CREDIT EXPANSION AND NEGLECTED CRASH RISK*

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By analyzing 20 developed economies over 1920–2012, we find the following evidence of overoptimism and neglect of crash risk by bank equity investors during credit expansions: (i) 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; (ii) 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 (iii) 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. *JEL Codes:* G01, G02, G15, G21.

I. Introduction

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 2016). 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,

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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 United States, the credit quality of corporate debt issuance deteriorates and this deterioration forecasts lower corporate bond excess returns. Although 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: 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 overoptimism in equity markets (Kindleberger 1978), even though it is challenging to find definitive evidence of excessive equity valuations.

In this article, 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

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).

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 nonfinancial corporations in a given country. We use this measure of credit expansion, which excludes debt securities held outside the banking sector, because data on nonbank credit is 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 nonbank 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 three-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 what the magnitude of average bank equity returns is 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 is sometimes taken as a measure of equity market sentiment. Interestingly, although 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 one another. Furthermore, credit expansion has strong predictive power for bank equity crash risk, whereas 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 time point 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: (i) we use only nonoverlapping equity returns (i.e., we delete intervening observations so that we are effectively estimating returns on annual, biennial, or triennial data for one-, two-, or three-year-ahead returns, respectively); (ii) 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 (iii) 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 1997–1998 East Asian Crisis, the 2007–2008 financial crisis, and many lesser known episodes involving sometimes one or many countries) and find statistically significant negative returns by averaging these 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 2007–2008 financial crisis. Finally, we 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

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 (2014) provide direct evidence that employees in the

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 even be 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 policy makers 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 article is structured as follows. Section II describes the data used in our analysis. Section III presents the main results using credit expansion to predict bank equity returns. Section IV provides a variety of robustness checks. Finally, Section V concludes. We also provide an Online Appendix, which contains additional details related to data construction, analogous results for

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.

nonfinancial equities in place of bank equities, and additional robustness analysis.

II. Data

We construct a panel data set for 20 developed economies 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 International Monetary Fund (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 onward, whereas for eight countries the data set is mostly complete from around 1950 onward. The sample length of each variable for each country can be found in Online Appendix Table I.

II.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 Online Appendix Section I.

1. 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 nonfinancial corporations. Note that *credit expansion* throughout this article refers to bank credit expansion except where specifically noted. It is expressed mathematically as

$$\Delta\left(\frac{bank\ credit}{GDP}\right)_t = \frac{\left(\frac{bank\ credit}{GDP}\right)_t - \left(\frac{bank\ credit}{GDP}\right)_{t-3}}{3}.$$

Figure I 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

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

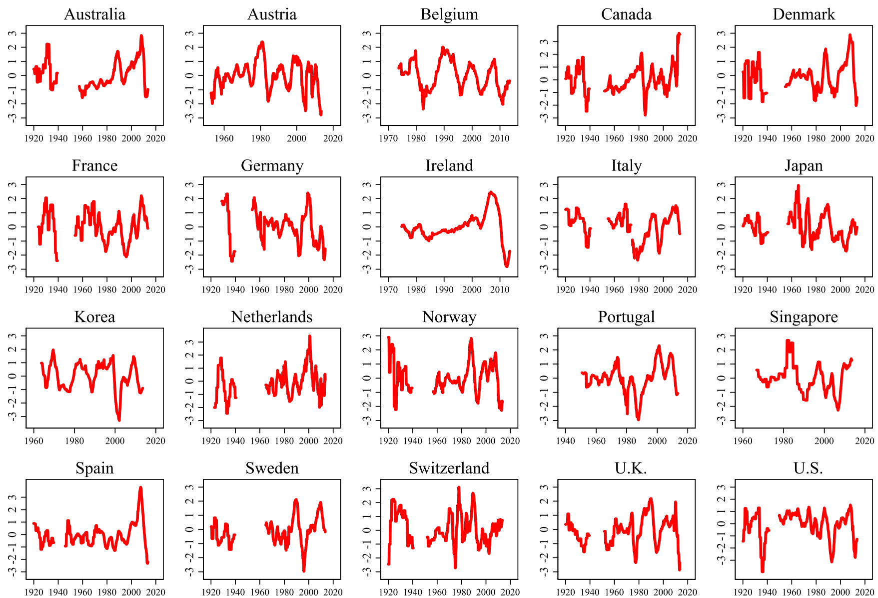

FIGURE I

Credit Expansion

Credit expansion, measured as the past three-year change of bank credit to GDP and denoted $\Delta(\frac{bank\ credit}{GDP})$, is plotted over time for the 20 countries in the sample. Observations are quarterly over the period 1920–2012 and in units of standard deviations. Bank credit refers to credit issued by banks to domestic households and domestic private nonfinancial corporations.

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.

Credit expansion is constructed by merging two sources: (i) "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 (ii) "bank loans" from Schularick and Taylor (2012), which extends 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 is 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 nonfinancial 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 nonfinancial corporations. Both data sets exclude interbank lending and lending to governments and government-related entities.

Whenever there is overlap, we use the BIS data, since they are provided at a quarterly frequency. Because there are discrepancies between the 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 breaks 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 forward-fill explanatory variables to avoid look-ahead bias in forecasting, because forward-filled information for each quarter would already be known. We

4. In the rest of the article, 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 I, the variable is standardized country by country on the entire time sample to present the data in a straightforward manner.

do the same for all other predictor variables (e.g., book to market) in cases in which only annual data are 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]

Because 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 that at each time point 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.

2. Equity Index Returns. The main dependent variable in our analysis is the future return of the bank equity index for each

5. Why do we choose the past three-year change and not use some other horizon? In Online Appendix Table VIII, we provide analysis to show that the greatest predictive power for subsequent equity returns comes from the second and third 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 second and third 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 United States, 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.

country. In Online Appendix Section II, results for the nonfinancials equity index are presented, but in all other places we always refer to the bank equity index for each country. Also, the term *returns* always refers to log excess total returns throughout the article.[7]

Our main source for price data for the bank equity index (and for price and dividend data for the nonfinancials index) 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 exchange websites and central bank statistics.[8] For both banks and nonfinancials, we choose market-capitalization-weighted indexes for each country that are as broad as possible within the banking or nonfinancial sectors (though often, due to limited historical data, the nonfinancials 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 retain only series that are highly correlated with other sources (see Online Appendix Table II).

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 one-, two-, and three-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 one, two, and three years ahead for the bank and nonfinancials equity indexes, which takes the value of 1 if the log excess total return of the underlying equity index is less than -30% for any quarter within the one-, two-, or three-year horizon, and 0 otherwise. Analogously, we also define a boom indicator for greater than $+30\%$ returns for any

7. We repeat our main results in Online Appendix Table IX with arithmetic equity returns as a robustness check. The results do not meaningfully change.

8. See Online Appendix Section I for additional details on constructing the bank and nonfinancials equity indexes and dividend yield indexes for each country, including links to spreadsheets detailing our source data. Online Appendix Section I also discusses further details regarding the construction of the three-month short-term interest rate, control variables, and other variables.

quarter within the one-, two-, or three-year horizon. We find that for the bank equity index, +30% and −30% quarterly returns happen in roughly 1.1% and 3.2% of quarters, respectively. As these threshold values were chosen somewhat arbitrarily, Section IV.C 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]

3. 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, nonresidential investment to capital $\frac{I}{K}$, and term spread. These variables are chosen because the data are available over much of the sample period for the 20 countries and because they 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 because it is simply a change of units.

4. 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 the Online Appendix.

II.B. Summary Statistics

Table I presents summary statistics for bank equity index returns, nonfinancials equity index returns, *credit expansion* (i.e.,

9. In unreported results, we verify that our analysis on crash risk is robust to choosing other thresholds of ±20% or ±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 Online Appendix Table VI, which shows that the main results of this article are robust to these alternative measures of dividend yield.

11. Online Appendix Table XI 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 the 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.

TABLE I
SUMMARY STATISTICS

	N	Mean	Median	Std. dev.	1%	5%	10%	90%	95%	99%	Average cross-country correlation (with U.S.)
Quarterly log returns, annualized											
Bank index: excess total returns	4,155	0.059	0.045	0.286	−1.376	−0.762	−0.507	0.597	0.857	1.803	0.394
Bank index: dividend yield	4,155	0.037	0.036	0.019	0.000	0.008	0.014	0.060	0.067	0.093	0.305
Nonfinancials index: excess total returns	4,092	0.064	0.060	0.256	−1.266	−0.748	−0.518	0.627	0.856	1.461	0.411
Market index: dividend yield	4,092	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 nonfinancial corporations, past three-year annualized percentage-point change											
$\Delta(\frac{bank\ credit}{GDP})$	4,155	0.013	0.011	0.032	−0.059	−0.032	−0.022	0.050	0.064	0.115	0.221
Control variables											
Inflation	4,147	0.037	0.028	0.043	−0.076	−0.011	0.001	0.090	0.119	0.185	0.686
Term spread	4,088	0.012	0.012	0.018	−0.042	−0.016	−0.007	0.030	0.036	0.053	0.184
Book to market	2,437	0.707	0.621	0.416	0.265	0.341	0.377	1.042	1.333	2.564	0.543
Investment to Capital	3,266	0.102	0.099	0.019	0.068	0.075	0.081	0.127	0.140	0.161	0.550

Notes. Summary statistics are reported for log total excess returns for both the bank and nonfinancials equity indexes. Summary statistics are also reported for the past three-year change in bank credit to GDP and the control variables. All statistics are pooled across countries and time. Observations are quarterly over the sample of 20 countries, 1920–2012.

the annualized past three-year change in bank credit to GDP, sometimes denoted mathematically as $\Delta(\frac{bank\ credit}{GDP})$), and control variables. Observations are pooled across time and countries. Statistics for returns are all expressed in units of annualized log returns.

The mean bank and nonfinancials 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 nonfinancials. In general, equity returns are moderately correlated across countries—bank index returns have an average correlation of 0.394 with the United States, and nonfinancials index returns have an average correlation of 0.411. Given that this article 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 five years, is -76.2% (in annualized log terms, thus corresponding to a quarterly drop of $\frac{-76.2\%}{4} = 19.1\%$), and the 1st percentile return is -137.6% (in annualized log terms).

Credit expansion is on average 1.3% a year. In terms of variability, *credit expansion* grows as rapidly as 6.4 percentage points of GDP a year (in the 95th percentile) and contracts as rapidly as -3.2 percentage points of GDP a year (in the 5th percentile). Table I reports that its time-series correlation with the United States, 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 2007–2008 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 I, helps our analysis, as *credit expansion*'s associations with equity returns and crashes may be attributed largely to local conditions and not through spillover from crises in other countries.[12]

Table II 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 II shows that,

12. Online Appendix Table X shows that the predictive power of *credit expansion* on subsequent returns is mostly due to country-specific *credit expansion* and not spillover effects from other countries.

TABLE II
CORRELATIONS

Correlation of $\Delta(\frac{bank\ credit}{GDP})$ and:	Average correlation	Std. err.
$\Delta(\frac{\text{total credit}}{\text{GDP}})$	.792***	(.048)
$\Delta(\frac{\text{total credit to HHs}}{\text{GDP}})$	.636***	(.054)
$\Delta(\frac{\text{total credit to private NFCs}}{\text{GDP}})$	.608***	(.067)
$\Delta(\frac{bank\ credit}{GDP})$	.592***	(.056)
Growth of household housing assets	.316***	(.085)
$\Delta(\frac{\text{gross external liabilities}}{\text{GDP}})$	.338***	(.073)
$\frac{\text{Current account deficit}}{\text{GDP}}$	.172***	(.057)
Market dividend yield	−.026	(.046)
Bank dividend yield	.052	(.046)
Book to market	−.094*	(.056)
Inflation	−.103***	(.039)
Term spread	−.136***	(.049)
Investment to Capital	.300***	(.070)

Notes. This table reports correlations of the past three-year change in bank credit to 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 nonresidential 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, respectively. Observations are quarterly over the sample of 20 countries, 1920–2012.

as expected, *credit expansion* is correlated with changes in other aggregate credit variables—including total credit (i.e., both bank and nonbank credit), total credit to households, total credit to nonfinancial corporations, bank assets to GDP, and growth of household housing assets—and with changes in international credit (current account deficits to GDP and changes 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 the bank equity index and with 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 further compare the predictability of bank credit expansion and bank dividend yield in Section III.D and argue that they capture different dimensions of market sentiment.

13. The construction of these variables and their data sources are described in the Online Appendix.

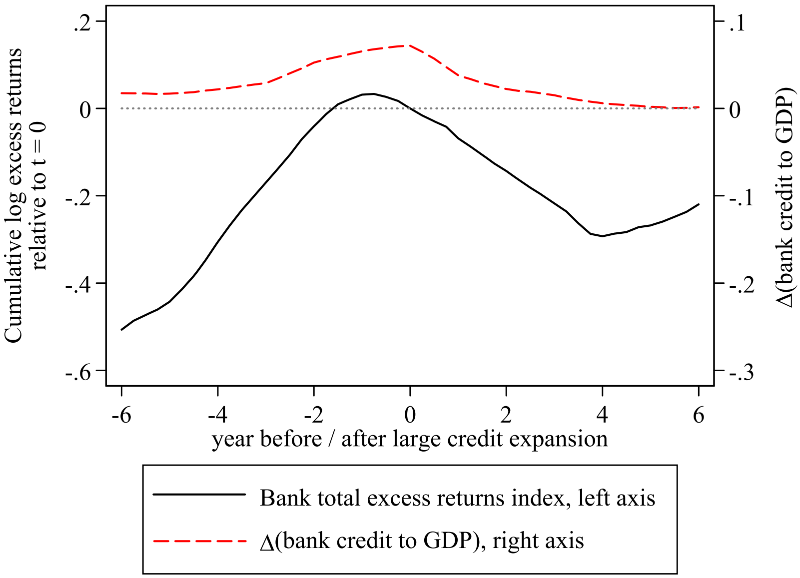

FIGURE II

Bank Equity Prices and Bank Credit before and after Large Credit Expansions

The past three-year change in bank credit to GDP (i.e., $\Delta(\frac{bank\ credit}{GDP})$) 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. $\Delta(\frac{bank\ credit}{GDP})$ 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.

II.C. Large Credit Booms and Bank Equity Declines

To understand the timing of credit expansions and bank equity declines, it is useful to plot their dynamics. Figure II 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 return to this definition in Section III.C.

To produce Figure II, 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 after the credit boom, *credit expansion* gradually slows down to 0, 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 2012), the decline in credit expansion is much steeper and turns negative after year two; see Online Appendix Figure II for the dynamics of *credit expansion* and equity prices before and after banking crises.

Figure II 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]

Figure II also highlights various other aspects of the dynamics of bank equity prices around large credit booms. For example, Figure II shows how bank equity prices tend to rise considerably leading up to the peak of the credit boom, with log excess returns of the bank equity index of 8.5% a 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.

III. Empirical Results

Because 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 nonfinancial equity prices. In this section, we report our empirical findings using credit

14. The magnitude of the decline in Figure II is slightly different from the results in Table V because Table V uses nonoverlapping one-, two-, and three-year-ahead returns for econometric reasons, as explained in Section III. However, the magnitudes are roughly similar.

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 nonfinancials; we leave the results for nonfinancials for Online Appendix Section II.

Our analysis proceeds as follows. 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 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 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, that is, equations (2) and (3), 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, that is, 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 nonoverlapping returns throughout the analysis. That is, in calculating one-, two-, or three-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 autocorrelation in the dependent variables (excess returns) is likely to be minimal. Using nonoverlapping 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 nonmissing.[16] This gives us a total of 4,155 quarterly observations. After deleting intervening observations to create nonoverlapping one-, two-, or three-year- ahead returns, there are 957, 480, and 316 observations for the one-, two-, and three-year-ahead regressions, respectively.

III.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:

$$\begin{aligned}&\Pr[Y_{i,t} = 1|(\textit{predictor variables})_{i,t}]\\ &\qquad = \Phi[\alpha_i{}^K + \beta^{K\prime}(\textit{predictor variables})_{i,t}], \qquad (1)\end{aligned}$$

where Φ is the c.d.f. of the standard normal distribution and $Y = 1_{\text{crash}}$ is a future crash indicator, which takes on a value of 1

15. Specifically, we look at returns from close December 31, 1919, to close December 31, 1920, and so on, for the one-year-ahead returns; from close December 31, 1919, to close December 31, 1921, and so on, for the two-year-ahead returns; and from close December 31, 1919, to close December 31, 1922, and so on, 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, to avoid any look-ahead bias in the predictive regressions. As shown in Online Appendix Table XI, 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.

if there is an equity crash in the next K years ($K = 1$, 2, and 3) and 0 otherwise.[17] As discussed in Section II.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 one-, two-, or three-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 $Y = 1_{\text{boom}}$, where 1_{boom} is a symmetrically defined positive tail event, and we compute the difference in the marginal effects between the two probit regressions (probability of a crash minus probability of a boom).[18]

Table III 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 III correspond to the one-, two-, and three-year-ahead increased probability of a crash event. Each regression is estimated with various controls: the first block of rows reports marginal effects conditional on *credit expansion* with no controls, the second block of rows reports marginal effects conditional on bank dividend yield with no controls, the third block of rows reports marginal effects conditional on both *credit expansion* and bank dividend yield, and the last block of rows uses *credit expansion*

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 II, 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 IV.C. We also note that similar results (unreported) hold for −20% and −25% thresholds.

TABLE III

CREDIT EXPANSION PREDICTS INCREASED CRASH RISK IN THE BANK EQUITY INDEX

		1 year ahead			2 years ahead			3 years ahead		
		(1) Crash dummy	(2) Boom dummy	(3) Difference	(4) Crash dummy	(5) Boom dummy	(6) Difference	(7) Crash dummy	(8) Boom dummy	(9) Difference
No controls	$\Delta(\frac{bank\ credit}{GDP})$	0.027**	−0.003	0.030**	0.033***	−0.002	0.035***	0.054***	−0.012***	0.065***
		[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 div. yield)	−0.015	0.005	−0.020	−0.022	0.009	−0.030	−0.020	0.005	−0.024
		[−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 div. yield as control	$\Delta(\frac{bank\ credit}{GDP})$	0.029**	−0.003	0.032**	0.034***	−0.002	0.036***	0.054***	−0.012***	0.066***
		[2.54]	[−0.59]	[2.49]	[3.04]	[−0.30]	[2.95]	[4.17]	[−3.02]	[5.13]
	log(bank div. yield)	−0.018	0.006	−0.023	−0.023	0.009	−0.032	−0.021	0.005	−0.026
		[−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 five controls	$\Delta(\frac{bank\ credit}{GDP})$	0.026***	−0.003	0.030***	0.027**	−0.002	0.028*	0.046***	−0.013***	0.059***
(coeff. on controls not reported)		[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

Notes. This table reports estimates from the probit regression model specified in equation (1) for the bank equity index in subsequent one, two, and three years. The main dependent variable is the crash indicator ($Y = 1_{\text{crash}}$), which takes on a value of 1 if there is a future equity crash, defined as a quarterly drop of −30% or more, in the next K years ($K = 1$, 2, and 3) and 0 otherwise. The crash indicator is regressed on $\Delta(\frac{bank\ credit}{GDP})$ 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 1 standard deviation increase in $\Delta(\frac{bank\ credit}{GDP})$ predicts a 2.7% increase in the likelihood of a future crash. This table also reports estimates from equation (1) with ($Y = 1_{\text{boom}}$), 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 the probability of a boom). Analogous results for the nonfinancials equity index are reported in Online Appendix Table III. 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.

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 III 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 one-, two-, and three-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%, respectively, all statistically significant at the 5% level. (As reference points, the unconditional probabilities of a bank equity crash event within the next one, two, and three years are 8.0%, 13.9%, and 19.3%, respectively, so a 2 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 only 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 $Y = 1_{\text{boom}}$ 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 IV.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 the subsequent one, two, and three years. This result expands the findings of Borio and Lowe (2002) and Schularick and Taylor (2012) by showing that credit expansion predicts not only banking crises but also bank equity crashes.

III.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:

$$r_{i,t+K} - r^{f}_{i,t+K} = \alpha_i^K + \beta^{K\prime}(\textit{predictor variables})_{i,t} + \epsilon_{i,t}, \tag{2}$$

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 0. 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. Although 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 IV estimates the panel regression model specified in equation (2). Various columns in Table IV 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).

Columns (1)–(4), (5)–(8), and (9)–(12) correspond to results associated with predicting one-, two-, and three-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% decreases in the subsequent one-, two-, and three-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 three 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 that the predictability using these control variables is considerably stronger for the nonfinancials equity index than for the bank equity index, as shown in Online Appendix Table III, 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 returns of the bank equity index across all

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 three years, implying that the predictability is mostly incorporated into returns within three years.

TABLE IV

CREDIT EXPANSION PREDICTS LOWER MEAN RETURNS OF THE BANK EQUITY INDEX

	1 year ahead				2 years ahead				3 years ahead			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\Delta(\frac{bank\ credit}{GDP})$	-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 div. yield)		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 to market)				0.030				0.046				0.083
				[0.792]				[0.782]				[1.037]
log(investment to capital)				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

Notes. 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 $\Delta(\frac{bank\ credit}{GDP})$ and several subsets of control variables known to predict the equity premium. Explanatory variables are in standard deviation units. Returns are nonoverlapping at one-, two-, and three-year-ahead horizons. A coefficient of −0.032 means that a one standard deviation increase in $\Delta(\frac{bank\ credit}{GDP})$ predicts a 3.2% decrease in subsequent returns. Analogous results for the nonfinancials equity index are reported in Online Appendix Table III. 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.

horizons and specifications.[21] Nevertheless, the coefficient for *credit expansion* retains 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 IV 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 one, two, and three 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

21. Note that in Online Appendix Table VI, 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 the bank equity index. Given that we are running a horse race between *credit expansion* and dividend yield, we choose to use bank dividend yield as the stronger measure to compete against *credit expansion*. Online Appendix Table VI also considers variations on market dividend yield and bank dividend yield in an effort to "optimize" dividend yield, but none of these alternatives meaningfully diminish 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 (1997) report R^2 for dividend yield: 0.015, 0.068, 0.144 (one, four, eight 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 (one, four, eight quarter overlapping horizons, respectively, 1952–2000); Cochrane (2011) reports R^2 for dividend yield: 0.10, for *cay* and dividend yield together: 0.16, and for investment to capital and dividend yield together: 0.11 (for four 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, investment to capital, and *cay*, respectively.

when a predictor variable is persistent and its innovations are highly correlated with returns, (e.g., Stambaugh 1999). In Online Appendix Section V, we use the methodology of Campbell and Yogo (2006) to show that small-sample bias is unlikely to be a concern for our estimates.

Taken together, the results in Sections III.A and III.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.

III.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 nonparametric model to estimate the magnitude of the predicted equity excess return subsequent to a large credit expansion:

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

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 at https://apps.lib.purdue.edu/abldars/); in periodicals such as *The Economist*, *Investors Monthly Manual*, *Bankers Magazine*, and so on; and in investor manuals such as the annual Moody's Banking Manuals (covering banks globally from 1928 onward) and the International Banking Directory (covering banks globally from 1920 onward). 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, and so on.

where $x \geqslant 50\%$ is a threshold for *credit expansion*, expressed in percentiles of *credit expansion* within a country. We then use the estimates to compute predicted returns: $E[r_{i,t+K} - r^f_{i,t+K} \mid \textit{credit expansion} > x] = \alpha^K + \beta^K_x$, which we report in Table V. 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 country.

Using this regression model to compute predicted returns 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 nonlinear 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 0.

Furthermore, to examine the predicted equity excess return subsequent to large credit contractions, we also estimate a similar model by conditioning on credit contraction, that is, *credit expansion* lower than a percentile threshold $y \leqslant 50\%$:

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

The predicted excess returns conditional on *credit expansion* exceeding or falling below given percentile thresholds are plotted in Figure III and reported in Table V. Specifically, Figure III plots the predicted two- and three-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

25. Note that equation (3) does not have country fixed effects 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 that can be verified empirically.

TABLE V

LARGE CREDIT EXPANSIONS PREDICT NEGATIVE RETURNS OF THE BANK EQUITY INDEX

		Bank equity index returns subsequent to $\Delta(\frac{bank\ credit}{GDP})$ being:									
		(1) <2%	(2) <5%	(3) <10%	(4) <25%	(5) <50%	(6) >50%	(7) >75%	(8) >90%	(9) >95%	(10) >98%
One-year-ahead returns	$E[r-r_f]$	0.074	0.126**	0.077**	0.059**	0.049**	−0.016	−0.042	−0.073	−0.094	−0.081
		[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
Two-year-ahead returns	$E[r-r_f]$	0.146*	0.19**	0.164***	0.128***	0.092**	−0.021	−0.077	−0.155*	−0.179**	−0.133*
		[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
Three-year-ahead returns	$E[r-r_f]$	0.232**	0.283***	0.264***	0.208***	0.179***	−0.075	−0.125	−0.24**	−0.373**	−0.561***
		[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

Notes. This table reports average log excess returns of the bank equity index subsequent to large credit expansions (when $\Delta(\frac{bank\ credit}{GDP})$ exceeds a given percentile threshold) and subsequent to large credit contractions (when $\Delta(\frac{bank\ credit}{GDP})$ 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 nonoverlapping one, two, and three-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 nonfinancials equity index are reported in Online Appendix Table III. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Observations are over the sample of 20 countries, 1920–2012.

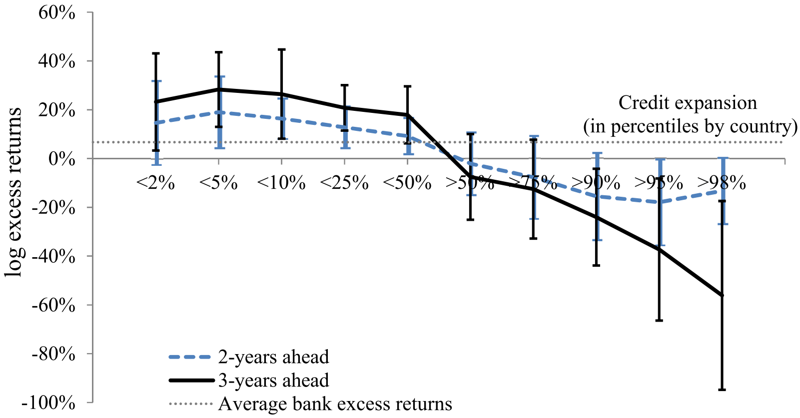

FIGURE III

Bank Equity Index Returns Subsequent to Large Credit Expansions and Contractions

This figure plots estimates reported in Table V. The plot shows the magnitude of bank equity index excess returns two and three years subsequent to large credit expansions (defined as when $\Delta(\frac{bank\ credit}{GDP})$ exceeds a given percentile threshold), in addition to average returns subsequent to large credit contractions (when $\Delta(\frac{bank\ credit}{GDP})$ 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 nonoverlapping returns. 95% confidence intervals are computed using dually clustered standard errors. Observations are over the sample of 20 countries, 1920–2012.

to 50th percentiles. A 95% confidence interval is plotted for each of the returns based on dually clustered standard errors.

Figure III 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 V reports the same information but in tabular form. The predicted negative returns are weaker for the one-year horizon but get increasingly stronger for the two- and three-year horizons. For example, at the 95th percentile threshold, the predicted negative returns are −9.4%, −17.9%, and −37.3% for the one-, two-, and three-year-ahead horizons, with t-statistics 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 V, there are 80, 40, and 19 nonoverlapping observations for one-, two-, and three-year-ahead horizons, respectively.

Finally, Figure III and Table V 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 subsequent two and three years is 19.0% and 28.3%, both significant at the 5% level.[26]

To sum up, Figure III and Table V 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 and 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: (i) 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 (ii) after reanalyzing 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 2007–2008 financial crisis).

In the aftermath of the recent financial crisis, a popular view posits that credit expansion may reflect 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 explain the largely negative bank equity premium reported in Figure III and Table V. 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,

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 2013 and Muir forthcoming). Alternatively, bank shareholders may systematically underestimate the probability of a government bailout during the depths of a financial crisis, only to be surprised later when a bailout happens.

Jin (2015) provides a theoretical model to incorporate this important feature in a dynamic equilibrium model of financial stability.

III.D. Sentiment Reflected by Credit Expansion versus 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 section, 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 a credit boom may arise in equilibrium only when both creditors and borrowers share similar beliefs about downside states. 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 II, nicely confirms this insight. More important, as shown by Table III, *credit expansion* has strong predictive power for bank equity crash risk, while dividend yield has no such predictive power. Furthermore, Online Appendix Figure III 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 III 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 with *credit expansion*, indicating that the sentiment associated with credit expansions is distinct from 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 VI reports estimation results interacting *credit expansion* with bank dividend yield. Specifically, we estimate the following specification:

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

where the interaction term is either the standard interaction term (*credit expansion* $\times$ bank dividend yield) or a nonlinear version interacting *credit expansion* with quintile dummies for bank dividend yield. As before, the regression is estimated for one-, two-, and three-year horizons (columns (1)–(3), (4)–(6), and (7)–(9), respectively, in Table VI). Coefficients and t-statistics are reported, along with the within-country R^2 and adjusted R^2 for the regressions.

In each group of columns corresponding to one-, two-, and three-year horizons, the first column reports estimates for just *credit expansion* and dividend yield with no interaction term (as in Table IV). The second column adds in the standard interaction term (*credit expansion* $\times$ bank dividend yield). Although the estimates are small and not significant at the one- and

TABLE VI

CREDIT EXPANSION HAS STRONGEST PREDICTABILITY WHEN DIVIDEND YIELD IS LOW

	1 year ahead			2 years ahead			3 years ahead		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta(\frac{bank\ credit}{GDP})$	-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 div. yield)	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]
$\Delta(\frac{bank\ credit}{GDP}) \times$ log(bank div. yield)		0.005			0.013			0.042^{***}	
		[0.855]			[1.186]			[2.725]	
$\Delta(\frac{bank\ credit}{GDP}) \times \ldots$									
(bank div. yield 1st quintile dummy)			-0.039^{*}			-0.062			-0.144^{**}
			[−1.786]			[−1.539]			[−2.244]
(bank div. yield 2nd quintile dummy)			-0.046			-0.058			-0.069
			[−1.438]			[−1.337]			[−0.676]
(bank div. yield 3rd quintile dummy)			-0.030			0.015			-0.032
			[−1.051]			[0.403]			[−0.745]
(bank div. yield 4th quintile dummy)			-0.035^{*}			-0.031			0.025
			[−1.690]			[−0.953]			[0.736]
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

Notes. This table reports estimates from the panel regression with fixed effects model specified in equation (2) and is similar to Table IV but analyzes the interaction of $\Delta(\frac{bank\ credit}{GDP})$ and bank dividend yield. Returns are nonoverlapping at one-, two-, and three-year horizons. The regressors are $\Delta(\frac{bank\ credit}{GDP})$, log bank dividend yield, and various interactions of those variables: specifically, $\Delta(\frac{bank\ credit}{GDP})$ interacted with log(bank dividend yield) 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 $\Delta(\frac{bank\ credit}{GDP})$ 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 nonfinancials equity index are reported in Online Appendix Table III. 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.

two-year-ahead horizons, the result of 0.042 is sizable and statistically significant at the three-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 one- and two-year-ahead horizons may be due to the fact that the predictive power of dividend yield is nonlinear and is strongest when dividend yield is very low. We therefore reestimate equation (5) in the third column with a nonlinear interaction term, interacting *credit expansion* with quintile dummies for bank dividend yield. Specifically, we interact *credit expansion* with the four 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 VI, 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 quintile, and its magnitude decreases somewhat monotonically across the four dividend yield quintiles. This suggests that dividend yield has a nonlinear 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 noninteracted *credit expansion* term, first row). 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.

IV. Robustness

We present various robustness checks in this section. First, we show that the 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 Online Appendix.

IV.A. Clustering Observations by Historical Episodes

Recall Table V, 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.

Table VII organizes credit expansion observation satisfying the 95th percentile threshold into 19 distinct historical episodes. These episodes are widely dispersed throughout the sample period. Some of them are well known (e.g., the booms preceding the Great Depression, the Japanese crisis of the 1990s, the Scandinavian financial crises, the 1997–1998 East Asian crisis, and the 2007–2008 global financial crisis), whereas others are less well known. Some of these episodes consist of a single country (Japan, 1989), and 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 episodes as a single, independent data point.

TABLE VII

BANK EQUITY INDEX RETURNS SUBSEQUENT TO LARGE EXPANSIONS: GROUPED BY HISTORICAL EPISODES

Episode	Associated crisis	Year: quarter	Country	Returns on bank equity (1) 1 year ahead	(2) 2 years ahead	(3) 3 years ahead
1	Great Depression	1929:1	France	−0.119	−0.338	−0.632
		1932:4	United States	−0.353	−0.173	0.244
2		1958:4	Japan	0.105	0.211	0.135
3		1960:4	United Kingdom	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	United Kingdom	−0.453	−1.457	−0.708
7		1974:1	United States	−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	United Kingdom	0.305	0.453	0.587
11	Savings and Loan crisis	1986:4	United States	−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	United States	−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
Average bank equity index returns over episodes				−0.099	−0.136	−0.180
				[−1.945]	[−1.524]	[−1.993]
N (episodes)				19	19	19

Notes. 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. It lists one-, two-, and three-year-ahead returns of the bank equity index subsequent to the initial quarter of all large credit expansions, defined as $\Delta(\frac{bank\ credit}{GDP})$ 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 2007–2008 global financial crisis). Returns from the resulting historical episodes are first averaged within each historical episodes; then, an average and t-statistic are calculated across historical episodes, taking each distinct historical episode as a single, independent observation. Observations are over the sample of 20 countries, 1920–2012.

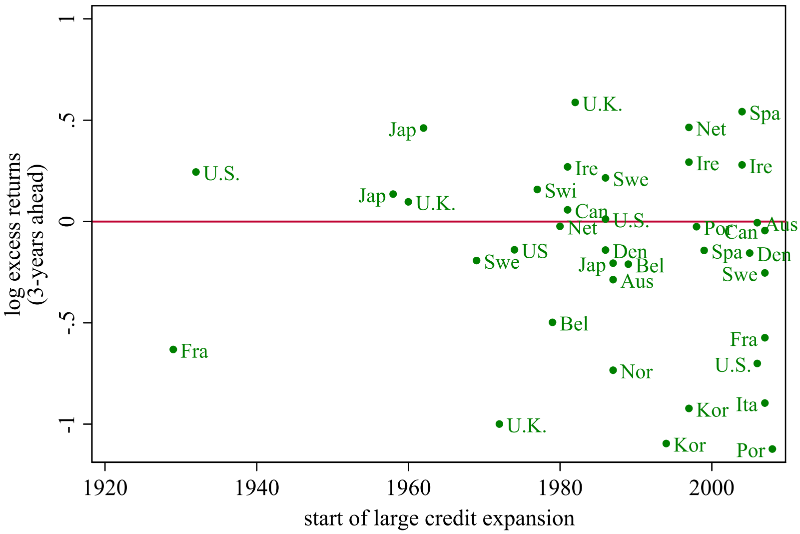

FIGURE IV

Bank Equity Index Returns Subsequent to Large Credit Expansions

This figure plots three-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 VII. 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.

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 to be robust to autocorrelation.) These events and their subsequent three-year-ahead returns of the bank equity index are plotted in Figure IV.

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 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 episodes are then themselves averaged together—taking each such episode as a single, independent observation—to generate the final average return reported at the bottom of Table VII.

In Table VII and Figure IV, 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 VII and Figure IV may sometimes look "off." Observations 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 VII reports that the average excess returns in the one, two, and three 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.

IV.B. Robustness in Subsamples

We reestimate the probit (Table III), OLS (Table IV), and nonparametric (Table V) regressions in various geographical and time subsamples and find that 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 important, are not simply driven by the Great Depression and the 2007–2008 global financial crisis.

Table VIII, Panels A and B, reports probit marginal effects and OLS coefficients for *credit expansion* on future excess returns of the bank equity index for various subsets of countries and time periods. Using a three-year forecasting horizon, the regressions are analogous to those reported in Tables III and IV. (Results also hold for one- and two-year forecasting horizons.) The sample

27. Many observations in Table VII and Figure IV miss the crash either because the large credit expansion is picked up too early (e.g., Spain 2004) or too late (e.g., United States 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.

TABLE VIII

ROBUSTNESS IN GEOGRAPHICAL AND TIME SUBSAMPLES

	(1) Full sample	(2) U.S.	(3) English-speaking	(4) W. Europe	(5) S. Europe	(6) Scandinavia	(7) 1950–2003, all countries
Panel A: Probit estimation of three-year-ahead bank index returns							
$\Delta(\frac{bank\ credit}{GDP})$	0.054***	0.112	0.070**	0.049***	0.102**	0.041	0.045**
	[4.27]	[1.06]	[2.33]	[3.59]	[2.22]	[0.05]	[2.29]
N	316	24	87	218	32	57	218
$\Delta(\frac{bank\ credit}{GDP})$	0.046***	0.037	0.003	0.039**	0.200***	0.038	0.038*
	[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 three-year-ahead bank index returns							
$\Delta(\frac{bank\ credit}{GDP})$	−0.114***	−0.090	−0.055*	−0.135***	−0.193**	−0.194***	−0.114***
	[−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
$\Delta(\frac{bank\ credit}{GDP})$	−0.106***	0.060	−0.037	−0.123***	−0.276*	−0.207***	−0.091***
	[−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

Notes. This table demonstrates that the estimates reported in Tables III and IV for the probit (Panel A) and OLS (Panel B) 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 2007–2008 financial crisis and the Great Depression). The table reports estimates—using the same methodology as in Tables III and IV—of future log excess returns of the bank equity index. Within 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 $\Delta(\frac{bank\ credit}{GDP})$; coefficients on control variables are omitted. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE IX

FURTHER ROBUSTNESS IN GEOGRAPHICAL AND TIME SUBSAMPLES

		3-year-ahead bank equity index excess returns subsequent to $\Delta(bank\ credit/GDP)$ being:		
		(1) >90%	(2) >95%	(3) >98%
Full sample	$E[r-r_f]$	-0.24^{**}	-0.373^{**}	-0.561^{**}
		[−2.384]	[−2.522]	[−2.857]
	R^2	0.04	0.041	0.048
	N	38	19	11
United States	$E[r-r_f]$	−0.435	−0.701	
		[−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	-0.298^{***}
		[−0.087]	[−0.73]	[−12.843]
	R^2	0.021	0.042	0.036
	N	12	5	2
Western Europe	$E[r-r_f]$	-0.302^{**}	-0.369^{**}	-0.561^{**}
		[−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	-0.282^{**}	-0.282^{**}
		[−1.082]	[−3.172]	[−3.172]
	R^2	0.033	0.018	0.018
	N	7	3	3
Scandinavia	$E[r-r_f]$	-0.353^{**}	-0.474^{***}	-0.783^{**}
		[−2.647]	[−5.877]	[−14.362]
	R^2	0.068	0.055	0.071
	N	8	4	2
1950–2003, all countries	$E[r-r_f]$	-0.187^{**}	-0.174^{*}	-0.297^{***}
		[−2.345]	[−1.775]	[−4.198]
	R^2	0.042	0.022	0.027
	N	22	13	8

Notes. This table demonstrates that the estimates reported in Tables V for the nonparametric regression model are robust within various geographical and time subsets. Time subsets are: 1920–2012 (the full sample) and 1950–2003 (i.e., excluding both the 2007–2008 financial crisis and the Great Depression). The table reports the three-year-ahead bank index returns subsequent to large credit expansions in various time and geographical subsets. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

is subdivided into geographical regions (e.g., the United States, Western Europe) and the time subsample 1950–2003 (i.e., excluding the Great Depression and the 2007–2008 financial crisis), and separate regressions are run for each of the subsets. In Table IX, we reanalyze returns subsequent to large credit expansions (using the 95th percentile threshold) for the various subsets.

In Table VIII, 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 United States 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 2007–2008 financial crisis.

Table IX shows the average three-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 2007–2008 financial crisis.

As a related robustness check, Online Appendix Figure II examines whether future returns are forecastable at various time points historically. This figure presents the coefficient from the OLS regressions for three-year-ahead bank index returns (Panel A) and three-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, Online Appendix Figure II can help assess how these estimates evolved throughout the historical sample and what could have been forecastable by investors in real time. See Online Appendix Section IV for further details on methodology.

As one can see in Online Appendix Figure II, 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 upward but subsequently declined. Similarly, the estimate of future three-year-ahead excess returns in Panel B is also robustly negative, except for a period in the 1950s and early

1960s when the past 20-year 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, Online Appendix Figure II shows that the main results have held since at least the 1980s and, more important, could have been forecastable at the time by investors during large historical credit expansions.

IV.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 approaches to confirm the results of the probit regression reported in Table III, 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—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:

$$\textit{Quantile}_q\left[r_{i,t+K} - r^f_{i,t+K} \mid (\textit{predictor variables})_{i,t}\right] = \alpha^K_{i,q} + \beta^{K\prime}_q (\textit{predictor variables})_{i,t}. \quad (6)$$

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:

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

where $\beta_{q=x}$ denotes the coefficient estimated for the x quantile. This statistic $\beta_{\text{negative skew}}$ 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]

28. Quantile regression estimates have a slightly different interpretation from the probit estimates: the probits analyze the likelihood of tail events, whereas quantile regressions indicate the severity of tail events. It is possible, for example, for the frequency of crash events to stay constant and the severity of such events to increase.

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 2nd/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 hypothesis H_0: $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}) = 0$, 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: $\beta_{\text{mean}} - \beta_{\text{median}} = 0$, is tested by simultaneously bootstrapping mean and median coefficients; the resulting Wald statistic is then used to compute a p-value.

TABLE X

QUANTILE REGRESSIONS AS AN ALTERNATIVE MEASURE OF CRASH RISK

		(1) 1 year ahead	(2) 2 years ahead	(3) 3 years ahead
$\Delta(\frac{bank\ credit}{GDP})$	Mean	$-.032^{**}$	$-.060^{***}$	$-.114^{***}$
		[−2.15]	[−3.46]	[−3.65]
	Median	-0.019^{***}	$-.041^{***}$	$-.077^{***}$
		[−3.14]	[−3.08]	[−4.21]
	Difference	$.014^{**}$	0.019	$.037^{**}$
	p-value	0.014	0.200	0.044
$\Delta(\frac{bank\ credit}{GDP})$	q = 5	$-.075^{***}$	-0.034	$-.124^{***}$
		[−3.16]	[−1.45]	[−5.19]
	q = 50	-0.019^{***}	$-.041^{***}$	$-.077^{***}$
		[−3.14]	[−3.08]	[−4.21]
	q = 95	$-.028^{**}$	$-.067^{***}$	$-.114^{**}$
		[−2.19]	[−2.67]	[−2.15]
	Negative skew	$.065^{***}$	0.018	$.083^{**}$
		[2.86]	[0.69]	[2.15]
	N	957	480	316

Notes. This table reports estimates from two alternative measures of crash risk for the bank equity index. The first measure is $\beta_{\text{difference}} = (\beta_{\text{median}} - \beta_{\text{mean}})$, the difference between the coefficients from mean and median regressions of bank index returns regressed on $\Delta(\frac{bank\ credit}{GDP})$; a larger difference between the coefficients corresponds to increased negative skewness in future returns. The second measure is derived from quantile regression estimates of bank index returns regressed on $\Delta(\frac{bank\ credit}{GDP})$; 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 $\beta_{\text{negative skew}} = ((\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}))$, 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 ($\beta_{\text{median}} - \beta_{\text{mean}}$); the coefficients from jointly estimated quantile regressions, $\beta_{q=5}, \beta_{q=50}, \beta_{q=95}$; and, last, the conditional negative skewness coefficient $\beta_{\text{negative skew}} = ((\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50}))$. $\Delta(\frac{bank\ credit}{GDP})$ 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.

Table X reports estimates from the quantile regressions. The columns correspond to one-, two-, and three-year-ahead excess returns for the bank equity index. The top part of the table reports results for the ($\beta_{\text{mean}} - \beta_{\text{median}}$) 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 −0.077 for the bank equity index at one-, two-, and three-year horizons, respectively; all coefficient estimates are significant at the 1% 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.

($\beta_{\text{mean}} - \beta_{\text{median}}$) 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., $\beta_{\text{mean}} - \beta_{\text{median}}$) 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 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 X 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 $\beta_{\text{negative skew}} = (\beta_{q=50} - \beta_{q=5}) - (\beta_{q=95} - \beta_{q=50})$—and its associated t-statistic. For bank equity index returns, the coefficient for negative skewness, $\beta_{\text{negative skew}}$, is estimated to be 0.065, 0.018, and 0.083 (the first and third significant at the 5% level) for one-, two-, and three-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.

IV.D. *Additional Robustness Checks*

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

1. 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*, is highly persistent on a quarterly level. In Online Appendix Section V, 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 to be a concern for our estimates.

2. "Optimizing" Dividend Yield. Online Appendix Table VI 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 Online Appendix Table VI, we therefore consider both market dividend yield and bank dividend yield, with each of those measures also smoothed over the past two, four, or eight 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*.

3. Decomposing the Credit Expansion Measure. Online Appendix Table VII addresses concerns that the predictive power of $\Delta(\frac{bank\ credit}{GDP})$ might be driven by the denominator (GDP) rather than the numerator (bank credit). However, by breaking down $\Delta(\frac{bank\ credit}{GDP})$ into $\Delta\log(bank\ credit)$ and $\Delta\log(GDP)$ or into $\Delta l\mathrm{og}(real\ bank\ credit)$ and $\Delta\log(real\ GDP)$, Online Appendix Table VII demonstrates that the predictability in returns is driven by changes in the numerator (i.e., by $\Delta\log(bank\ credit)$).

Furthermore, in Online Appendix Table VIII, 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: $\Delta(\frac{bank\ credit}{GDP})_{t-3,t-2}$ and $\Delta(\frac{bank\ credit}{GDP})_{t-2,t-1}$, 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 one- to three-year horizon subsequent to credit expansion.

4. Robustness in Arithmetic Returns. Online Appendix Table IX addresses the potential concern that our results might be driven by the use of log returns rather than arithmetic returns. Although log returns are most appropriate for time-series regressions as they reflect compounded returns over time, they can accentuate negative skewness. Online Appendix Table IX replicates the main results of the article but using arithmetic returns and shows that the main results (Tables III, IV, V, and VI) are robust to using arithmetic returns as the dependent variable.

5. Global versus Country-Specific Credit Expansions. Online Appendix Table X 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. Although this concern would not in any way invalidate this article'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. Online Appendix Table X 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 reestimate the regressions in Table IV 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 Online Appendix Table X. 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.

V. Conclusion

By analyzing the predictability of bank credit expansion for bank equity index returns in a set of 20 developed economies over the years 1920–2012, we document empirical evidence supporting the long-standing view of Minsky (1977) and Kindleberger (1978) regarding overoptimism as an important driver of credit expansion. Specifically, we find that (i) 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; (ii) conditional on bank credit expansion of a country exceeding a 95th percentile threshold, the predicted excess return of the bank equity index in subsequent three years is -37.3%, strongly indicating the presence of overoptimism and neglect of crash risk at times of rapid credit expansions; (iii) 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). Although 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 the presence of overoptimism or elevated risk appetite of shareholders.

Our study also has important implications for the pricing of tail risk. Following Rietz (1988) and Barro (2006), a quickly growing body of literature (e.g., Gabaix 2012; Wachter 2013), highlights rare disasters as a potential resolution of the equity premium puzzle. Gandhi and Lustig (2015) 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 United States, 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 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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SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

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