time throughout our predictive regressions to avoid any look-ahead bias. In particular, the negative excess returns conditional on large credit expansions are forecasted at each point in time using only past information. Second, to avoid potential biases in computing *t*-statistics, we take extra caution along the following dimensions: a) we use only *non-overlapping* equity returns (i.e. we delete intervening observations so that we are effectively estimating returns on annual, biennial, or triennial data for 1-, 2-, or 3-year-ahead returns, respectively), b) we dually cluster standard errors both on country and time as in Thompson (2011), since returns and credit expansion may each be correlated both across countries and over time, and c) as a further robustness test to account for correlations across countries, we collapse all large credit expansions into 19 distinct historical episodes (e.g., the Great Depression, the East Asian Crisis, the 2007–08 Financial Crisis, and many lesser known episodes involving sometimes one or many countries) and find statistically significant negative returns by averaging these 19 historical episodes as distinct, independent observations. Third, we repeat our analysis in subsamples of geographical regions and time periods and find consistent results across the subsamples; in particular, the results hold over the subsample 1950–2003, which excludes the Great Depression and the 2007–08 financial crisis. Finally, we also examine a variety of alternative regression specifications and variable constructions to avoid potential concerns of specification optimizing. We obtain consistent results even after using these conservative measures and robustness checks.

Our analysis thus demonstrates the clear presence of overoptimism by bank shareholders during bank credit expansions.[2] Our findings shed light on several important issues. First, in the aftermath of the recent crisis, an influential view argues that credit expansion may reflect active risk seeking by bankers as a result of their misaligned incentives with their shareholders, e.g., Allen and Gale (2000) and Bebchuk, Cohen, and Spamann (2010). Our study suggests that as shareholders do not recognize the risk taken by bankers, such risk taking is not against the will of the shareholders and may have even been encouraged by them, as suggested by Stein (1996), Bolton, Scheinkman, and Xiong (2006), and Cheng, Hong, and Scheinkman (2013). In this sense, policies that aim to tighten the corporate governance of banks and financial firms are unlikely to fully prevent future financial crises caused by bank credit expansions.

Second, our results have implications for the design of financial regulations and other efforts to prevent future financial crises. For example, there is increasing recognition by policymakers across the world of the importance of developing early warning systems of future financial crises. While prices of financial securities are often considered as potential indicators, the overvaluation of bank equity and the neglect of crash risk associated with large credit expansions suggest that market prices are poor predictors of financial distress. Similarly, Krishnamurthy and Muir (2016) find that credit spreads in the run-up to historical crises are "abnormally low"; the same may be said about credit-default swap spreads on U.S. banks in 2006 and early 2007. Thus, our analysis suggests that the use of market prices for predicting future financial crises (or, for example, for implementing countercyclical capital buffers) is limited because market prices do not price in the risk of financial crises until it is too late. Quantity variables such as growth of bank credit to GDP may be more promising indicators.

The paper is structured as follows. Section I describes the data used in our analysis. Section II presents the main results using credit expansion to predict bank equity returns. Section III provides a variety of robustness checks. Finally, Section IV concludes. We also provide an online

[2] In this regard, our analysis echoes some earlier studies regarding the beliefs of financial intermediaries during the housing boom that preceded 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.

Appendix, which reports additional details related to data construction, analogous results for non-financial equities in place of bank equities, and additional robustness analysis.

I. Data

We construct a panel data set for 20 developed countries with quarterly observations from 1920 to 2012. Specifically, for a country to be included in our sample, it must currently be classified as an advanced economy by the IMF and have at least 40 years of data for both credit expansion and bank equity index returns.[3] For 12 countries, the data set is mostly complete from around 1920 onwards, while for 8 countries the data set is mostly complete from around 1950 onwards. The sample length of each variable for each country can be found in Appendix Table 1.

A. Data Construction

The data set primarily consists of three types of variables: credit expansion, bank equity index returns, and various control variables known to predict the equity premium. The construction of the data is outlined below, and more detail can be found in Appendix Section A.

Credit expansion. The key explanatory variable in our analysis is referred to as *credit expansion* and is defined as the annualized past three-year percentage point change in bank credit to GDP, where bank credit is credit from the banking sector to domestic households and non-financial corporations. Note that *credit expansion* throughout this paper refers to bank credit expansion except where specifically noted. It is expressed mathematically as

$$\Delta(bank\ credit/GDP)_t = [(bank\ credit/GDP)_t - (bank\ credit/GDP)_{t-3}]\ /\ 3.$$

Figure 1 plots this variable over time for the 20 countries in the sample, where *credit expansion* is expressed in standard deviation units by standardizing it by its mean and standard deviation within each country.[4] *Credit expansion* appears cyclical and mean-reverting for all countries, with periods of rapid credit expansion often followed by periods of credit contraction.

[3] The latter criterion excludes advanced economies such as Finland, Iceland, and New Zealand, for which there is limited pre-1990s data.

[4] In the rest of the paper, in order to avoid look-ahead bias in predictive regressions, *credit expansion* is standardized country-by-country using only past information at each point in time, as explained later. However, in Figure 1, the variable is standardized country-by-country on the entire time sample to present the data in a straightforward manner.

Insert Figure 1 here

Credit expansion is constructed from merging two sources: 1) "bank credit" from the Bank for International Settlements' (BIS) "long series on credit to private non-financial sectors," which covers a large range of countries but generally only for the postwar era, and 2) "bank loans" from Schularick and Taylor (2012), which extend back over a century but only for a subset of the countries. In both data sets, the term "banks" is broadly defined—for example, Schularick and Taylor's definition includes all monetary financial institutions such as savings banks, postal banks, credit unions, mortgage associations, and building societies for which data are available. As for the term "credit", in the BIS data set, "bank credit" refers broadly to credit in various forms (e.g., loans, leases, securities) extended from banks to domestic households and private non-financial corporations. In the Schularick and Taylor (2012) data set, "bank loans" is more narrowly defined as bank loans and leases to domestic households and private non-financial corporations. Both data sets exclude interbank lending and lending to governments and related entities.

Whenever there is overlap, we use the BIS data, since it is provided at a quarterly frequency. Because there are discrepancies between the two data sources, most likely stemming from differing types of institutions defined as "banks," differing types of instruments considered "credit," and differing original sources used to compile the data, we take care when merging the data to avoid break between the series: the Schularick-Taylor data is scaled for each country by an affine function so that the overlap between the series joins without a break and has similar variance for the overlap. (We find that the overlap between the data sets is highly correlated for all countries.) To interpolate the Schularick-Taylor annual data to quarterly observations, we *forward-fill* for the three subsequent quarters. In general, we fill forward explanatory variables to avoid look-ahead bias in forecasting, since forward-filled information for each quarter would already be known. We do the same for all other predictor variables (e.g., book to market) in cases in which only annual data is given for a variable in certain historical periods.

Our analysis uses the change in bank credit to GDP, rather than the level, for the following reasons. The change of credit emphasizes the cyclicality of credit and represents the amount of net new lending to the private sector. When the change in bank credit is high, the rapid increase in new lending may coincide with lower lending quality, as shown by Greenwood and Hanson (2013), which may in turn increase subsequent losses in the banking sector and lead to a financial crisis.

In contrast to the change, the level of credit 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.[5]

As the magnitude of *credit expansion* varies substantially across countries due to their size and institutional differences, we standardize *credit expansion* for each country separately to make this variable comparable across countries.[6] However, to avoid look-ahead bias in the predictability regressions, we normalize in such a way so that at each point in time we use only past information. That is, for each country and each point in time, we calculate the mean and standard deviation using only prior observations in that country and use these values to standardize the given observation.

Equity index returns. The main dependent variable in our analysis is the future return of the *bank equity index* for each country. In Appendix Section B, results for the *non-financials equity index* are presented, but in all other places, we always refer to the bank equity index for each country. Also, the terminology *returns* always refers to *log excess total returns* throughout the paper.[7]

Our main source for price data for the bank equity index (and for price and dividend data for the non-financials indices) is Global Financial Data (GFD). Our main source of bank dividend yield data is hand-collected data from Moody's Banking Manuals. In many cases, both price and dividend data are supplemented with data from Compustat, Datastream, and data directly from stock exchanges' websites and central bank statistics.[8] For both banks and non-financials, we

[5] Why do we choose the past *three-year* change and not use some other horizon? In Appendix Table 8, we provide analysis to show that the greatest predictive power for subsequent equity returns comes from the 2nd and 3rd lags in the one-year change in bank credit to GDP, with predictability strongly dropping off at longer lags. It should also be noted that Schularick and Taylor (2012) find similar results for the greatest predictability of future financial crises with the 2nd and 3rd one-year lags. Thus, we cumulate the three one-year lags to arrive at the past three-year change in bank credit to GDP as the main predictor variable in our analysis.

[6] For example, *credit expansion* in Switzerland has substantially greater variance than in the U.S., because Switzerland has a much larger banking sector relative to GDP. Preliminary tests suggested that it is crucial to standardize by country: it is the relative size of credit booms relative to the past *within a given country* (perhaps, relative to what a country's institutions are designed to handle) that best predicts returns.

[7] We also repeat our main results in Appendix Table 9 with arithmetic equity returns as a robustness check. The results do not meaningfully change.

[8] See Appendix Section A for additional details on constructing the bank and non-financials equity indices and dividend yield indices for each country, including links to spreadsheets detailing our source data. Appendix Section

choose market-capitalization-weighted indices for each country that are as broad as possible within the banking or non-financial sectors (though often, due to limited historical data, the non-financials index is a broad manufacturing or industrials index). We compare many historical sources to ensure accuracy of the historical data. For example, we compare our main bank price index for each country with several alternative series from GFD and Datastream, along with an index constructed using hand-collected bank stock prices (annual high and low prices) from Moody's Manuals; we retained only series that are highly correlated with other sources (see Appendix Table 2).

Excess total returns are constructed by taking the quarterly price returns, adding in *dividend yield*, and subtracting the *three-month short-term interest rate*. For forecasting purposes, we construct 1-, 2-, and 3-year-ahead log excess total returns by summing the consecutive quarterly log returns and applying the appropriate lead operator.

Finally, we also define a *crash indicator* for 1-, 2-, and 3-years ahead for the bank and non-financials equity indices, which takes on the value of 1 if the log excess total return of the underlying equity index is less than -30% for any quarter within the 1-, 2-, or 3-year horizon, and 0 otherwise. Analogously, we also define a *boom indicator* but for greater than +30% returns for any quarter within the 1-, 2-, or 3-year horizon. We find that, for the bank equity index, +30% and -30% quarterly returns happen roughly 1.1% and 3.2% of quarters, respectively. As these threshold values were chosen somewhat arbitrarily, Section IV.C also provides additional analysis to show that our results on crash risk are robust to using an alternative, quantile-regression approach, which does not rely on the choice of a particular crash definition.[9]

Control variables. We also employ several financial and macroeconomic variables, which are known to predict the equity premium, as controls. The main control variables are *dividend yield* of the bank equity index[10], *book-to-market*, *inflation, non-residential investment to capital (I/K),* and

A also discusses further details regarding the construction of the *three-month short-term interest rate*, control variables, and other variables.

[9] In unreported results, we verify that our analysis on crash risk is robust to choosing other thresholds of $\pm 20\%$ or $\pm 25\%$ for booms and crashes.

[10] The dividend yield of the entire equity market and smoothed variations of both bank and broad-market measures are employed in Appendix Table 6, which shows that the main results of this paper are robust to these alternative measures of dividend yield.

term spread. These variables are chosen because the data are available over much of the sample period for the 20 countries and because these variables have the strongest predictive power for bank equity index returns in a univariate framework.[11] Bank dividend yield is trimmed if it exceeds 40% annualized (i.e. 10% in a given quarter) to eliminate outliers. We standardize the control variables across the entire sample pooled across countries and time, which does not introduce forward-looking bias, as it is simply a change of units.

Other variables. We also employ various other measures of aggregate credit 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 Appendix Section A.

B. *Summary Statistics*

Table 1 presents summary statistics for bank equity index returns, non-financials equity index returns, *credit expansion* (i.e. the annualized past-three-year change in bank credit to GDP, sometimes denoted mathematically as $\Delta(bank\ credit\ /\ GDP)$), and control variables. Observations are pooled across time and countries. Statistics for returns are all expressed in units of annualized log returns.

Insert Table 1 here

The mean bank and non-financials equity index returns are 5.9% and 6.4%, respectively, comparable to the historical U.S. equity premium. The standard deviation of bank index returns is 28.6%, slightly higher than the standard deviation of 25.6% for non-financials. In general, equity returns are moderately correlated across countries—bank index returns have an average correlation of 0.394 with the U.S., and non-financials index returns have an average correlation of 0.411. Given that this paper studies crash events, it is useful to get a sense of the magnitude of price drops in various percentiles. The 5th percentile quarterly return, which occurs on average once every 5 years, is -76.2% (in annualized log terms, thus corresponding to a quarterly drop of -76.2% / 4 = 19.1%), and the 1st percentile return is -137.6%.

[11] Appendix Table 11 analyzes other possible control variables, for which there is limited data availability (such as the *corporate yield spread* and realized *daily volatility*) or little predictive power (such as *three-month short-term interest rate* (trailing 12-month average), *real GDP growth,* and *sovereign default spread*) and shows that the addition of these control variables does not meaningfully change the main results.

Credit expansion is on average 1.3% per year. In terms of variability, *credit expansion* grew as rapidly as 6.4 percentage points of GDP per year (in the 95th percentile) and contracted as rapidly as -3.2 percentage points of GDP per year (in the 5th percentile). Table 1 reports that its time-series correlation with the U.S., averaged across countries, is 0.221. This correlation is rather modest, considering that the two most prominent credit expansions, those leading up to the Great Depression and the 2007–08 Financial Crisis, were global in nature. In fact, the average correlation of bank credit expansions in 1950–2003 (i.e. outside of these two episodes) is only 0.109. The relatively idiosyncratic nature of historical credit expansions, which is also visible in Figure 1, helps our analysis, as *credit expansion*'s associations with equity returns and crashes may be attributed in large part to local conditions and not through spillover from crises in other countries.[12]

Insert Table 2 here

Table 2 examines time-series correlations between *credit expansion* and other variables. We first compute these time-series correlations within each country and then average the correlation coefficients across the countries in our sample. Table 2 shows that, as expected, bank *credit expansion* is correlated with changes in other aggregate credit variables—including total credit (i.e. both bank and non-bank credit), total credit to households, total credit to non-financial corporations, bank assets to GDP, and growth of household housing assets—and with change in international credit (current account deficits to GDP and change in gross external liabilities to GDP), verifying that all these measures of credit generally coincide.[13] However, the correlations of *credit expansion* with the dividend yield of both the bank equity index and the broad market index are statistically indistinguishable from zero, which suggests that *credit expansion* and dividend yield are relatively orthogonal variables in predicting future equity returns. We will further compare the predictability of bank *credit expansion* and bank dividend yield in Section II.D and argue that they capture different dimensions of market sentiment.

C. Large Credit Booms and Bank Equity Declines

[12] Appendix Table 10 shows that predictive power of *credit expansion* on subsequent returns is in large part due to country-specific credit expansion and not spillover effects from other countries.

[13] The construction of these variables and their data sources are described in Appendix Section A.

To understand the timing of credit expansions and bank equity declines, it is useful to plot their dynamics. Figure 2 depicts the bank equity index, together with *credit expansion*, before and after large credit booms, where a large credit boom is defined as any observation in which *credit expansion* is above the 95th percentile relative to past data in that country. We will return to this definition of a large credit boom again in Section II.C.

To produce Figure 2, the past-three-year change in bank credit to GDP and bank total excess log returns are averaged, pooled across time and country, conditional on the given number of years before or after a large credit boom (from t = -6 to t = +6). To convert from returns to an index, the average bank log returns are then cumulated from t = -6 to t = +6, and the level is adjusted to be 0 at t = 0, the onset of the large credit boom.

The solid curve is the bank equity index (a cumulative log excess total returns index relative to t = 0, the time of the large credit boom), and the dashed line is *credit expansion* (the three-year past change in bank credit to GDP), which reaches a peak of around a 7.2 percentage point annualized change in bank credit to GDP at t = 0. In subsequent years, *credit expansion* gradually slows down to zero, below its historical trend growth rate of 1.3 percentage points; however, when a large credit boom is followed by a banking crisis, as it often is (Borio and Lowe 2002, Schularick and Taylor 2014), the decline in *credit expansion* is much steeper and turns negative after year 2; see Appendix Figure 2 for the dynamics of *credit expansion* and equity prices before and after banking crises.

Figure 2 previews our main result that credit booms forecast large declines in bank equity prices. On average, the equity market decline starts around the peak of the credit boom and continues for just over three years. From peak to trough, the average bank index declines over 30% in log return.[14]

Insert Figure 2 here

Figure 2 also highlights various other aspects of the dynamics of bank equity prices around large credit booms. For example, Figure 2 shows how bank equity prices tend to rise considerably

[14] The magnitude of the decline in Figure 2 is slightly different from the results in Table 5 because Table 5 uses non-overlapping 1-, 2-, and 3-year-ahead returns for econometric reasons, as explained in Section II. However, the magnitudes are roughly similar.

leading up to the peak of the credit boom, with log excess returns of the bank equity index of 8.5% per year, which is considerably above the historical average of 5.9%. Thus, bank equity prices rise rapidly during the boom years, only to crash on average after the peak of the boom.

II. Empirical Results

As banks directly suffer from potential defaults of borrowers during credit expansions and the risk of a run, bank equity prices should better reflect market expectations of the consequences of credit expansions than non-financial equity prices. In this section, we report our empirical findings using *credit expansion* to predict both crash risk and mean returns of the bank equity index. We also find similar, albeit less pronounced, results from using *credit expansion* to predict crash risk and equity returns of non-financials; we leave the results for non-financials for Appendix Section B.

Our analysis follows an intuitive and logical sequence. We first examine whether *credit expansion* predicts an increased equity crash risk in subsequent quarters and indeed find supportive evidence. We then examine whether *credit expansion* predicts an increase in mean equity excess returns to compensate investors for the increased crash risk and find the opposite result. We then examine the magnitude of the mean equity excess returns and find that conditional on a large credit expansion, the predicted mean equity excess returns over the subsequent two or three years can be significantly negative. Finally, we compare the sentiment reflected by bank credit expansion and dividend yield and examine their interaction in predicting bank equity returns.

Before turning to the regression specifications and estimation results, we note two econometric issues, which apply to all the following analyses. The first is that special care is needed in computing standard errors of these predictive return regressions with a financial panel data setting. This is because both outcome variables (e.g. K-year-ahead excess returns, K = 1, 2, and 3) and explanatory variables (e.g. *credit expansion* and controls) may be correlated across countries (due to common global shocks) and over time (due to persistent country-specific shocks). Therefore, we estimate standard errors that are dually clustered on time and country, following Thompson (2011), to account for both correlations across countries and over time. For panel linear regression models with fixed effects, i.e., equations (2) and (3) below, we implement dually clustered standard errors by using White standard errors adjusted for clustering on time and country separately, and then combined into a single standard error estimate as explicitly derived in Thompson (2011). For the probit regression, i.e., equation (1), and the quantile regressions specified in Section IV.C, we estimate dually clustered standard errors by block bootstrapping, drawing blocks that preserve the correlation structure both across time and country.

Second, due to well-known econometric issues arising from using overlapping returns as the dependent variable (Hodrick 1992; Ang and Bekaert 2007), we also take a deliberately conservative approach by using non-overlapping returns throughout the analysis in this paper. That is, in calculating 1-, 2- or 3-year- ahead returns, we drop the intervening observations from our data set, in effect estimating the regressions on annual, biennial, or triennial data.[15] 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.

To carry out the regression analyses, we collect the series of *credit expansion* and bank equity index returns together in a final consolidated data set. Observations are included only if both *credit expansion* and bank equity index returns are both non-missing.[16] This gives us a total of 4155 quarterly observations. After deleting intervening observations to create non-overlapping 1-, 2- or 3-year- ahead returns, there are 957, 480, and 316 observations for the 1-, 2- and 3-year-ahead regressions, respectively.

A. Predicting Crash Risk

We first estimate probit regressions with an equity crash indicator as the dependent variable to examine whether *credit expansion* predicts increased crash risk. Specifically, we estimate the following probit model, which predicts future equity crashes using *credit expansion* and various controls:

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[15] Specifically, we look at returns from close December 31, 1919 to close December 31, 1920, etc., for the 1-year-ahead returns; from close December 31, 1919 to close December 31, 1921, etc. for the 2-year-ahead returns; and from close December 31, 1919 to close December 31, 1922, etc. for the three-year-ahead returns.

[16] Given that the control variables are sometimes missing for certain countries and time periods due to historical limitations, missing values for control variables are imputed using each country's mean, where the mean is calculated at each point in time using only past information, in order to avoid any look-ahead bias in the predictive regressions. As shown in Appendix Table 11, mean imputation of control variables has little effect on the regression results but is important in preventing shifts in sample composition when control variables are added.

$$\Pr\left[Y = 1 \mid (predictor\ variables)_{i,t}\right] = \Phi\left[\alpha_i + \beta' \ (predictor\ variables)_{i,t}\right], \qquad (1)$$

where Φ is the CDF of the standard normal distribution and $Y = 1_{crash}$ is a future crash indicator, which takes on a value of 1 if there is an equity crash in the next K years (K = 1, 2, and 3) and 0 otherwise.[17] As discussed previously in Section I.A, we define the *crash indicator* to take on the value of 1 if the log excess total return of the underlying equity index is less than -30% for any quarter within the subsequent 1-, 2-, or 3-year horizon, and 0 otherwise. Given that an increased crash probability may be driven by increased volatility rather than increased crash risk on the downside, we also estimate equation (1) with $Y = 1_{boom}$, where 1_{boom} is a symmetrically defined positive tail event, and compute the difference in the marginal effects between the two probit regressions (probability of a crash minus probability of a boom).[18]

Insert Table 3 here

Table 3 reports the marginal effects corresponding to crashes in the bank equity index conditional on a one-standard-deviation increase in *credit expansion*. Regressions are estimated with and without the control variables. The blocks of columns in Table 3 correspond to the 1-, 2- and 3-year-ahead increased probability of a crash event. Each regression is estimated with various 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 4-6) reports marginal effects conditional on bank dividend yield with no controls, the third block of rows (rows 7-11) reports marginal effects conditional on both *credit expansion* and bank dividend yield, and the last block of rows (rows 12-

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[17] Another potential way is to use option data to measure tail risk, or, more precisely, the market perception of tail risk. However, such data are limited to recent years in most countries. Furthermore, as we will see, the market perception of tail risk may be different from the objectively measured tail risk.

[18] Probit regressions have been widely used to analyze currency crashes, e.g., Frankel and Rose (1996), who define a currency crash as a nominal depreciation of a currency of at least 25% and use a probit regression approach to examine the occurrence of such currency crashes in a large sample of developing countries. The finance literature tends to use conditional skewness of daily stock returns to examine equity crashes, e.g., Chen, Hong, and Stein (2001), but this approach would not work in the present context. As large credit expansions tend to be followed by large equity price declines over several quarters, as showed by Figure 2, such large equity price declines cannot be simply captured by daily stock returns. Furthermore, as the Central Limit Theorem implies that skewness in daily returns is averaged out in quarterly returns, we opt to define equity crashes directly as large declines in quarterly stock returns, following the literature on currency crashes. One might be concerned that the threshold of -30% is arbitrary. We address this concern by using a quantile regression approach as a robustness check in Section III.C. We also note that similar results (unreported) hold for -20% and -25% thresholds.

14) uses *credit expansion* and all five main control variables (bank dividend yield, book to market, term spread, investment to capital, and inflation; coefficients on controls omitted to save space).

Table 3 shows that *credit expansion* predicts an increased probability of bank equity crashes. The interpretation of the reported marginal effects is as follows: using the estimates for 1-, 2-, and 3-year-ahead horizons without controls, a one standard deviation rise in *credit expansion* is associated with an increase in the probability of a subsequent crash in the bank equity index by 2.7, 3.3, and 5.4 percentage points, respectively, all statistically significant at the 5% level. (As reference points, the unconditional probabilities of a bank equity crash event within the next 1, 2, and 3 years are 8.0%, 13.9%, and 19.3%, respectively, so a two-standard deviation credit expansion increases the probability of a crash event by approximately 50–70%.) Bank dividend yield is not significant in predicting the crash risk of bank equity. More important, the marginal effects of *credit expansion* are not affected after adding bank dividend yield and are slightly reduced but still significant after adding all five controls.

To distinguish increased crash risk from the possibility of increased return volatility 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 an alternative measure of crash risk in Section III.C using a quantile-regression-based approach, which studies crash risk without relying on a particular choice of thresholds for crash indicator variables.

In summary, we find that bank *credit expansion* predicts an increase in the crash risk of the bank equity index in subsequent 1, 2, and 3 years. This result expands the findings of Borio and Lowe (2002) and Schularick and Taylor (2012) by showing that *credit expansion* not only predicts banking crises but also bank equity crashes.

B. Predicting Mean Equity Returns

Given the increased crash risk subsequent to credit expansions, we now turn to examining whether the expected returns of the bank equity index are also higher to compensate equity holders for the increased risk. If bank shareholders recognize the increased equity crash risk associated with bank credit expansions, we expect them to lower current share prices, which in turn would lead to higher average returns from holding bank stocks despite the increased equity crash risk in the lower tail.

To examine whether *credit expansion* predicts higher or lower mean returns, we use an OLS panel regression with country fixed effects:

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

which predicts the K-year ahead excess returns (K = 1, 2 and 3) of the equity index, conditional on a set of predictor variables including *credit expansion*. We test whether the coefficient of *credit expansion* is different from zero. By using a fixed effects model, we focus on the time series dimension within countries.

From an empirical perspective, it is useful to note that *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, term spread, and investment to capital. 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.

When estimating regressions with bank equity returns, we do not control for market returns. While it is true that market and bank returns are highly correlated and that bank equity crashes are typically accompanied by contemporaneous declines in the broad market index, our research question focuses specifically on bank shareholders: why do bank shareholders hold bank stocks during large credit booms when the predicted returns are sharply negative? To study this question, we choose to directly analyze how *credit expansion* predicts bank equity returns, without explicitly differentiating the market component versus the bank idiosyncratic component.[19]

Table 4 estimates the panel regression model specified in equation (2). Various columns in Table 4 report estimates of regressions on *credit expansion* without controls, with bank dividend yield only, with *credit expansion* and bank dividend yield together, and with *credit expansion* and all five main controls (bank dividend yield, book to market, term spread, investment to capital, and inflation).

Insert Table 4 here

Columns 1-4, 5-8, and 9-12 correspond to results associated with predicting 1-, 2-, and 3-year-ahead excess returns, respectively. Coefficients and *t*-statistics are reported, along with the (within-country) R^2 and adjusted R^2 for the mean regressions. A one standard deviation increase in *credit expansion* predicts 3.2, 6.0, and 11.4 percentage point decreases in the subsequent 1-, 2-, and 3-year-ahead excess returns, respectively, all significant at the 5% level. When the controls are included, the coefficients are slightly lower but have similar statistical significance. In general, coefficients for the mean regressions are roughly proportional to the number of years, meaning that the predictability is persistent and roughly constant per year up to 3 years.[20]

Regarding the controls, higher dividend yield, term spread, and book to market are all associated with a higher bank equity premium (though these coefficients are generally not significant when estimated jointly with *credit expansion*; however, it should be noted the predictability using these control variables is considerably stronger for the non-financials equity index than for the bank equity index, as shown in Appendix Table 3, which is not surprising). The signs of these coefficients are in line with prior work on equity premium predictability. In particular, bank dividend yield has statistically significant predictive power for mean excess

[19] Nevertheless, we verify that the coefficients for the bank equity index are not higher due to bank stocks having a high market beta. The bank equity index has an average market beta of about 1. Also, even after estimating a time-varying beta for the bank stock index using daily returns, the idiosyncratic component of bank returns also exhibits increased crash risk and lower mean returns subsequent to credit expansion.

[20] The coefficients level off after about 3 years, implying that the predictability is mostly incorporated into returns within 3 years.

returns of the bank equity index across all horizons and specifications.[21] Nevertheless, the coefficient for *credit expansion* remains roughly the same magnitude and significance, despite the controls that are added. Thus, *credit expansion* adds new predictive power beyond these other variables and is not simply reflecting another known predictor of the equity premium.

Table 4 also reports within-country R^2 and adjusted within-country R^2 (as both have been reported in the equity premium predictability literature). In the univariate framework with just *credit expansion* as the predictor, the R^2 is 2.8%, 6.4%, and 13.1% for bank returns for 1-, 2- and 3-years ahead, respectively. Adding the five standard controls increases the R^2 to 5.7%, 10.4, and 23.3% for the same horizons. The relatively modest R^2 implies that it may be challenging for policy makers to adopt a sharp, real-time policy to avoid the severe consequences of credit expansion and for traders to construct a high Sharpe ratio trading strategy based on *credit expansion*. Nevertheless, the return predictability of *credit expansion* is strong compared to other predictor variables examined in the literature.[22]

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 Appendix Section E, we use the methodology of Campbell and Yogo (2006) to show that small-sample bias is unlikely a concern for our estimates.

[21] Note that in Appendix Table 6, we use market dividend yield as an alternative control variable. While market dividend yield is perhaps a better measure of the time-varying equity premium in the broad equity market, bank dividend yield performs uniformly better than market dividend yield in predicting both crash risk and mean excess returns of bank equity index. Given that we are running a horserace between *credit expansion* and dividend yield, we choose to use bank dividend yield as the stronger measure to compete against *credit expansion*. Appendix Table 6 also considers variations on market dividend yield and bank dividend yield in an effort to "optimize" dividend yield, but none of these alternatives meaningfully diminishes the magnitude and statistical significance of the coefficient on *credit expansion*.

[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.

Taken together, the results in subsections II.A and II.B show that despite the increased crash risk associated with bank credit expansion, the predicted bank equity excess return is lower rather than higher.[23] It is important to note that bank credit expansions are directly observable to the public through central bank statistics and banks' annual reports.[24] Thus, it is rather surprising that bank shareholders do not demand a higher equity premium to compensate themselves for the increased crash risk.

C. Excess Returns Subsequent to Large Credit Expansions and Contractions

We further examine the magnitude of predicted bank equity returns subsequent to "large" credit expansions and contractions. We find that predicted bank equity excess returns subsequent to large credit expansions are significantly negative and large in magnitude. This analysis helps to isolate the role of overoptimism in driving large credit expansions from that of elevated risk appetite, which does not cause the equity premium to go negative.

Specifically, we use a non-parametric model to estimate the magnitude of the predicted equity excess return subsequent to a large credit expansion:

$$r_{i,t+K} - r^{f}_{i,t+K} = \alpha + \beta_x \cdot 1_{\{credit\ expansion > x\}} + \epsilon_{i,t}, \tag{3}$$

where $x \geq 50\%$ is a threshold for credit expansion, expressed in percentiles of *credit expansion* within a country. We then use the estimates to compute predicted returns: $E[r - r_f \mid credit\ expansion > x] = \alpha + \beta_x$, which we report in Table 5. As a benchmark, we often focus on a "large credit expansion" using the 95th percentile threshold ($x = 95\%$). To avoid any look-ahead bias, percentile thresholds are calculated for each country and each point in time using only past information. 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

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

[24] In all the countries in our sample over the period of 1920–2012, balance sheet information of individual banks was widely available in "real-time" on at least an annual basis to investors in the form of annual reports (a historical database can be found here: https://apps.lib.purdue.edu/abldars/); in periodicals such as The Economist, Investors Monthly Manual, Bankers Magazine, etc.; and in investor manuals such as the annual Moody's Banking Manuals (covering banks globally from 1928 onwards) and the International Banking Directory (covering banks globally from 1920 onwards). In addition to the balance sheets of individual banks, The Economist and other publications also historically published *aggregated* quarterly or annual statistics of banking sector assets, deposits, loans, etc.

country.

Using this regression model to compute predicted is equivalent to simply computing average excess returns conditional on *credit expansion* exceeding the given percentile threshold x.[25] The advantage of this formal estimation technique over simple averaging is that it allows us to compute dually clustered standard errors for hypothesis testing, since the error term $\epsilon_{i,t}$ is possibly correlated both across time and across countries. This model specification is non-linear with respect to *credit expansion* and thus also serves to ensure that our analysis is robust to the linear regression model in equation (2). After estimating this model, we report a *t*-statistic to test whether the predicted equity premium $E[r_{i,t+K} - r^f_{i,t+K} \mid \cdot]$ 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 percentile threshold $y \leq 50\%$:

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

The predicted excess returns conditional on *credit expansion* exceeding or falling below given percentile thresholds are plotted in Figure 3 and reported in Table 5. Specifically, Figure 3 plots the predicted 2- and 3-year-ahead excess returns conditional on *credit expansion* exceeding various high percentile thresholds varying from the 50th to 98th percentiles and on *credit expansion* below various low percentile thresholds from the 2nd to 50th percentiles. A 95% confidence interval is plotted for each of the returns based on dually clustered standard errors.

Insert Figure 3 here

Figure 3 shows that the predicted excess returns for the bank equity index are decreasing with the threshold and remain negative across the upper percentile thresholds. Table 5 reports the same information but in tabular form. The predicted negative returns are weaker for the 1-year horizon but get increasingly stronger for the 2- and 3-year horizons. For example, at the 95th percentile

[25] Note that equation (3) does not have country fixed effects, both to avoid look-ahead bias and to be able to compute average returns conditional on a large credit boom. Only without fixed effects is our approach mathematically equivalent to hand-picking all large credit booms and taking a simple average of the subsequent returns, a fact which can be verified empirically.

threshold, the predicted negative returns are -9.4%, -17.9%, and -37.3% for the 1-, 2-, and 3-year-ahead horizons, with *t*-statistic of -0.918, -2.021, and -2.522, respectively. Also note that there are a reasonably large number of observations satisfying the 95th percentile threshold, which comes from having a large historical data set across 20 countries. According to Table 5, there are 80, 40, and 19 non-overlapping observations for 1-, 2-, and 3-year-ahead horizons, respectively.

Insert Table 5 here

Finally, Figure 3 and Table 5 also show that subsequent to credit contractions, the excess returns are positive. When credit contraction is less than the 5th percentile threshold, the predicted excess return for the bank equity index in the subsequent 2 and 3 years is 19.0% and 28.3%, both significant at the 5% level.[26]

To sum up, Figure 3 and Table 5 document a full picture of the time-varying bank equity premium across credit cycles. The expected excess return of the bank equity index is substantially negative during large bank credit expansions while positive during large contractions.

We provide various robustness checks in Section III to show that predicted excess returns subsequent to large credit expansions are robustly negative: 1) even after grouping concurrent observations of large credit expansions into distinct episodes and then averaging across these episodes (addressing the concern that concurrent credit expansions in multiple countries during the same global episode ought to be treated as a single observation rather than separate observations), and 2) after re-analyzing the results on various geographical subsets and time subsets (most importantly, over the period 1950–2003, showing that the results are not simply driven by the Great Depression and the 2007–08 financial crisis).

In the aftermath of the recent financial crisis, a popular view posits that credit expansion may reflect largely increased risk appetite of financial intermediaries due to relaxed Value-at-Risk constraints (Danielsson, Shin, and Zigrand 2012; Adrian, Moench, and Shin 2013). While elevated risk appetite may lead to a reduced equity premium during periods of credit expansions, it cannot

[26] The large positive returns subsequent to credit contractions may reflect several possible mechanisms. First, this pattern is consistent with intermediary capital losses during credit contraction episodes causing asset market risk premia to rise sharply, e.g., Adrian, Etula and Muir (2014) and Muir (2016). Alternatively, bank shareholders may systematically underestimate the probability of a government bailout during the depth of a financial crisis, only to be surprised later when a bailout happens.

explain the largely negative bank equity premium reported in Figure 3 and Table 5. Instead, this finding suggests the need to incorporate an additional feature that bank shareholders are overly optimistic and neglect crash risk during credit expansions. Recently, Jin (2015) provides a theoretical model to incorporate this important feature in a dynamic equilibrium model of financial stability.

D. Sentiment Reflected by Credit Expansion vs Dividend Yield

Given the presence of overoptimism during credit expansions, one might naturally wonder how the optimism associated with credit expansions is related to equity market sentiment. In this subsection, we further relate the return predictability of *credit expansion* to that of dividend yield, as the strong predictability of dividend yield for equity returns is sometimes acknowledged by the literature as a reflection of equity market sentiment. We are particularly interested in examining whether *credit expansion* and equity market sentiment may amplify each other in predicting bank equity returns.

We first note that booms in equity and credit markets might be driven by different types of sentiment. Credit valuation is particularly sensitive to the belief held by the market about the lower tail risk, while equity valuation is primarily determined by the belief about the mean or upper end of the distribution of future economic fundamentals. Geanakoplos (2010) develops a tractable framework to analyze credit cycles driven by heterogeneous beliefs between creditors and borrowers. Simsek (2013) builds on this framework to show that only when both creditors and borrowers share similar beliefs about downside states, a credit boom may arise in equilibrium. This credit boom is then able to fuel the optimism of the borrowers about the overall distribution and lead to an asset market boom.

Simsek's analysis generates two particularly relevant points for our study. First, a credit boom is mainly determined by the beliefs of both creditors and borrowers about the lower tail states and can occur without necessarily being accompanied by an overall asset market boom. The negligible correlation between *credit expansion* and bank dividend yield, as shown by Table 2, nicely confirms this insight. More important, as shown by Table 3, *credit expansion* has strong predictive power for bank equity crash risk, while dividend yield has no such predictive power. Furthermore, Appendix Figure 3 plots average bank equity index returns subsequent to high values of bank dividend yield (when it exceeds a given percentile threshold) and low values (when bank dividend yield falls below a given percentile threshold), similar to Figure 3 but with bank dividend yield rather than *credit expansion*. This figure shows that conditional on bank dividend yield being lower than its 2nd- or 5th-percentile value, the predicted returns are somewhat negative in magnitude though not significantly different from zero. These observations about the predictability of bank dividend yield all contrast that of bank *credit expansion*, indicating that the sentiment associated with credit expansions is distinct from the equity market sentiment.

Second, when a credit boom occurs together with overoptimistic beliefs of the borrowers about the upper states of the distribution of future economic fundamentals, the borrowers are able to use leverage to bid up asset prices, or put differently, the predictability of the credit boom for a negative bank equity premium is particularly strong. This important insight suggests that *credit expansion* may interact with bank dividend yield to provide even stronger predictive power of the bank equity premium, in particular when bank dividend yield is low (i.e., when there is overoptimism about the overall distribution). We now examine this insight empirically.

Table 6 reports estimation results interacting *credit expansion* with bank dividend yield. Specifically, we estimate the following specification:

$$r_{i,t+K} - r^{f}_{i,t+K} = \alpha_i + \beta_1(credit\ expansion)_{i,t} + \beta_2(bank\ dividend\ yield)_{i,t} + \beta_3(interaction)_{i,t} + \epsilon_{i,t} \tag{5}$$

where the interaction term is either the standard interaction term (*credit expansion* x *bank dividend yield*) or a non-linear version interacting *credit expansion* with quintile dummies for *bank dividend yield*. As before, the regression is estimated for 1-, 2-, and 3-year horizons (column groups 1-3, 4-6, and 7-9, respectively, in Table 6). Coefficients and *t*-statistics are reported, along with the (within-country) R^2 and adjusted R^2 for the regressions.

Insert Table 6 here

In each group of columns corresponding to 1-, 2-, and 3-year horizons, the first column reports estimates for just *credit expansion* and dividend yield with no interaction term (as in Table 4).The second column adds in the standard interaction term (*credit expansion* x *bank dividend yield*).

Although the estimates are small and not significant at the 1- and 2-year-ahead horizons, the result of 0.042 is sizeable and statistically significant at the 3-year-ahead horizon. A positive coefficient is what we expect: a one-standard-deviation *increase* in *credit expansion* combined with a one-standard-deviation *decrease* in dividend yield predicts an interaction effect of *lower* log excess returns of 4.2% (that is, beyond what is predicted with *credit expansion* and dividend yield individually).

However, the small and insignificant coefficients at the 1- and 2-year-ahead horizons may be due to the fact that the predictive power of dividend yield is non-linear and is strongest when dividend yield is very low. We therefore re-estimate equation (5) in the third column with a non-linear interaction term, interacting *credit expansion* with quintile dummies for *bank dividend yield*. Specifically, we interact *credit expansion* with the 4 lowest quintile groups, leaving in *credit expansion* on its own to capture the highest group. As a result, the coefficients test the interactions relative to the omitted group, the highest bank dividend yield quintile.

In Table 6, the third column shows that, in fact, the predictive power of *credit expansion* is particularly strong when bank dividend yield is low, specifically in its lowest quintile: the regression coefficient is significantly negative. To interpret the magnitudes, take, for example, the coefficient of -0.039 for the one-year horizon. A one standard deviation increase in *credit expansion* predicts an additional lower mean return of 3.9% when dividend yield is in its lowest quintile relative to its highest quintile (beyond what is predicted with *credit expansion* and dividend yield individually). The magnitude is considerably larger, 14.4%, at the three-year-ahead horizon.

Across all the quintiles of bank dividend yield, the coefficients are statistically significant generally only when bank dividend yield is in the lowest quartile, and its magnitude decreases somewhat monotonically across the four dividend yield quintiles. This suggests that dividend yield has a non-linear interaction effect with *credit expansion*. When dividend yield is high, the predictive power of *credit expansion* is minimal (as shown by the coefficient on the non-interacted *credit expansion* term, row 1). However, when dividend yield is very low (in its lowest quintile), the predictive power of *credit expansion* is particularly strong.

Overall, we observe that the sentiment associated with *credit expansion* is different from equity market sentiment reflected by dividend yield, and yet they interact with each other to give *credit expansion* even stronger predictive power for lower bank equity premium when equity market sentiment is high.

III. Robustness

We present a battery of robustness checks in this section. First, we show that predicted excess returns subsequent to large credit expansions remain negative even after robustly accounting for correlations across time and countries. Second, we show that the main results hold on various geographical and time subsets. Finally, we outline a variety of other robustness checks, the results of which can be found in the Appendix.

A. Clustering Observations by Historical Episodes

Recall Table 5, which analyzes equity excess returns subsequent to large credit expansions and contractions. Approximately concurrent observations of large credit expansions across multiple countries might reflect a single global episode rather than various local events. Accordingly, the episode may have correlated effects across countries and over the duration of the episode 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 historical episodes and then averaging across these episodes.

Insert Table 7 here

Table 7 organizes credit expansion observation satisfying the 95th percentile threshold into 19 distinct historical episodes. These 19 historical episodes are widely dispersed throughout the sample period. Some of these 19 distinct historical episodes are well known (e.g. the booms preceding: the Great Depression, the Japanese crisis of the 1990s, the Scandinavian financial crises, the 1997–98 East Asian crisis, and the 2007–08 global financial crisis), while other historical episodes are less well known. Some of these episodes consist of just a single country (Japan, 1989), while other episodes consist of either a few countries (the late-1980s booms in Scandinavian countries) or nearly all the countries in the sample (the 2000s global credit boom). This robustness check first averages large credit expansion observations across multiple countries and years that are part of the same historical episode, and then considers each of the resulting 19 historical episodes as a single, independent data point.

The procedure is specifically as follows. Looking at the *credit expansion* series for each individual country, we select observations in which *credit expansion* first crosses the 95th percentile thresholds. (Given that there is a potential for multiple successive observations to be over the 95th percentile due to autocorrelation, we select only the first in order to be robust to autocorrelation.) These events and their subsequent 3-year-ahead returns of the bank equity index are plotted in Figure 4.

Insert Figure 4 here

Then, to be robust to potential correlations across countries, we group approximately concurrent observations across countries into 19 distinct historical episodes and average the returns within each historical episode. Note that the returns within each of the 19 historical episodes are not necessarily exactly concurrent: for example, in the Scandinavian credit booms of the late 1980s, Denmark, Sweden, and Norway crossed the 95th percentile *credit expansion* threshold in 1986:q3, 1986:q4, and 1987:q4, respectively. Finally, the average returns from these 19 historical episodes are then themselves averaged together—taking each such historical episode as a single, independent observation—to generate the final average return reported at the bottom of Table 7.

In Table 7 and Figure 4, it is important to note that timing the onset of a bank equity crash is difficult, especially when restricted to using only past information at each point in time. Therefore, it is to be expected that the timing of events in Table 7 and Figure 4 may sometimes look "off." They do not necessarily correspond to the peak of the credit expansion or the stock market; they are what an observer in real-time could infer about the credit boom using the 95th percentile rule.[27]

Even after averaging observations within distinct historical episodes and then averaging across these historical episodes, the subsequent returns are robustly negative. Table 7 reports that

[27] Many observations in Table 7 and Figure 4 miss the crash either because the large credit is picked up too early (e.g., Spain 2004) or too late (e.g., U.S. 1932). In addition, in the early part of the sample (i.e. the late 1920s), many credit booms are not picked up at all because there is a limited historical sample on which to calibrate the 95th percentile threshold using only past data.

the average excess returns in the 1, 2, and 3 years following the start of historical episodes of large credit expansions are: -9.9%, -13.6%, and -18.0% with t-statistics of -1.945, -1.524, and -1.993, respectively.

B. Robustness in Subsamples

We re-estimate the probit (Table 3), OLS (Table 4), and non-parametric (Table 5) regressions in various geographical and time subsamples and find the coefficients have similar magnitudes regardless of the subsamples analyzed. The evidence demonstrates that our results are not driven by any particular subsets of countries or by specific time periods but hold globally and, most importantly, are not simply driven by the Great Depression and the 2007–08 global financial crisis.

Insert Table 8 here

Table 8, Panels A and B, reports probit marginal effects and OLS coefficients for $\Delta(bank\ credit\ /\ GDP)$ on future excess returns of the bank equity index for various subsets of countries and time periods. Using a 3-year forecasting horizon, the regressions are analogous to those reported in Tables 3 and 4. (Results also hold for 1- and 2-year forecasting horizons.) The sample is subdivided into geographical regions (e.g., the U.S., Western Europe) and the time subsample 1950–2003 (i.e. excluding the Great Depression and the 2007–08 financial crisis), and separate regressions are run for each of the subsets. In Panel C, we reanalyze returns subsequent to large credit expansions (using the 95th percentile threshold) for the various subsets.

In Panels A and B, 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 OLS coefficients are slightly larger for some regions (Southern Europe, Western Europe, Scandinavia) and slightly lower for other regions (the U.S. and English-speaking countries). The statistical power is reduced for several regions due to the smaller sample size of the subsets. The probit coefficients are similar in magnitude across regions, though with somewhat less statistical power, again due to the smaller sample size. In the last column, the coefficients have almost the same magnitude and statistical significance over the subperiod 1950–2003, implying that the main results are not driven simply by the Great Depression or the 2007–08 financial crisis.

Panel C shows the average 3-year-ahead returns subsequent to large credit expansions (using the 95th percentile threshold) over the various subsets. In general, the coefficients have similar magnitude regardless of the sample period we use, though the statistical power is reduced for several subsets due to the often much smaller sample size. In particular, the results are sharply negative and statistically significant over the subperiod 1950-2003, again implying that the main results are not driven simply by the Great Depression or the 2007–08 financial crisis.

As a related robustness check, Appendix Figure 2 examines whether future returns are forecastable at various points historically. This figure presents the coefficient from the OLS regressions for 3-year-ahead bank index returns (Panel A) and 3-year-ahead returns subsequent to large credit expansions (Panel B) estimated at each point in time t with past data up to time t (top plot) and over a rolling past-20-years window (bottom plot). Thus, Appendix Figure 2 can help assess how these estimates evolved throughout the historical sample and what could have been forecastable by investors in "real-time." See Appendix Section D for further details on methodology.

As one can see in Appendix Figure 2, the estimate of beta in Panel A is quite stable over the entire sample period, except for a period in the 1950s and early 1960s when the coefficient trended upwards but subsequently declined. Similarly, the estimate of future 3-year-ahead excess returns in Panel B is also robustly negative, except for a period in the 1950s and early 1960s when the 20-year-past rolling window saw positive returns. (Perhaps credit booms were not always bad for bank shareholders in an era of high underlying productivity growth and highly regulated banking.) Thus, Appendix Figure 2 shows that the main results have held since at least the 1980s and, more importantly, could have been forecastable at the time by investors during large historical credit expansions.

C. Quantile regressions as an alternative measure of crash risk.

We use quantile regressions to construct two alternative measures of crash risk subsequent to credit expansion. We use these two quantile regression approaches to confirm the results of the probit regression reported in Table 3, that *credit expansion* predicts increased crash risk of the bank equity index. The first approach uses a quantile regression to examine the difference between the predicted mean and median (50th quantile) returns—is the difference being a measure of crash risk or negative skewness risk—subsequent to credit expansion. The second approach uses quantile regressions to construct another measure of negative skewness of future returns, which compares the increase in extreme left-tail events relative to extreme right-tail events subsequent to credit expansion.

A quantile regression estimates the best linear predictor of the qth quantile of future equity excess returns conditional on the predictor variables:

$$Quantile_q\left[r_{i,t+K} - r^f_{i,t+K} \mid (predictor\ variables)_{i,t}\right]$$
$$= \alpha_{i,q} + \beta'_q (predictor\ variables)_{i,t} \qquad (6)$$

This quantile regression allows one to study how predictor variables forecast the entire shape of the distribution of subsequent excess returns.

For the first alternative measure of increased crash risk, we analyze a median regression (50th quantile regression) and compare the mean and median excess returns predicted by bank credit expansions. β_{median} estimated from equation (6) measures how much bank equity returns decrease "most of the time" during a credit expansion. A negative β_{median} indicates that equity excess returns subsequent to credit expansions are likely to decrease even in the absence of the occurrence of crash events. Such a negative coefficient reflects gradual correction of equity overvaluation induced by shareholders' overoptimism during credit expansions. Thus, the difference between β_{mean} (estimated from equation (2)) and β_{median} measures the degree to which crash risk pulls down the mean returns subsequent to credit expansion.

For the second alternative measure of increased crash risk, we adopt a direct quantile-based approach to study crash risk without relying on a particular choice of thresholds for crash indicator variables.[28] Specifically, we employ jointly estimated quantile regressions to compute the following negative skewness statistic to ask whether *credit expansion* predicts increased crash risk:

$$\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=2}) - (\beta_{q=98} - \beta_{q=50}) \qquad (7)$$

[28] 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.

where $\beta_{q=x}$ denotes the coefficient estimated for the x quantile. This statistic $\beta_{negative\ skew}$ equals the increased distance from the median to the lower tail minus the distance to the upper tail, conditional on *credit expansion*. 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, in equation (7), we measure the asymmetry of the return distribution conditional on *credit expansion*, specifically the increase in the lower tail minus the increase in the upper tail.[29]

Insert Table 9 here

Table 9 reports estimates from the quantile regressions. The columns correspond to 1-, 2-, and 3- year-ahead excess returns for the bank equity index. The top part of the table reports results for the (β_{mean} - β_{median}) measure: specifically, the coefficients and *t*-statistics for the estimates of β_{mean} and β_{median}, as well as their difference and its associated p-value. The estimates for β_{median}, which measures how much bank equity index returns decrease "most of the time" subsequent to credit expansion, are -0.019, -0.041, and -0.086 for the bank equity index at 1-, 2-, and 3-year horizons, respectively; all coefficient estimates are significant at the 5% level. As this decrease in the median excess return is not related to the occurrence of crash events, it reflects either the gradual correction of shareholders' overoptimism over time or the elevated risk appetite of shareholders.

(β_{mean} - β_{median}) measures how much the mean return is reduced due to the occurrence of tail events in the sample. In general, the median coefficients are about two-thirds of the level of corresponding mean coefficients. The remaining third of the decrease (i.e., β_{mean} - β_{median}) reflects the contribution of the occurrence of crash events in the sample to the change in the mean return associated with credit expansion. If shareholders have rational expectations, they would fully anticipate the frequency and severity of the crash events subsequent to credit expansions and thus

[29] In the statistics literature, this measure is called the quantile-based measure of skewness. We use the 5th and 95th quantiles to represent tail events, though the results from the quantile regressions are qualitatively similar for various other quantiles (for example, 1st/99th or 2th/98th 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. 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: $\beta_{negative\ skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}) = 0$, standard errors are generated by block bootstrapping simultaneous estimates of the q=5, 50, and 95 quantile regressions. Similarly, the difference between the mean and median coefficients, H_0: $\beta_{mean} - \beta_{median} = 0$, is tested by simultaneously bootstrapping mean and median coefficients; the resulting Wald statistic is then used to compute a p-value.

demand a higher equity premium ex ante to offset the subsequent crashes. To the extent that the median return predicted by *credit expansion* is lower rather than higher, shareholders do not demand an increased premium to protect them against subsequent crash risk.

The bottom part of Table 9 reports the coefficients and *t*-statistics for *credit expansion* from the three quantile regressions, $\beta_{q=5}$, $\beta_{q=50}$, and $\beta_{q=95}$, followed by the alternative crash risk measure —the conditional negative skewness coefficient $\beta_{negative\ skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$—and its associated *t*-statistic. For bank equity index returns, the coefficient for negative skewness, $\beta_{negative\ skew}$, is estimated to be 0.088, 0.053, and 0.172 (all significant at the 5% level) for 1-, 2-, and 3-year horizons, respectively. Overall, the alternative quantile measure of crash risk confirms our earlier finding from probit regressions of increased crash risk associated with *credit expansion*.

D. Additional Robustness Checks

We perform a variety of other robustness checks in the Appendix, which we briefly describe below.

Test for possible 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). This small-sample bias could potentially pose a problem for estimating coefficients in our study because the main predictor variable, *credit expansion* (i.e. the three-year change in bank credit to GDP), is highly persistent on a quarterly level. In Appendix Section E and Appendix Tables 4 and 5, we test for the possibility of small-sample bias using the methodology of Campbell and Yogo (2006) and find that small-sample bias is not likely a concern for our estimates.

"Optimizing" dividend yield. Appendix Table 6 addresses concerns that perhaps dividend yield does not drive out the significance of *credit expansion* because dividend yield is not "optimized" to maximize its predictive power. In Appendix Table 6, we therefore consider both market dividend yield and bank dividend yield, with each of those measures also alternatively smoothed over the past 2, 4, or 8 quarters. The results with these alternative dividend yield measures as controls demonstrate that even "optimizing" dividend yield does not meaningfully diminish the magnitude and statistical significance of the returns predictability of *credit expansion.*

Decomposing the credit expansion measure. Appendix Table 7 addresses concerns that the predictive power of $\Delta(bank\ credit/GDP)$ might be driven by the denominator (GDP) rather than the numerator (bank credit). However, by breaking down $\Delta(bank\ credit/GDP)$ into $\Delta log(bank\ credit)$ and $\Delta log(GDP)$ or into $\Delta log(real\ bank\ credit)$ and $\Delta log(real\ GDP)$, Appendix Table 7 demonstrates that the predictability in returns is driven by changes in the numerator (i.e. by $\Delta log(bank\ credit)$).

Furthermore, in Appendix Table 8, we motivate the use of the *three* year change in bank credit to GDP by breaking down this variable into a series of successive one-year-change lags. We find that the predictive power of the *three* year change in bank credit comes mainly from the second and third one-year lags: $\Delta(bank\ credit/GDP)_{t-3,t-2}$ and $\Delta(bank\ credit/GDP)_{t-2,t-1}$, dropping off at lags greater than t – 3. This finding sheds light on the timing of financial distress, which seems generally to take place at a 1- to 3-year horizon subsequent to credit expansion.

Robustness in arithmetic returns. Appendix Table 9 addresses the potential concern that our results might be driven by the use of log returns rather than arithmetic returns. While log returns are most appropriate for time-series regressions as they reflect compounded returns over time, they can accentuate negative skewness. Appendix Table 9 replicates the main results of the paper but using arithmetic returns and shows that the main results (Tables 3, 4, 5, and 6) are robust to using arithmetic returns as the dependent variable.

Global vs. country-specific credit expansions. Appendix Table 10 addresses concerns that the predictive power of *credit expansion* is not due to country-specific credit expansion but from its correlation with a global credit expansion—in other words, that the financial instability comes from spillover effects from correlated credit expansions in other countries. While this concern would not in any way invalidate this paper's argument that bank shareholders overvalue bank equity and neglect tail risk during credit booms, it would suggest that it might be more useful to analyze global credit expansion rather than country-specific components. Appendix Table 10 shows that the predictive power of *credit expansion* on subsequent returns is mostly due to country-specific effects and not spillover effects from other countries. To disentangle the effects of local versus global credit expansions, we re-estimate the regressions in Table 4 but control for three additional explanatory variables that measure global credit expansion: U.S. credit expansion, U.S. broker-dealer leverage, and the first principal component of *credit expansion* across countries, which are all plotted in Appendix Table 10. U.S. credit expansion has no predictive power for equity returns in other countries, U.S. broker-dealer leverage is a significant pricing factor for foreign equity returns but does not reduce the predictive power of local credit expansion, and the first principal component only partially reduces the predictive power of local credit expansion. We also try various specifications with time fixed effects to control for global average bank returns. As a result, we conclude that the predictive power of *credit expansion* on subsequent returns is in large part due to country-specific credit expansion and not spillover effects from other countries.

IV. Conclusion

By analyzing the predictability of bank credit expansion for bank equity index returns in a set of 20 developed countries over the years 1920–2012, we document empirical evidence supporting the longstanding view of Minsky (1977) and Kindleberger (1978) regarding overoptimism as an important driver of credit expansion. Specifically, we find that 1) bank credit expansion predicts increased crash risk in the bank equity index, but, despite the elevated crash risk, bank credit expansion predicts lower mean bank equity returns in subsequent one to three years; 2) conditional on bank credit expansion of a country exceeding a 95th percentile threshold, the predicted excess return of the bank equity index in the subsequent three years is -37.3%, strongly indicating the presence of overoptimism and neglect of crash risk at times of rapid credit expansions; 3) the sentiment associated with bank credit expansion is distinct from equity market sentiment captured by dividend yield, and yet dividend yield and credit expansion interact with each other to make credit expansion a particularly strong predictor of lower bank equity returns when dividend yield is low (i.e. when equity market sentiment is strong).

In the aftermath of the recent financial crisis, an influential view argues that credit expansion may reflect active risk seeking by bankers as a result of their misaligned incentives with their shareholders, e.g., Allen and Gale (2000) and Bebchuk, Cohen, and Spamann (2010). While shareholders may not be able to effectively discipline bankers during periods of rapid bank credit expansions, they can always vote with their feet and sell their shares, which would in turn lower equity prices and induce a higher equity premium to compensate the remaining shareholders for the increased equity risk. In this sense, there does not appear to be an outright tension between shareholders and bankers during bank credit expansions. Our finding thus implies that bank credit expansions are not simply caused by bankers acting against the will of shareholders. Instead, there is a need to expand this view by taking into account of the presence of overoptimism or elevated risk appetite of shareholders.

Our study also has important implications for the pricing of tail risk. Following Rietz (1998) and Barro (2006), a quickly growing body of literature, e.g., Gabaix (2012) and Wachter (2013), highlights rare disasters as a potential 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., aggregate bank credit expansion predicts lower bank returns and argues that this finding is driven by reduced tail risk during credit expansion. In contrast to this argument, we find increased rather than decreased crash risk subsequent to bank credit expansion, which we can do by taking advantage of our large historical data set to forecast rare crash events. 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 finding also 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 the equity premium. Instead, it highlights that shareholders' perceived tail risk may or may not be consistent with realized tail risk, as suggested by Weitzman (2007)—and may even be reversed across credit cycles.

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Figure 1: Credit expansion

Credit expansion, measured as the past three-year change of bank credit to GDP and denoted $\Delta(bank\,credit/GDP)$, 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.

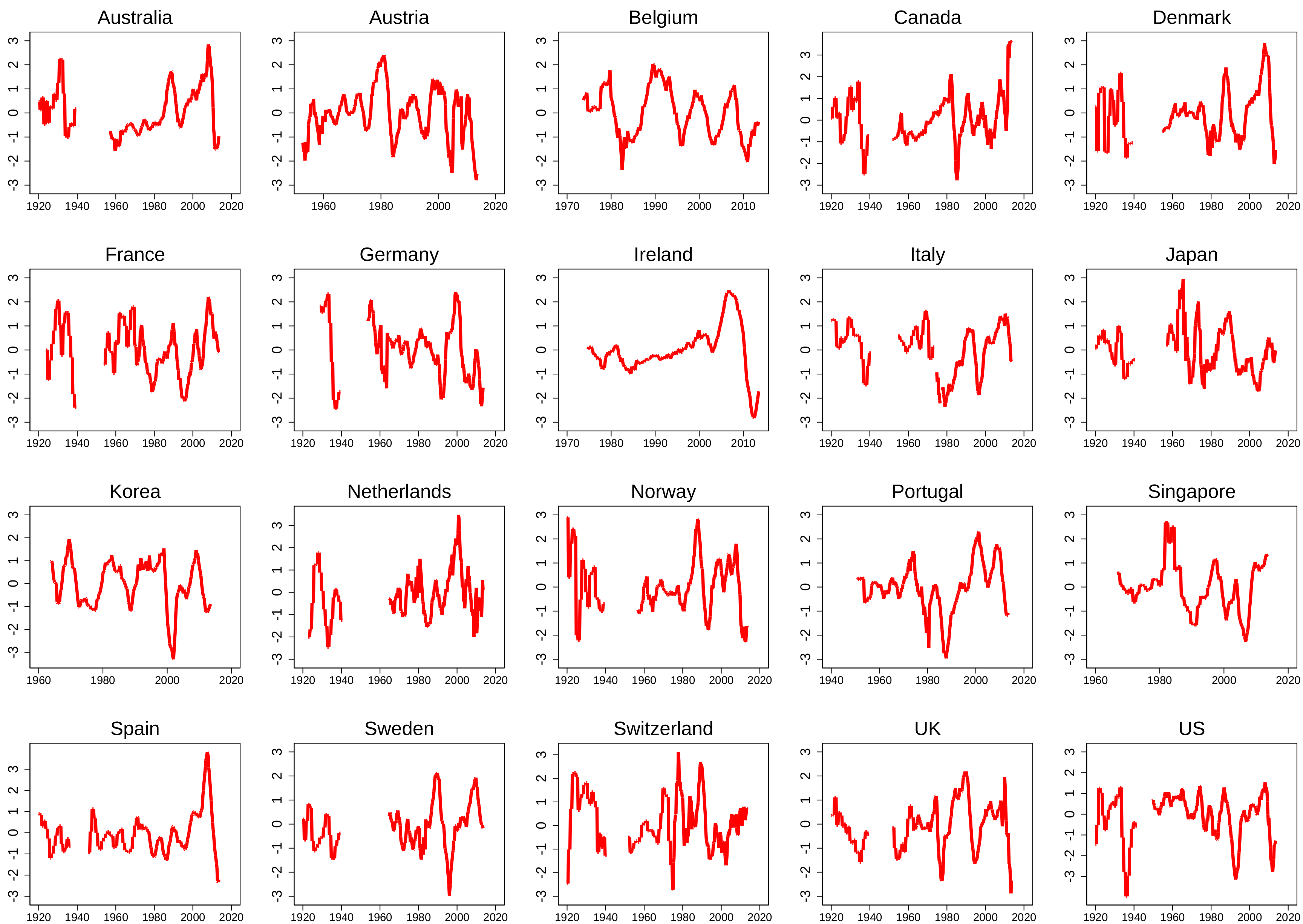

Figure 2: Bank equity prices and bank credit before and after large credit expansions

The past three-year change in bank credit to GDP ($\Delta(bank\,credit/GDP)$) and the bank total excess log returns index are plotted before and after a large credit expansion. A large credit expansion is defined as credit expansion exceeding the 95th percentile threshold, which is calculated for each country and each point in time using only past information to avoid any future-looking bias. $\Delta(bank\,credit/GDP)$ and bank total excess log returns are pooled averages across time and countries, conditional on the given number of years before or after the start of a banking crisis. The average bank log returns are then cumulated from t = -6 to t = +6, and the level is adjusted to be 0 at t = 0. Observations are over the sample of 20 countries, 1920–2012.

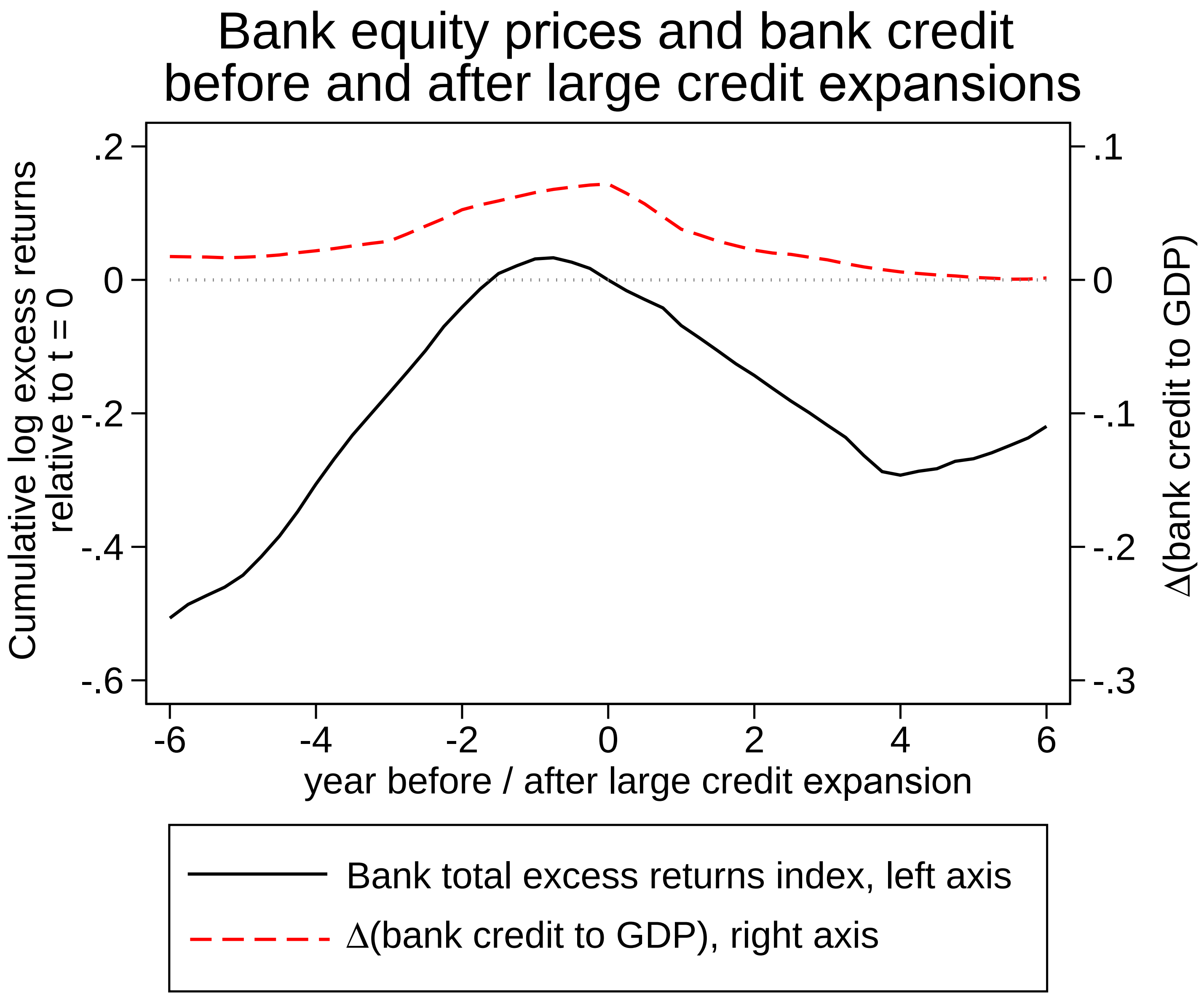

Figure 3: Bank equity index returns subsequent to large credit expansions & contractions

This figure plots estimates reported in Table 5. The plot shows the magnitude of bank equity index excess returns 2 and 3 years subsequent to large credit expansions (defined as when $\Delta(bank\,credit/GDP)$ exceeds a given percentile threshold), in addition to average returns subsequent to large credit contractions (when $\Delta(bank\,credit/GDP)$ falls below a given percentile threshold). To avoid any future-looking bias, percentile thresholds are calculated for each country and each point in time using only past information. Average returns conditional on the thresholds are computed using regression models (3) and (4) with non-overlapping returns. 95% confidence intervals are computed using dually-clustered standard errors. Observations are over the sample of 20 countries, 1920–2012.

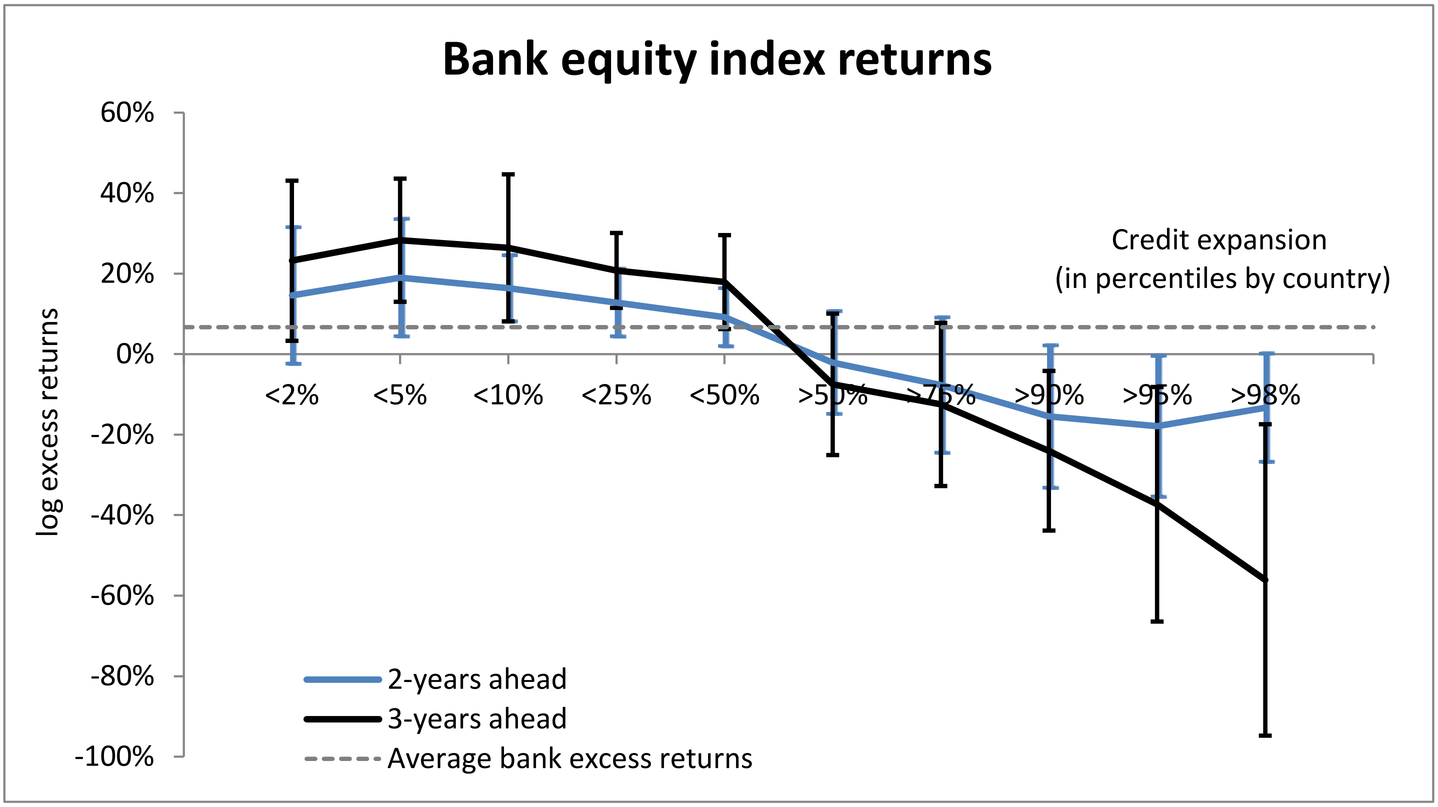

Figure 4: Bank equity index returns subsequent to large credit expansions, individual episodes

This figure plots 3-year-ahead returns of the bank equity index subsequent to the initial year of all large credit expansions. This figure corresponds to the observations listed in Table 7. A large credit expansion is defined as credit expansion exceeding the 95th percentile threshold, which is calculated for each country and each point in time using only past information to avoid any future-looking bias. Observations are over the sample of 20 countries, 1920–2012.

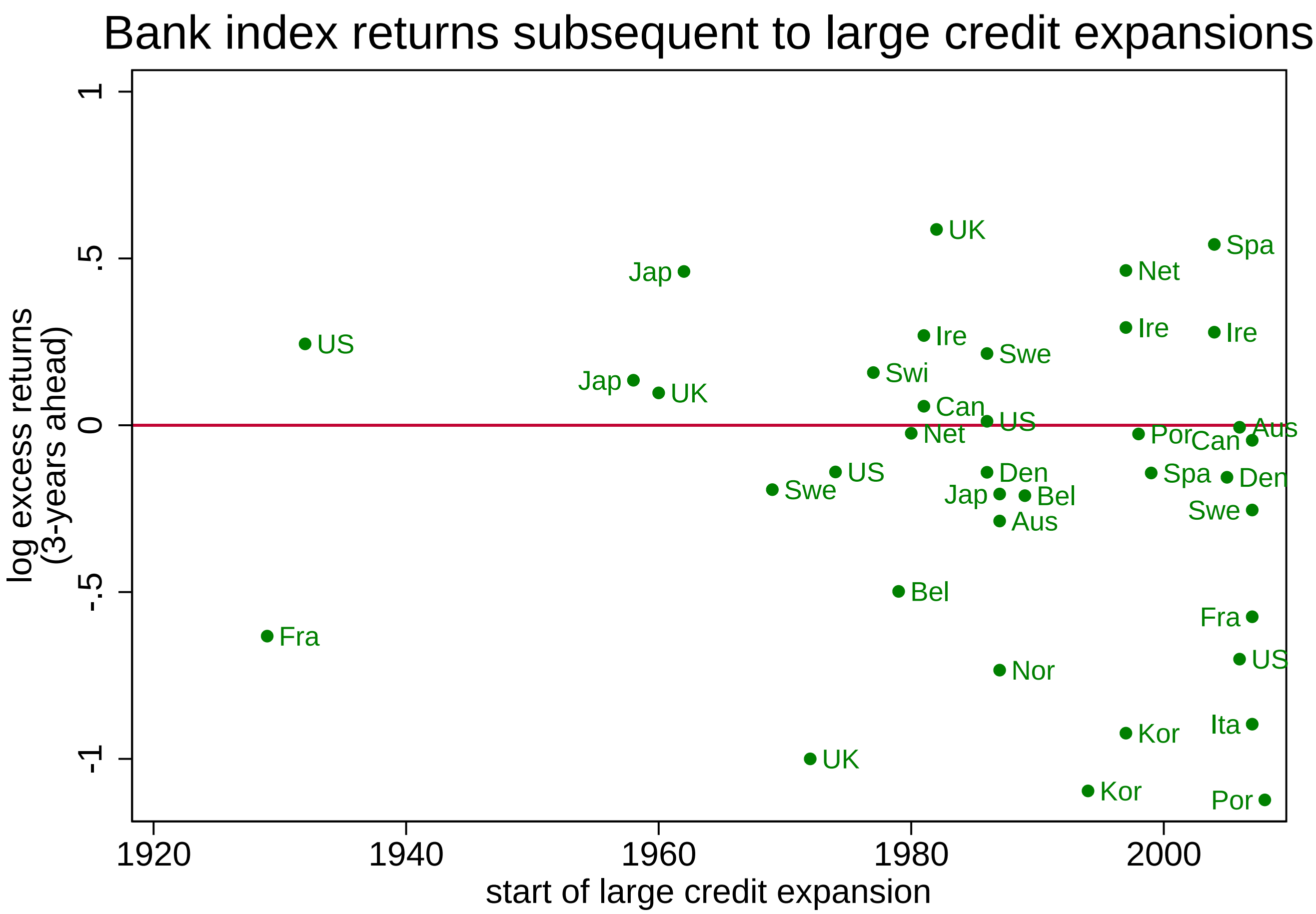

Table 1: Summary statistics

Summary statistics are reported for log total excess returns for both the bank and non-financials equity indices. Summary statistics are also reported for the three-year past change in (bank credit / GDP) and the control variables. All statistics are pooled across countries and time. Observations are quarterly over the sample of 20 countries, 1920 - 2012.

	N	Mean	Median	Stdev.	1%	5%	10%	90%	95%	99%	Average cross-country correlation (with U.S.)
Quarterly log returns, annualized											
Bank index: excess total returns	4155	0.059	0.045	0.286	-1.376	-0.762	-0.507	0.597	0.857	1.803	0.394
Bank index: dividend yield	4155	0.037	0.036	0.019	0.000	0.008	0.014	0.060	0.067	0.093	0.305
Non-financials index: excess total returns	4092	0.064	0.060	0.256	-1.266	-0.748	-0.518	0.627	0.856	1.461	0.411
Market index: dividend yield	4092	0.036	0.033	0.020	0.008	0.013	0.016	0.059	0.068	0.117	0.606
Credit to private households and non-financial corporations, past-three-year annualized percentage-point change											
Δ (Bank credit / GDP)	4155	0.013	0.011	0.032	-0.059	-0.032	-0.022	0.050	0.064	0.115	0.221
Control variables											
Inflation	4147	0.037	0.028	0.043	-0.076	-0.011	0.001	0.090	0.119	0.185	0.686
Term spread	4088	0.012	0.012	0.018	-0.042	-0.016	-0.007	0.030	0.036	0.053	0.184
Book / market	2437	0.707	0.621	0.416	0.265	0.341	0.377	1.042	1.333	2.564	0.543
I / K	3266	0.102	0.099	0.019	0.068	0.075	0.081	0.127	0.140	0.161	0.550

Table 2: Correlations

This table reports correlations of the past-three-year change in (bank credit/GDP) with various other measures of aggregate credit and with the control variables (market dividend yield, year-over-year inflation, term spread, book to market, and non-residential investment to capital). Because the measurement of these variables may be different from country to country, each correlation is first calculated country-by-country; then, the correlation coefficient is averaged (and standard errors are calculated) across the 20 countries. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. Observations are quarterly over the sample of 20 countries, 1920–2012.

Correlation of Δ (bank credit / GDP) and:

Variable	Average correlation	(S.E.)
Δ (total credit / GDP)	.792***	(.048)
Δ (total credit to HHs / GDP)	.636***	(.054)
Δ (total credit to private NFCs / GDP)	.608***	(.067)
Δ (Bank assets / GDP)	.592***	(.056)
Growth of household housing assets	.316***	(.085)
Δ (gross external liabilities / GDP)	.338***	(.073)
Current account deficit / GDP	.172***	(.057)
Market D / P	-.026	(.046)
Bank D / P	.052	(.046)
Book / market	-.094*	(.056)
Inflation	-.103***	(.039)
Term spread	-.136***	(.049)
I / K	.300***	(.070)

Table 3: Credit expansion predicts increased crash risk in the bank equity index

This table reports estimates from the probit regression model specified in equation (1) for the bank equity index in subsequent 1, 2, and 3 years. The dependent variable is the crash indicator ($Y = 1_{crash}$), which takes on a value of 1 if there is a future equity crash, defined as a quarterly drop of -30%, in the next K years (K = 1, 2, and 3) and 0 otherwise. The crash indicator is regressed on $\Delta(bank\,credit/GDP)$ and several subsets of control variables known to predict the equity premium. Explanatory variables are in standard deviation units. All reported estimates are marginal effects. A coefficient of 0.027, for example, means that a one-standard deviation increase in $\Delta(bank\,credit/GDP)$ predicts a 2.7 percentage point increase in the likelihood of a future crash. This table also reports estimates from equation (1) with ($Y = 1_{boom}$), a symmetrically defined right tail event, along with the difference in the marginal effects between the two probit regressions (the probability of a crash minus probability of a boom). Analogous results for the non-financials equity index are reported in Appendix Table 3. *T*-statistics in brackets are computed from standard errors dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Observations are over the sample of 20 countries, 1920–2012.

Probit estimates of increased crash likelihood of the bank equity index

		1 year ahead			2 years ahead			3 years ahead		
		Crash	Boom	Difference	Crash	Boom	Difference	Crash	Boom	Difference
No controls	Δ (bank credit / GDP)	0.027**	-0.003	0.030**	0.033***	-0.002	0.035***	0.054***	-0.012***	0.065***
	T-stat	[2.40]	[-0.46]	[2.24]	[3.11]	[-0.27]	[3.04]	[4.27]	[-2.91]	[5.20]
	N	957	957	957	480	480	480	316	316	316
No controls	log(bank D/P)	-0.015	0.005	-0.020	-0.022	0.009	-0.030	-0.020	0.005	-0.024
	T-stat	[-1.16]	[0.86]	[-1.28]	[-1.30]	[1.44]	[-1.37]	[-0.98]	[0.46]	[-0.87]
	N	957	957	957	480	480	480	316	316	316
With Bank D/P as control	Δ (bank credit / GDP)	0.029**	-0.003	0.032**	0.034***	-0.002	0.036***	0.054***	-0.012***	0.066***
	T-stat	[2.54]	[-0.59]	[2.49]	[3.04]	[-0.30]	[2.95]	[4.17]	[-3.02]	[5.13]
	log(bank D/P)	-0.018	0.006	-0.023	-0.023	0.009	-0.032	-0.021	0.005	-0.026
	T-stat	[-1.33]	[1.01]	[-1.47]	[-1.39]	[1.48]	[-1.46]	[-1.09]	[0.49]	[-0.96]
	N	957	957	957	480	480	480	316	316	316
With all 5 controls	Δ (bank credit / GDP)	0.026***	-0.003	0.030***	0.027**	-0.002	0.028*	0.046***	-0.013***	0.059***
(coeff on controls not reported)	T-stat	[3.03]	[-0.66]	[2.96]	[2.21]	[-0.29]	[1.80]	[3.11]	[-3.24]	[3.48]
	N	957	957	957	480	480	480	316	316	316

Table 4: Credit expansion predicts lower mean returns of the bank equity index

This table reports estimates from the panel regression with fixed effects model specified in equation (2) for the bank equity index. The dependent variable is log excess total returns, which is regressed on $\Delta(bank\,credit/GDP)$ and several subsets of control variables known to predict the equity premium. Explanatory variables are in standard deviation units. Returns are non-overlapping at 1, 2, and 3 year ahead horizons. A coefficient of -0.032 means that a one-standard deviation increase in $\Delta(bank\,credit/GDP)$ predicts a 3.2 percentage point decrease in subsequent returns. Analogous results for the non-financials equity index are reported in Appendix Table 3. T-statistics in brackets are computed from standard errors dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

OLS estimation of the bank equity index

	1 year ahead				2 years ahead				3 years ahead			
Δ (bank credit / GDP)	-0.032**		-0.034**	-0.035***	-0.060***		-0.061***	-0.057***	-0.114***		-0.119***	-0.106***
	[-2.146]		[-2.295]	[-2.985]	[-3.455]		[-3.355]	[-3.150]	[-3.655]		[-3.609]	[-3.226]
log(bank D/P)		0.040**	0.042**	0.042*		0.069**	0.070**	0.067**		0.111***	0.117***	0.115***
		[2.158]	[2.257]	[1.840]		[2.468]	[2.568]	[2.236]		[3.818]	[4.682]	[3.842]
inflation				-0.184				-0.011				0.015
				[-0.970]				[-0.040]				[0.042]
term spread				0.019				0.024				0.099*
				[0.718]				[0.742]				[1.783]
log(book / market)				0.030				0.046				0.083
				[0.792]				[0.782]				[1.037]
log(I/K)				0.015				0.002				0.016
				[0.641]				[0.075]				[0.307]
R^2	0.028	0.028	0.048	0.057	0.064	0.06	0.097	0.104	0.131	0.102	0.194	0.233
Adj. R^2	0.007	0.008	0.026	0.031	0.023	0.019	0.055	0.055	0.072	0.041	0.137	0.167
N	957	957	957	957	480	480	480	480	316	316	316	316

Table 5: Large credit expansions predict negative returns of the bank equity index

This table reports average log excess returns of the bank equity index subsequent to large credit expansions (when $\Delta(bank\,credit/GDP)$ exceeds a given percentile threshold) and subsequent to large credit contractions (when $\Delta(bank\,credit/GDP)$ falls below a given percentile threshold). Estimates, along with corresponding *t*-statistics and adjusted R^2 values, are computed using regression models (3) and (4) with non-overlapping 1, 2, and 3 years ahead returns. To avoid any future-looking bias, percentile thresholds are calculated for each country and each point in time using only past information. *T*-statistics in brackets are computed from standard errors dually clustered on country and time. Analogous results for the non-financials equity index are reported in Appendix Table 3. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Observations are over the sample of 20 countries, 1920–2012.

Bank equity index returns subsequent to large credit expansions and contractions

	Threshold in percentiles:	<2%	<5%	<10%	<25%	<50%	>50%	>75%	>90%	>95%	>98%
1 year ahead returns	$E[r - r_f]$	0.074	.126**	.077**	.059**	.049**	-0.016	-0.042	-0.073	-0.094	-0.081
	[t-stat]	[1.185]	[2.216]	[1.987]	[2.256]	[2.058]	[-0.385]	[-0.767]	[-0.812]	[-0.918]	[-1.292]
	Adj. R^2	0.002	0.009	0.005	0.006	0.01	0.01	0.012	0.011	0.01	0.004
	# obs. meeting threshold	51	72	110	235	464	493	271	121	80	44
2 year ahead returns	$E[r - r_f]$	.146*	.19**	.164***	.128***	.092**	-0.021	-0.077	-.155*	-.179**	-.133*
	[t-stat]	[1.697]	[2.575]	[3.958]	[3.018]	[2.52]	[-0.325]	[-0.904]	[-1.729]	[-2.021]	[-1.951]
	Adj. R^2	0.004	0.011	0.012	0.016	0.017	0.017	0.027	0.028	0.022	0.008
	# obs. meeting threshold	24	35	54	118	227	253	139	60	40	23
3 year ahead returns	$E[r - r_f]$	.232**	.283***	.264***	.208***	.179***	-0.075	-0.125	-.24**	-.373**	-.561***
	[t-stat]	[2.298]	[3.644]	[2.846]	[4.406]	[3.022]	[-0.841]	[-1.215]	[-2.384]	[-2.522]	[-2.857]
	Adj. R^2	0.008	0.018	0.023	0.03	0.059	0.059	0.047	0.04	0.041	0.048
	# obs. meeting threshold	18	25	36	73	147	169	99	38	19	11

Table 6: Credit expansion has strongest predictability when dividend yield is low

This table reports estimates from the panel regression with fixed effects model specified in equation (2) and is similar to Table 4 but analyzes the interaction of $\Delta(bank\,credit/GDP)$ and bank dividend yield. Returns are non-overlapping at 1, 2, and 3 year horizons. The regressors are $\Delta(bank\,credit/GDP)$, log bank dividend yield, and various interactions of those variables: specifically, $\Delta(bank\,credit/GDP)$ interacted with $log(bank\,D/P)$ or interacted with dummies indicating whether bank dividend yield is in each of its five quintiles. The 5th dividend yield quintile is omitted from the regression, so that the coefficient on $\Delta(bank\,credit/GDP)$ captures the highest quintile and the coefficients on the other quintile dummies effectively test the difference between the other quintiles and the highest quintile. Analogous results for the non-financials equity index are reported in Appendix Table 3. T-statistics in brackets are computed from standard errors dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Observations are over the sample of 20 countries, 1920–2012.

OLS estimation of the bank equity index

	1 year ahead			2 years ahead			3 years ahead		
Δ(bank credit / GDP)	-0.034**	-0.033**	-0.005	-0.061***	-0.058***	-0.034	-0.119***	-0.105***	-0.068*
	[-2.295]	[-2.150]	[-0.296]	[-3.355]	[-3.291]	[-1.373]	[-3.609]	[-3.271]	[-1.841]
log(bank D/P)	0.042**	0.043**	0.043**	0.070**	0.071**	0.070**	0.117***	0.125***	0.123***
	[2.257]	[2.242]	[2.222]	[2.568]	[2.564]	[2.493]	[4.682]	[4.946]	[5.289]
Δ(bank credit / GDP) x log(bank D/P)		0.005			0.013			0.042***	
		[0.855]			[1.186]			[2.725]	
Δ(bank credit / GDP) x ...									
(bank D/P 1st quintile dummy)			-0.039*			-0.062			-0.144**
			[-1.786]			[-1.539]			[-2.244]
(bank D/P 2nd quintile dummy)			-0.046			-0.058			-0.069
			[-1.438]			[-1.337]			[-0.676]
(bank D/P 3rd quintile dummy)			-0.030			0.015			-0.032
			[-1.051]			[0.403]			[-0.745]
(bank D/P 4th quintile dummy)			-0.035*			-0.031			0.025
			[-1.690]			[-0.953]			[0.736]
(bank D/P 5th quintile dummy)									
R^2	0.048	0.049	0.052	0.097	0.100	0.107	0.194	0.218	0.220
Adj. R^2	0.026	0.026	0.027	0.055	0.056	0.058	0.137	0.159	0.153
N	957	957	957	480	480	480	316	316	316

Table 7: Clustering expansions by historical episodes

This table presents an alternative method of calculating average bank equity returns subsequent to large credit expansions, along with standard errors, taking into account correlations across countries and over time. First, this table lists 1-, 2-, and 3-year-ahead returns of the bank equity index subsequent to the initial quarter of all large credit expansions, defined as $\Delta(bank\,credit/GDP)$ exceeding a 95th percentile threshold within each country. To avoid any future-looking bias, percentile thresholds are calculated at each point in time using only past information. Then, concurrent observations of large credit expansions across countries are clustered into distinct historical episodes (e.g., the Great Depression, the East Asian crisis, the 2007–8 global financial crisis). Returns from the resulting historical episodes are first averaged within each historical episodes; then, an average and t-statistic is calculated across historical episodes, taking each distinct historical episode as a single, independent observation. Observations are over the sample of 20 countries, 1920–2012.

Large credit expansions (credit growth > 95th percentile by country) grouped by episodes

Episode	Name of associated crisis	Year:qtr	Country	Returns on bank equity 1 yr ahead	2 yr ahead	3 yr ahead
1	Great Depression	1929:1	France	-0.119	-0.338	-0.632
		1932:4	US	-0.353	-0.173	0.244
2		1958:4	Japan	0.105	0.211	0.135
3		1960:4	UK	0.243	0.141	0.097
4		1962:4	Japan	0.268	0.243	0.461
5		1969:2	Sweden	-0.405	-0.177	-0.193
6	Secondary banking crisis	1972:4	UK	-0.453	-1.457	-0.708
7		1974:1	US	-0.384	-0.147	-0.140
8		1977:4	Switzerland	-0.044	0.105	0.158
9		1979:2	Belgium	-0.271	-0.656	-0.498
		1980:4	Netherlands	-0.211	-0.250	-0.024
10		1981:1	Ireland	-0.429	-0.245	0.269
		1981:3	Canada	-0.181	0.237	0.057
		1982:4	UK	0.305	0.453	0.587
11	S&L crisis	1986:4	US	-0.273	-0.108	0.012
12	Scandinavian financial crises	1986:3	Denmark	0.004	-0.116	-0.141
		1986:4	Sweden	-0.170	0.197	0.215
		1987:4	Norway	-0.253	-0.062	-0.734
13	Japanese financial crisis	1987:2	Japan	-0.105	-0.062	-0.206
14		1987:3	Australia	0.108	0.034	-0.287
15		1989:1	Belgium	-0.124	-0.231	-0.211
16		1994:3	Korea	-0.162	-0.502	-1.096
17		1997:1	Netherlands	0.408	0.304	0.464
		1997:2	Ireland	0.661	0.533	0.293
		1998:3	Portugal	0.074	0.282	-0.026
		1999:2	Spain	0.096	0.071	-0.143
18	East Asian crisis	1997:4	Korea	-0.119	-0.225	-0.923
19	Great Recession	2004:1	Spain	0.130	0.415	0.542
		2004:3	Ireland	0.263	0.430	0.279
		2005:2	Denmark	0.234	0.330	-0.156
		2006:3	Australia	0.136	-0.243	-0.006
		2006:4	US	-0.253	-0.727	-0.701
		2007:2	Canada	-0.234	-0.184	-0.045
		2007:3	France	-0.401	-0.476	-0.574
		2007:3	Sweden	-0.465	-0.392	-0.254
		2007:4	Italy	-0.813	-0.566	-0.896
		2008:4	Portugal	0.164	-0.165	-1.123

Averages across historical episodes

Years ahead:	Returns on bank equity 1 yr ahead	 2 yr ahead	 3 yr ahead
Average over episodes:	-0.099	-0.136	-0.180
T-STAT	-1.945	-1.524	-1.993
S.E.	0.051	0.089	0.090
N (episodes)	19	19	19

Table 8: Robustness in geographical and time subsamples

This table demonstrates that the estimates reported in Tables 3, 4, and 5 for the probit (Panel A), OLS (Panel B), and non-parametric (Panel C) regression models are robust within various geographical and time subsets. Time subsets are: 1920–2012 (the full sample) and 1950–2003 (i.e. excluding both the 2007–08 financial crisis and the Great Depression). The table reports estimates — using the same methodology as in Tables 3, 4, and 5 — of future log excess returns of the bank equity index. In Panels A and B, the probit and OLS coefficients are estimated with (top) or without (bottom) the five standard controls. Coefficients reported in this table are on $\Delta(bank\,credit/GDP)$; coefficients on control variables are omitted. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Probit estimation of 3-year-ahead bank index returns

	All	US	English-speaking	W. Europe	S. Europe	Scandi-navia	All, 1950-2003
Δ (bank credit / GDP)	0.054***	0.112	0.070**	0.049***	0.102**	0.041	0.045**
T-STAT	[4.27]	[1.06]	[2.33]	[3.59]	[2.22]	[0.05]	[2.29]
N	316	24	87	218	32	57	218
Δ (bank credit / GDP)	0.046***	0.037	0.003	0.039**	0.200***	0.038	0.038*
T-STAT	[3.11]	[0.00]	[0.00]	[2.31]	[5.64]	[0.01]	[1.75]
N	316	24	87	218	32	57	218

Panel B: OLS estimation of 3-year-ahead bank index returns

	All	US	English-speaking	W. Europe	S. Europe	Scandi-navia	All, 1950-2003
Δ (bank credit / GDP)	-0.114***	-0.090	-0.055*	-0.135***	-0.193**	-0.194***	-0.114***
T-STAT	[-3.655]	[-1.553]	[-1.809]	[-3.484]	[-2.705]	[-3.040]	[-2.880]
Adj. R^2	0.072	0.058	0.021	0.080	0.127	0.232	0.134
N	316	24	87	218	32	57	218
Δ (bank credit / GDP)	-0.106***	0.060	-0.037	-0.123***	-0.276*	-0.207***	-0.091***
T-STAT	[-3.226]	[0.859]	[-1.032]	[-2.755]	[-1.923]	[-3.911]	[-2.301]
Adj. R^2	0.167	0.311	0.172	0.176	0.116	0.333	0.231
N	316	24	87	218	32	57	218

Panel C: 3-year-ahead bank index returns subsequent to large credit expansions

Credit boom percentile:	>90th	>95th	>98th
All			
$E[r - r_f]$	-.24**	-.373**	-.561**
T-STAT	-2.384	-2.522	-2.857
R^2	0.04	0.041	0.048
N	38	19	11
US			
$E[r - r_f]$	-0.435	-0.701	
T-STAT	-1.527	-1.741	
R^2	0.126	0.146	
N	2	1	0
English speaking countries			
$E[r - r_f]$	-0.011	-0.164	-.298***
T-STAT	-0.087	-0.73	-12.843
R^2	0.021	0.042	0.036
N	12	5	2
Western Europe			
$E[r - r_f]$	-.302**	-.369**	-.561**
T-STAT	-2.194	-2.314	-2.808
R^2	0.046	0.038	0.059
N	25	15	11
Southern Europe			
$E[r - r_f]$	-0.235	-.282**	-.282**
T-STAT	-1.082	-3.172	-3.172
R^2	0.033	0.018	0.018
N	7	3	3
Scandinavia			
$E[r - r_f]$	-.353**	-.474***	-.783**
T-STAT	-2.647	-5.877	-14.362
R^2	0.068	0.055	0.071
N	8	4	2
1950-2003, all countries			
$E[r - r_f]$	-.187**	-.174*	-.297***
T-STAT	-2.345	-1.775	-4.198
R^2	0.042	0.022	0.027
N	22	13	8

Table 9: Quantile regressions as an alternative measure of crash risk

This table reports estimates from two alternative measures of crash risk for the bank equity index. The first measure is $\beta_{difference} = (\beta_{median} - \beta_{mean})$, the different between the coefficients from mean and median regressions of bank index returns regressed on $\Delta(bank\, credit/GDP)$; a larger difference between the coefficient corresponds to increased negative skewness in future returns. The second measure is derived from quantile regression estimates of bank index returns regressed on $\Delta(bank\, credit/GDP)$; it captures the left-tail of subsequent returns becoming more extreme than the right-tail and is also a measure of increased negative skewness in future returns. This measure is calculated as $\beta_{negative\, skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$, where $\beta_{q=5}$, $\beta_{q=50}$, $\beta_{q=95}$ are coefficients from jointly-estimated quantile regressions with quantiles q. Starting from the top row and working down, the table reports the following estimates (together with their associated t-statistics or p-value): β_{mean}, the coefficient from estimating the OLS regression model (2), β_{median}, the coefficient from a median regression (50th quantile regression), the difference $(\beta_{median} - \beta_{mean})$, the coefficients from jointly-estimated quantile regressions, $\beta_{q=5}$, $\beta_{q=50}$, $\beta_{q=95}$, and lastly the conditional negative skewness coefficient $\beta_{negative\, skew} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$. $\Delta(bank\, credit/GDP)$ is in standard deviation units within each country, but is standardized at each point in time using only past information to avoid any future-looking bias. T-statistics and p-values are computed from standard errors that are block bootstrapped and dually clustered on country and time. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Observations are over the sample of 20 countries, 1920–2012.

		Bank index returns		
Explanatory variables:		1 yr ahead	2 yr ahead	3 yr ahead
Δ (bank credit / GDP)	Mean	-.032**	-.06***	-.124***
	(t stat)	(-2.14)	(-3.45)	(-3.64)
	Median	-.019***	-.041**	-.086***
	(t stat)	(-2.76)	(-2.47)	(-3.84)
	Difference	**.014*** **	**.019***	**.038***
	(p-value)	**(.001)**	**(.066)**	**(.089)**
	Q5	-.104***	-.071**	-.271***
	(t stat)	(-20.59)	(-2.14)	(-5.74)
	Q50	-.019***	-.041**	-.086***
	(t stat)	(-2.76)	(-2.47)	(-3.84)
	Q95	-.021	-.064**	-.072*
	(t stat)	(-1.02)	(-2.44)	(-1.88)
	Negative skew	**.088*** **	**.053** **	**.172*** **
	(t stat)	**(3.24)**	**(2.08)**	**(3.04)**
	N	957	480	316