NBER WORKING PAPER SERIES

HOW CREDIT CYCLES ACROSS A FINANCIAL CRISIS

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Working Paper 23850
http://www.nber.org/papers/w23850

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2017

We thank Michael Bordo, Gary Gorton, Robin Greenwood, Francis Longstaff, Emil Siriwardane, Jeremy Stein, David Romer, Chris Telmer, Alan Taylor, Egon Zakrajsek, and seminar/conference participants at Arizona State University, AFA 2015 and 2017, Chicago Booth Financial Regulation conference, NBER Monetary Economics meeting, NBER Corporate Finance meeting, FRIC at Copenhagen Business School, Riksbank Macro-Prudential Conference, SITE 2015, Stanford University, University of Amsterdam, University of California-Berkeley, University of California-Davis, and Utah Winter Finance Conference. We thank the International Center for Finance for help with bond data, and many researchers for leads on other bond data. We thank Jonathan Wallen for research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 23850
September 2017
JEL No. E0,G01

ABSTRACT

We study the behavior of credit and output across a financial crisis cycle using information from credit spreads. We show the transition into a crisis occurs with a large increase in credit spreads, indicating that crises involve a dramatic shift in expectations and are a surprise. The severity of the subsequent crisis can be forecast by the size of credit losses (change in spreads) coupled with the fragility of the financial sector (as measured by pre-crisis credit growth), and we document that this interaction is an important feature of crises. We also find that recessions in the aftermath of financial crises are severe and protracted. Finally, we find that spreads fall pre-crisis and appear too low, even as credit grows ahead of a crisis. This behavior of both prices and quantities suggests that credit supply expansions are a precursor to crises. The 2008 financial crisis cycle is in keeping with these historical patterns surrounding financial crises.

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1 Introduction

We characterize the dynamics of credit markets and output across a financial crisis cycle. We answer questions such as, do credit markets appear "frothy" before a crisis, what conditions in credit markets typically lead to a crisis, and are financial crises associated with deeper recessions than non-financial crises. The 2007-2009 US financial crisis was preceded by high credit growth and low credit spreads, and has been associated with a deep recession and slow recovery. But this is one episode. Our paper examines over 40 financial crises in an international panel and shows that the US boom/bust pattern is a regularity of financial crises. We also provide magnitudes associated with these patterns, which we will argue to be more precise than previous research, and can guide the development of quantitative macro-financial crisis models.

Our research brings in information from credit spreads, i.e., the spreads between higher and lower grade bonds within a country. The bulk of the literature examining international financial crises explore quantity data, such as credit-to-GDP and its association with output (see Bordo *et al.* (2001), Reinhart and Rogoff (2009b), and Jorda *et al.* (2010)). In US data, credit spreads are known to contain information on the credit cycle and recessions (see Mishkin (1990), Gilchrist and Zakrajsek (2012), Bordo and Haubrich (2010), and Lopez-Salido *et al.* (2015)). However, the US has only experienced two significant financial crises over the last century. We collect information on credit spreads internationally, and thus provide systematic evidence relating credit and financial crises.

Defining crises: In order to describe patterns around financial crises, we need to know what is a financial crisis. Theoretical models describe crises as the result of a shock or trigger (losses, defaults on bank loans, the bursting of an asset bubble) that affects a fragile financial sector. Denote these losses as $z_{i,t}$ ($E_t[z_{i,t}] = 0$, for country-i, time t). Theory shows how the shock is amplified, with the extent of amplification driven by the fragility of the financial sector (low equity capital, high leverage, high short-term debt financing). Denote $\mathcal{F}_{i,t}$ as the fragility of the financial sector. Then models suggest that the severity of the crisis should depend on $\mathcal{F}_{i,t} \times z_{i,t}$. A sizable shock to a fragile financial sector results in a financial crisis with bank runs as well as a credit crunch, i.e., a decrease in loan supply and a rise in lending rates relative to safe rates. Asset market risk premia also rise as investors shed risky assets. All of this leads to a rise in credit spreads. See Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), He and Krishnamurthy (2012), Brunnermeier and Sannikov (2012), and Moreira and Savov (2014) for theoretical models of credit markets and crises.

We label this theoretical characterization of financial crises as the "FZ" model of crises.

To have a crisis, we must have that $\mathcal{F}_{i,t}$ is high and that a sizable shock occurs so that crisis severity is increasing in $z_{i,t} \times \mathcal{F}_{i,t}$. If fragility is low, and there are losses, then there is no financial crisis. Higher losses in a more fragile state lead to a more severe crises.

We then turn to the data to identify crises. We take two approaches, a narrative and a quantitative approach. The narrative approach is commonly used in the literature (see Bordo *et al.* (2001), Reinhart and Rogoff (2009b), and Jorda *et al.* (2010)). We rely on a chronology based on Jorda *et al.* (2010) and Jordà *et al.* (2013), and show that our results are robust to other chronologies. Jorda *et al.* (2010) state:

> We define financial crises as events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions

Jordà *et al.* (2013) provides dates for the start of the recession associated with the banking crisis, which typically occurs before the actual bank run or failure. We refer to these financial crisis recession dates as "ST" dates.

We also take a quantitative approach that is based on the FZ theory and utilizes our credit spread data. Romer and Romer (2014) critique the qualitative approach to crisis dating stating that it has a "we know one when we see one" feel. They point out that such an approach can lead to dating biases that may affect inference. The quantitative approach avoids this problem. We measure fragility based on credit-to-GDP growth in an economy. We define a dummy ("HighCredit") equal to one if credit-to-GDP growth exceeds a threshold (which we describe below). We interact this dummy with a measure of losses, z, based on reductions in asset prices and study the behavior of output around events with large losses and high credit growth.

Figure 1 provides a visual summary of the typical behavior of output, spreads, and credit across a financial crisis cycle. The figure is based on dating $t = 0$ as an ST crisis, and is compiled from 44 financial crises. We plot the mean path of all variables, after normalizing the variables at the country level. The figure shows the typical path of a crisis, with a reduction in output at the start of the crisis, a sharp rise in spreads, as well as a boom/bust pattern in the quantity of credit. Although not apparent from the figure, we will show that the spread pre-crisis is too low in a sense that we will make clear.

Main Results: We have two findings. First, we show that the FZ model accurately represents the severity of financial crises in the cross-section of crises. For this result, we focus on the ST narrative dating of crises. There is considerable variation across the 44 financial crises dated by ST in our sample. The mean peak-to-trough decline in GDP is -6.8%. The standard deviation of this decline is 7.6%. We show that the change in spreads, $s_{i,t} - s_{i,t-1}$, where t is dated as the crisis, forecasts this peak-to-trough decline quite well, explaining 3.4% of the variation (R-squared of 18%).

Importantly, the forecasting power comes from the change in spreads rather than the level of spreads. The result is consistent with the FZ model. Bank assets are credit sensitive whose prices will move along with credit spreads. Thus the change in spreads from pre-crisis to crisis will be closely correlated with bank losses, and measure the z-shock in the FZ model.

Moreover, the result is not consistent with other models of the relation between spreads and subsequent GDP outcomes. Spreads may be passive forecasters of GDP outcomes because they are forward looking measures of expected default by corporations. But under this passive forecast model, the level of spreads at time t, $s_{i,t}$, should be the best signal regarding future output growth. Indeed we find that in non-financial recessions, the level of spreads at time t rather than the change in spreads better predicts output declines. This is the common finding in the literature examining the forecasting power of credit spreads for GDP growth (see Friedman and Kuttner (1992), Gertler and Lown (1999), Philippon (2009), and Gilchrist and Zakrajsek (2012)). Under this passive-forecast model, one would expect that the change in spreads is more directly related to the change in the expectation of output growth rather than the level of output growth.

Another possible explanation of the relation between spread changes and subsequent output growth is a "cost-of-credit" model. Under this model, investment and GDP are related to the cost-of-credit, as measured by credit spreads. Thus changes in GDP are related to the changes in the cost-of-credit, and hence changes in spreads. However, in this case changes in spreads should always be the best predictor of GDP growth, not just during crises. But this is not true. In recessions the level of spreads better forecasts GDP growth. We consider other non-crisis dates and show that the sharp forecasting power of the change in spreads is unique to the ST crisis dates.

Under the FZ model, large losses coupled with high financial fragility lead to financial crises. We have shown that on ST dates, there are large spread changes (losses). Jorda *et al.* (2010) show that growth in credit-to-GDP helps forecast the occurrence of an ST crisis as well as the severity of the crisis. Growth in credit from the banking sector is largely funded by bank debt issues and hence through increased leverage of the banking sector (see Krishnamurthy and Vissing-Jorgensen (2015)). This suggests that growth in credit-to-GDP can measure the increase in fragility of the financial sector. We examine a set of dates which are based on the product of a dummy for high fragility at date t and a large loss episode at date t. The large loss dummy is equal to one when there are large increases in credit spreads and reductions in the stock market. We show that large losses that are coupled with high credit growth are the events with the most severe crises. Large losses or high credit growth by themselves only predict mild declines in GDP. This result gives an answer to the question of why some episodes which feature high spreads and financial disruptions, such as the failure of Penn Central in the US in 1970 or the LTCM failure in 1998, have no measurable translation to the real economy. While in others, such as the 2007-2009 episode, the financial disruption leads to a protracted recession.

These results establish that the FZ model of crises well describes crisis outcomes by showing that the behavior of spreads and credit around the ST dates accord with the FZ model. With this result in hand, we directly examine the behavior of output following an episode of high credit growth and a large increase in spreads. We show that these episodes are followed by large and persistent output declines, similar to those after the ST dates. We also compare these results to non-financial recessions showing much smaller declines for these dates.

Our second main finding relates to the pre-crisis period. We address the question of, are spreads "too low" before financial crises. That is, do frothy financial market conditions set the stage for a crisis? Fragility, as measured by Jorda *et al.* (2010), is observable. We have shown that large losses preceded by high credit growth lead to adverse real outcomes. Credit spreads reflect the risk-neutral probability (true probability times risk-premium adjustment, denoted $\mathcal{Q}$), of a large loss and the (risk-neutral) expectation of output declines following a crisis:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{ Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z}) \overbrace{E_{t-1}^{\mathcal{Q}} \left[ln \ \frac{y_{i,t+k}}{y_{i,t}} | \text{crisis} \right]}^{\downarrow \text{ in } \mathcal{F}_{i,t}}.$$

Holding $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$ fixed, we may expect that as $\mathcal{F}_{i,t}$ rises before a crisis, that credit spreads also rise.

We show that the opposite is true. Unconditionally, spreads and credit growth are positively correlated. But if we condition on the 5 years before a crisis, credit growth and spreads are negatively correlated. That is, investors' risk-neutral probability of a large loss, $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$ falls as credit growth rises. We show that spreads are about 25% "too low" pre-crisis, after controlling for fundamental drivers of spreads, because of this effect.

These results are consistent with the view that expansions in credit supply are an important precursor to crises. Jorda *et al.* (2010) show that unusually high credit growth helps to predict crises, but their evidence does not speak to the important question of whether it is credit supply or credit demand that sets up the fragility before crises. Our results suggest that it is unusually high credit growth coupled with unusually low spreads that help to predict crises. The fall in spreads and rise in quantity are suggestive of an expansion in credit supply and indicate that froth in the credit market precedes crises. Mian *et al.* (2016) in independent work provide similar evidence for a credit supply effect in an international sample going back to the 1970s.

Finally, we use our credit spread data to revisit Jorda *et al.* (2010)'s result that credit growth can predict crises. We create a froth variable based on credit spreads, measuring when credit spreads are unusually low. We show that combining the froth measure and the credit growth measure better predicts crises than either measure in isolation.

These two sets of results, describing the evolution of crises based on fragility $\times$ losses and describing the runup to crises in terms of froth, are our main findings. They provide guidance for theories of financial crises. Models such as Gertler and Kiyotaki (2010), He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2012) are FZ models and are the types of models that can match the evolution and aftermath of a crisis. However, these models will not match the pre-crisis spread evidence. In the models, a prolonged period in which fragility and leverage rises will also be coupled with an increase in spreads and risk premia. That is, the logic of these models is that asset prices are forward looking and will reflect the increased risk of a crisis as fragility grows. The spread evidence is more consistent with models of belief formation in which agents discount the likelihood of a crisis. In Moreira and Savov (2014), severe crises are preceded by periods of low spreads where agents think a crisis is unlikely and hence increase leverage. But in their rational model, it also does not follow that a period of lower spreads predicts a more likely crisis. Expectations are rational. Low spreads still indicate an unlikely crisis, it is just that if the unlikely event occurs, the crisis will be severe. Behavioral models such as Gennaioli *et al.* (2013) can capture the predictive power of froth for crises because agents' beliefs are systematically biased and this bias is a driver of fragility and crises. Finally, models of agent beliefs such as Caballero and Krishnamurthy (2008), Moreira and Savov (2014) and Gennaioli *et al.* (2013) also imply that crises will be triggered by a large "surprise." We have discussed how spread changes correlate with the subsequent severity of a crisis because the change proxies for credit losses. Another possibility is that the change in spreads directly measures the surprise to investors, and is thus consistent with these theories.

Literature: Our paper contributes to a growing recent literature on the aftermath of financial crises. The most closely related papers to ours are Reinhart and Rogoff (2009b), Jorda *et al.* (2010), Bordo *et al.* (2001), Bordo and Haubrich (2012), Cerra and Saxena (2008), Claessens *et al.* (2010) and Romer and Romer (2014). This literature generally finds that the recoveries after financial crises are particularly slow compared to deep recessions, although Bordo and Haubrich (2012) examine the US experience and dispute this finding, showing that the slow-recovery pattern is true only in the 1930s, the early 1990s and the 2008-2009 financial crisis. Relative to these papers, we consider data on credit spreads. In much of the literature, crisis dating is binary, and variation within events that are dated as crises is left unstudied. An important contribution of our paper is to use credit spreads to understand the variation within crises. Romer and Romer (2014) take a narrative approach based on a reading of OECD accounts of financial crises to examine variation within crises. They also find that more intense crises are associated with slower recoveries. Our paper is also closely related to work on credit spreads and economic growth, most notably Mishkin (1990), Gilchrist and Zakrajsek (2012), Bordo and Haubrich (2010), and Lopez-Salido *et al.* (2015). Relative to this work we study the behavior of spreads specifically in financial crises and study an international panel of bond price data as opposed to only US data. Our paper is also related to Giesecke *et al.* (2012) who study the knock-on effects of US corporate defaults and US banking crises, in a sample going back to 1860, and find that banking crises have significant spillover effects to the macroeconomy.

2 Data and Definitions

We primarily use crisis dates from Jorda *et al.* (2010) as well as Jordà *et al.* (2013) (henceforth, ST). The data from Jorda *et al.* (2010) and Jordà *et al.* (2013) date both the year of the crisis as well as the business cycle peak associated with the crisis. This typically occurs before the actual bank run or bank failure. We mainly focus on the ST business cycle peak dates. Bordo *et al.* (2001) and Reinhart and Rogoff (2009b) (henceforth BE and RR) offer two other prominent crisis chronologies covering our sample. We discuss these alternative chronologies in Section 7.

Our data on credit spreads come from a variety of sources. Table 1 details the data coverage. The bulk of our data covers a period from 1869 to 1929. We collect bond price, and other bond specific information (maturity, coupon, etc.), from the Investors Monthly Manual, a publication from the Economist, which contains detailed monthly data on individual corporate and sovereign bonds traded on the London Stock Exchange from 1869-1929.

The foreign bonds in our sample include banks, sovereigns, and railroad bonds, among other corporations. The appendix describes this data source in more detail. We use this data to construct credit spreads, formed within country as high yield minus lower yield bonds. Lower yield bonds are meant to be safe bonds analogous to Aaa rated bonds. We select the cutoff for these bonds as the 10th percentile in yields in a given country and month. An alternative way to construct spreads is to use safe government debt as the benchmark. We find that our results are largely robust to using UK government debt as this alternative benchmark.[1] We form this spread for each country in each month and then average the spread over the last quarter of each year to obtain an annual spread measure.[2] This process helps to eliminate noise in our spread construction. Lastly, we deal with compositional changes in the sample by requiring at least 90% of the bonds in a given year to be the same bonds as the previous year. Our data appendix describes the construction of spreads during this period in more detail.

From 1930 onward, our data comes from different sources. These data include a number of crises, such as the Asian crisis, and the Nordic banking crisis. We collect data, typically from central banks on the US, Japan, and Hong Kong. We also collect data on Ireland, Portugal, Spain and Greece over the period from 2000 to 2014 using bond data from Datastream, which covers the recent European crisis. For Australia, Belgium, Canada, Germany, Norway, Sweden, the United Kingdom, and Korea we use data from Global Financial Data when available. We collect corporate and government bond yields and form spreads. Our data appendix discusses the details and construction of this data extensively.

Finally, data on real per capita GDP are from Barro and Ursua (see Barro *et al.* (2011)). We examine the information content of spreads for the evolution of per capita GDP.

Figure 2 plots the incidence of crises, as dated by both RR and ST over our sample (i.e. the intersection of their sample and ours that contain data on bond spreads).

3 Normalizing Spreads

There is a large literature examining the forecasting power of credit spreads for economic activity (see Friedman and Kuttner (1992), Gertler and Lown (1999), Philippon (2009), and

[1] One issue with UK government debt is that it does not appear to serve as an appropriate riskless benchmark during the period surrounding World War I as government yields rose substantially in this period. Because of this we follow Jorda *et al.* (2010) and drop the wars year 1913-1919 and 1939-1947 from our analysis

[2] We use the average over the last quarter rather than simply the December value to have more observations for each country and year. Our results are robust to averaging over all months in a given year but we prefer the 4th quarter measure as our goal is to get a current signal of spreads at the end of each year.

Gilchrist and Zakrajsek (2012)). Almost all of this literature examines the forecasting power of a credit spread (e.g., the Aaa-Baa corporate bond spread in the US) within a country. As we run regressions in an international panel, there are additional issues that arise.

Table 2 examines the forecasting power of spreads for 1-year output growth in our sample. We run,

$$\ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = a_i + a_t + b_0 \times spread_{i,t} + b_{-1} \times spread_{i,t-1} + \varepsilon_{i,t+k}. \tag{1}$$

We include country and time fixed effects. Country fixed effects pick up different mean growth rates across countries. We include time fixed effects to pick up common shocks to growth rates and spreads, although our results do not materially depend on whether time fixed effects are included. We report coefficients and standard errors, clustered by country, in parentheses.

Column (1) shows that spreads do not forecast well in our sample. But there is a simple reason for this failing. Across countries, our spreads measure differing amounts of credit risk. For example, in US data, we would not expect that Baa-Aaa spread and Ccc-Aaa spread contain the same information for output growth, which is what is required in running (1) and holding the bs constant across countries. In the 2007-2009 Great Recession in the US, high yield spreads rose much more than investment grade spreads. It is necessary to normalize the spreads in some way so that the spreads from each country contain similar information. We try a variety of approaches.

In, column (2), we normalize spreads by dividing by the average spread for that country. That is, for each country we construct:

$$\hat{s}_{i,t} \equiv Spread_{i,t}/\overline{Spread^i} \tag{2}$$

A junk spread is on average higher than an investment grade spread, and its sensitivity to the business cycle is also higher. By normalizing by the mean country spread we assume that the sensitivity of the spread to the cycle is proportional to the average spread. The results in column (2) show that this normalization considerably improves the forecasting power of spreads. Both the R^2 of the regression and the t-statistic of the estimates rise.

The rest of the columns report other normalizations. The mean normalization is based on the average spread from the full sample, which may be a concern. In column (3) we instead normalize the year t spread by the mean spread up until date $t-1$ for each country. That is, this normalization does not use any information beyond year t in its construction. In column (4), we report results from converting the spread into a Z-score for a given country, while in columns (5) we convert the spread into its percentile in the distribution of spreads for that country. All of these approaches do better than the non-normalized spread, both in terms of the R^2 and the t-statistics in the regressions. But none of them does measurably better than the mean normalization. We will focus on the mean normalization in the rest of the paper: a variable we refer to as $\hat{s}_{i,t}$. Our results are broadly similar when using other normalizations.

Credit spreads help to forecast economic activity because they contain an expected default component, a risk premium component, and an illiquidity component. Each of these components will correlate with a worsening of economic conditions, and a crisis. Theoretical financial accelerator models such as He and Krishnamurthy (2012)) further imply that the widening of spreads reflects a tightening of credit and hence causes the reduction in output, so that spreads are not merely passive forecasters of economic activity. We acknowledge at the outset that our data do not allow one to definitively sort out the causation/correlation question. That being said, in the next sections we present evidence that is most consistent with the financial accelerator models.

4 Fragility $\times$ Losses

We first present results consistent with the FZ model of crises. We focus on the ST narrative dating of crisis and show that the fragility-loss model well describes ST crises.

4.1 Variation within crises

There is enormous variation in financial crises outcomes. Figure 3 illustrates this point. We focus on crisis dates (start of recession associated with a financial crisis) identified by ST and plot histograms of different output measures across the crisis dates. We use two measures of severity of a crisis. The first is to use the standard peak to trough decline in GDP locally as the last consecutive year of negative GDP growth after the crisis has started. The results in our paper do not change substantially if we instead take the minimum value of GDP in a 10 year window following the crisis which allows for the possibility of a "double dip." The second measure of severity is simply the 3 year cumulative growth in GDP after a crisis has occurred. We choose 3 years to account for persistent negative effects to GDP after crises. The 3 year growth rate will also capture experiences where growth is low relative to trend but not necessarily persistently negative (i.e., Japan in 1990). Our other measure will not pick up these effects.

Focusing on the peak-to-trough decline, in the left panel of the figure, we see that there is considerable variation within crises. Moreover, we see that the distribution is left-skewed. The top panel of Table 3 provides statistics on the variation for the ST dates. The mean peak-to-trough decline is -7.2%, but the standard deviation is 8.0%. The median is -4.9%, which is smaller in magnitude than the mean, indicating that the distribution is left-skewed. The table also reports statistics for the RR and BE dates. The declines are smaller under BE and RR's dating convention because the declines are measured based on a date that occurs after the start of the recession. But we see the same general pattern of enormous variation and a left-skewed distribution.

4.2 Spreads as a measure of the severity of crises

The extent of variation within crises is in large part due to the convention of dating an episode a "crisis" or "non-crisis." With this binary approach, different crises with varying severity are grouped together. We can do better in understanding crises with a more continuous measure of the severity of crises. Romer and Romer (2014) pursue such an approach based on narrative assessments of the health of countries' financial systems. They describe financial stress using an index that takes on integer values from zero to 15, and show that this index offers guidance in forecasting the evolution of GDP over a crisis. We follow the Romer-Romer approach, but use credit spreads in the first year of a crisis to index the severity of the crisis. Relative to the Romer-Romer approach, credit spreads have the advantage that they are market-based. In addition, since they are based on asset prices they are automatically forward-looking indicators of economic outcomes.

Table 4 presents regressions of credit spreads on the peak-to-trough decline in GDP, as a measure of the severity of crises. Each data point in these regressions is a crisis in a given country-year (i, t), where crises are defined using the ST chronology:

$$decline_{i,t} = a + b_0 \times \hat{s}_{i,t} + b_{-1} \times \hat{s}_{i,t-1} + c \times \Delta credit_{i,t} + \varepsilon_{i,t} \tag{3}$$

The spread has statistically and economically significant explanatory power for crisis severity. Focusing on column (1), an increase in spreads $\hat{s}_{i,t}$ of 1 (doubling of spreads) translates to a 1.73% decrease in peak-to-trough GDP. The spreads also meaningfully capture variation in crisis severity. In column (1), the standard deviation of the peak-to-trough decline in GDP for the ST dates is 7.6%. The variation that the spread variable captures is 2.5%.

Columns (2) - (5) present results where we include lagged spreads, $\hat{s}_{i,t-1}$ and credit growth ($\Delta credit_t$, the 3 year growth in credit/GDP) from Jorda *et al.* (2010) which is known to be a predictor of financial crises. The sample shrinks when using the credit-growth variable because it is not available for all of our main sample. We note that the explanatory power increases measurably when including these other variables. Comparing columns (2) and (5) corresponding to the ST crises, the variation that is picked up by the independent variables rises from 3.6% of GDP to 5.8% of GDP. The R-squared in column (5) is 47% indicating the strong explanatory power of credit spreads and credit growth. If we repeat the regression in column (5), dropping spreads and only including $\Delta credit_t$ we find that the coefficients are quite close to the regression coefficients in the regression with spreads. That is, spreads and credit growth have independent forecasting power for crises. This latter result is similar to Greenwood and Hanson (2013) who find that a quantity variable that measures the credit quality of corporate debt issuers deteriorates during credit booms, and that this deterioration forecasts low excess returns on corporate bonds even after controlling for credit spreads. Our finding confirms the Greenwood and Hanson (2013) result in a much larger cross-country sample. We return to discussing the separate role of credit growth in crises later in the paper.

Across columns (2) - (5), we see that the lagged spread has a positive and significant sign for the crisis dates, indicating that the change in the spread from the prior year is more indicative of the severity of the recession. In fact, the autocorrelation of spreads is about 0.70 in our sample, which is also roughly the ratio of the coefficients on $\hat{s}_{i,t-1}$ and $\hat{s}_{i,t}$, indicating a special role for the innovation in spreads. Column (3) of the table presents a specification using the change in spreads, confirming the explanatory power of the change in spreads.

We show in Column (4) that the predictive results are not driven solely by the Great Depression. In unreported results, we also find including data on stock prices, such as dividend yields or stock returns, does not help to forecast crisis variation. Thus these results appear specific to credit markets.

Lastly in column (6) and(7), we consider the forecasting power of spreads for output in non-financial recessions, as dated by ST. As expected, we see that spreads negatively forecast output growth. Two further points are worth noting. First, the highest R-squared in the recession regressions is only 7% compared to the 47% R-squared in the crisis regression of column (5). The comparison underscores the strength of the spread-signal in financial crises. Second, the lagged value of the spread has little explanatory in the regression of column (7). We return to this result below.

4.3 Panel data regressions

We consider both crisis and non-crisis data and run panel data regressions. We estimate,

$$\begin{aligned} \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) &= a_i + a_t + 1_{crisis,i,t}\left(b_0^{crisis} \times \hat{s}_{i,t} + b_{-1}^{crisis} \times \hat{s}_{i,t-1}\right) \\ &\quad +1_{no-crisis,i,t}\left(b_0^{no-crisis} \times \hat{s}_{i,t} + b_{-1}^{no-crisis} \times \hat{s}_{i,t-1}\right) + c'x_t + \varepsilon_{i,t+k} \end{aligned} \tag{4}$$

We also include two lags of GDP growth as controls, as well as year fixed effects which means that the crisis coefficient on spreads is based on cross-sectional differences in spreads.

Column (1) of Table 5 presents a baseline where we pool crises and non-crises, forcing the b coefficients to be the same across these events. Panel A corresponds to 3-year GDP growth and Panel B corresponds to 5-year GDP growth. These regressions indicate that there is a negative relation between spreads and subsequent GDP growth, consistent with results from the existing literature (see, for example, Gilchrist and Zakrajsek (2012)).

The rest of the columns report results where we allow the coefficient on spreads to vary across crises and non-crises (or recessions and non-recessions). The results are in line with our findings in Table 4. Higher current spreads forecast more severe downturns. The coefficient on the level spreads is similar across crises, recessions, and in the unconditional regression. However, the change in spreads comes in with a positive coefficient that is large and statistically significant only for the crisis dates. In the recession dates, the change in spreads has less information than the level of spreads. Finally, all of these effects are present both at the 3-year horizon and 5-year horizon.

4.4 Change in spreads at the start of a crisis

In Tables 4 and 5 we find that the change in spreads in the year of financial crisis driven recessions (as dated by ST) comes in with a positive and significant coefficient, but that the change in spreads has little explanatory power in recessions.

The empirical importance of the change in spreads for forecasting output in crises, but not for recessions, is consistent with FZ crises theories. Since the financial sector primarily holds credit-sensitive assets, the change in spreads can proxy for financial sector losses. As losses suffered by levered financial institutions play a central role in trigger/amplification theories of crises, under these theories we should expect that the change in spreads, more so than the level of spreads, should correlate with the subsequent severity of a crisis.

To be more formal, suppose that spreads are:

$$s_{i,t} = \gamma_{i,0} + \gamma_1 E_t\left[ln\ \frac{y_{i,t+k}}{y_{i,t}}\right] + l_{i,t}.$$

where $l_{i,t}$ is an illiquidity component of spreads. In a crisis, lliquidity/fire-sale effects in asset markets cause $l_{i,t}$ to spike up, leading to unexpected losses to the financial sector (i.e., a large $z_{i,t}$ shock). Thus, although the term $\gamma_1 E_t\left[ln\ \frac{y_{i,t+k}}{y_{i,t}}\right]$ is more directly correlated with subsequent output growth, the term $l_{i,t}$ is more directly correlated with $z_{i,t}$ which is particularly informative for output growth during crises. On the other hand, outside of crises (or in the recovery from a crisis), spreads are better represented as,

$$s_{i,t} = \gamma_{i,0} + \gamma_1 E_t\left[ln\ \frac{y_{i,t+k}}{y_{i,t}}\right].$$

That is, outside crises, we would expect that all of the information for forecasting output growth would be contained in the time t value of the spread. Spreads in this case are a passive forecaster of output declines. [3] Our results in Tables 4 and 5 confirm these predictions and the differential importance of lagged spreads in crises and recessions.

Another possible explanation of the relation between spread changes and subsequent output growth is a "cost-of-credit" model. Under this model, investment and GDP are related to the cost-of-credit, as measured by credit spreads. Thus changes in GDP are related to the changes in the cost-of-credit, and hence changes in spreads.

To be more formal, suppose that GDP can be related to spreads as:

$$Y_{i,t} = \sum_{j\geq 0} l_j s_{i,t-j}$$

Here $s_{i,t-j}$ is the spread, which we can think of as a cost of capital. The specification allows time-to-build, so that lagged spreads enter the determination of output. Let us project output on $s_{i,t-k}$ and $s_{i,t-k-1}$ assuming spreads are unit root, for simplicity:

$$Y_{i,t} = s_{i,t-k}\sum_{j=0}^{k} l_j + s_{i,t-k-1}\sum_{j=k+1}^{\infty} l_j$$

Then, we compute for $n \leq k$:

$$Y_{i,t} - Y_{i,t-n} = s_{i,t-k}\sum_{j=0}^{k} l_j + s_{i,t-k-1}\sum_{j=k+1}^{\infty} l_j - s_{i,t-k}\sum_{j=0}^{k-n} l_j - s_{i,t-k-1}\sum_{j=k-n+1}^{\infty} l_j$$

or,

$$Y_{i,t} - Y_{i,t-n} = s_{i,t-k}\left(\sum_{j=k-n+1}^{k} l_j\right) - s_{i,t-k-1}\left(\sum_{j=k-n+1}^{k} l_j\right).$$

[3] Indeed, much of the literature examining the forecasting power of credit spreads for GDP growth finds a relation between the level of spreads and GDP growth (see Friedman and Kuttner (1992), Gertler and Lown (1999), Philippon (2009), and Gilchrist and Zakrajsek (2012)).

We can rewrite this relation as:

$$Y_{i,t} - Y_{i,t-n} = G(k,n) \times (s_{i,t-k} - s_{i,t-k-1})$$

where, $G(k,n) = \sum_{j=k-n+1}^{k} l_j$

This equation indicates that growth is a function of spread changes, for any n and k. And it raises the concern with our regressions of running spread changes on future growth and calling it a "loss" effect. The effect is also consistent with a time-to-build model.

How do we rule out the time-to-build model? Observe that $G(k,n)$ is not a function of the date t. That is for any date t, the coefficient of a regression of output growth on spread changes should be the same. We can check this directly and reject this hypothesis. In recessions the level of spreads better forecasts GDP growth. Table 5 considers other non-crisis dates and show that the sharp forecasting power of the change in spreads is unique to the ST crisis dates. Specifically, in columns (4) and (5) we show results where we include a dummy outside of a crisis window (defined as the five years prior to and including a crisis date) and find that the coefficient on spread changes in this regression is small compared to the crisis dates, and similar to the coefficient on the level of spreads. Moreover, spread changes have no explanatory power at the 5-year horizon, while the level of the spread continues to have explanatory power.

4.5 Spread spikes and output skewness

The start of a crisis is associated with a spike in spreads. We next show that a spike in spreads shifts down the conditional distribution of output growth, fattening the left tail.

Table 6 presents quantile regressions of output growth on $\hat{s}_{i,t}$ and $\hat{s}_{i,t-1}$. We see that the forecasting power of spreads for output increases as we move to the lower quantiles of the output distribution. At the median, the coefficient on $\Delta \hat{s}_t$ is -0.71, while it is -1.06 at the 25th quantile.

Figure 7 plots the distribution of GDP growth at the 1-year and 5-year horizons based on a kernel density estimation. The blue line plots the distribution of GDP growth when spreads are in the lower 30% of their realizations, while the red-dashed line plots the distribution when spreads are in the highest 30% of their realizations. A comparison of the blue to red lines indicates that high spreads shifts the conditional distribution of output growth to the left, with a fattening of the left tail.

4.6 Large losses, fragility, and crises

When do large losses to financial intermediaries lead to the tail event of a deep and protracted crisis? Theory tells us that a negative shock (high $z_{i,t}$) coupled with a fragile financial sector (high $\mathcal{F}_{i,t}$) triggers a chain of events involving disintermediation, a credit crunch, output contraction, and further losses. We further investigate whether this view of crises is consistent with the data.

We define events based on large losses:

$$\text{LargeLoss} = 1 \text{ if} \begin{cases} \hat{s}_{i,t} - \hat{s}_{i,t-1} \text{ in 90th percentile} \\ D_{i,t}/P_{i,t} > \text{median} \end{cases}$$

Here $D_{i,t}/P_{i,t}$ refers to the dividend-to-price ratio on country-i's stock market. Thus, the LargeLoss dummy defines events with widespread asset losses.

The first row of the top panel of Table 7 presents regression coefficients that describe the average path of GDP conditional on a LargeLoss event. We see that there is reduction in output that persists for many years. The trough of the decline is -4.48% around 3 years, with output coming back beyond that point.

Next we construct a financial-sector fragility indicator based on Jorda *et al.* (2010). In the second row of Table 7 we interact LargeLoss with a dummy (HighCredit) for whether credit growth has been above median in the 3 years before the crisis. Note that ideally we would measure equity capitalization or leverage as the fragility indicator, but given data limitations we are forced to rely on the credit growth variable, which plausibly correlates with low equity/high leverage of the financial sector. We see that the GDP declines in the LargeLoss/HighCredit events are larger than in the LargeLoss event. The reduction in output is also more persistent, with a reduction 5 years out of -4.83% compared to -2.51%.

The bottom panel of Table 7 presents this interaction regression a different way. We create a dummy for when credit growth is in the 92nd percentile of the unconditional distribution of credit growth across our entire sample. We use the 92% cutoff to give us the same number of crises as ST, which allows us to directly compare the numbers in this table to those of Table 5. We interact this HighCredit dummy with the current and lagged spreads, thus tracing out the impact of a shock, $z_{i,t}$, when the financial sector is fragile.

At the 3-year horizon, the coefficient on the HighCredit $\times$ Spread interaction is -4.85, which compares to the coefficient in Table 5 on $\hat{s}_{i,t} \times 1_{STcrisis,i,t}$ of -7.17. The effects we pick up with this credit growth/spread interaction are substantial but not as large as ST. This suggests that there is a unique component of the qualitative information used by ST in dating crises, and this information perhaps better picks out crises. Finally, we note that the results in the bottom panel do not include time fixed effects (the results in the top panel include both time and country fixed effects). The 92nd percentile episodes of credit growth are global phenomena, so that these regressions are largely based on time series variation.

These results provide an answer to the question of why some episodes which feature high spreads and financial disruptions, such as the failure of Penn Central in the US in 1970 or the LTCM failure in 1998, have no measurable translation to the real economy. While in others, such as the 2007-2009 episode, the financial disruption leads to a protracted recession. We find that, conditional on a large increase in spreads, episodes in which credit growth had been high result in substantially worse real outcomes.

5 Aftermath of financial crises

We have shown that the FZ description of crises is consistent with crisis behavior around ST dates. With this evidence in hand, we compare the evolution of output following (a) dates based on the FZ model; (b) dates based on ST; and (c) dates based on ST's dating of non-financial recessions.

5.1 Slow recoveries from financial crises

Table 4 and 5 also reveal that the coefficient on spreads in crises is larger in magnitude than the coefficient outside crises (which is near -1.06 as in the full sample regression, and which we omit to save space).[4] We use this difference in coefficients to compare recoveries from financial crises to non-financial recessions.

Cerra and Saxena (2008) and Claessens, Kose and Terrones (2010) document that recessions that accompany financial crises are deeper and more protracted than recessions that do not involve financial crises. They reach this conclusion by examining the average non-financial crisis recession to the average financial recession. Using spreads, we can offer a new estimate for recovery patterns.

Suppose we are able to observe two episodes, one where a negative shock (z_t) leads to a deep recession but no financial disruption, and one where the same negative z_t shock lead

[4]Note that it is tempting to read the higher coefficients associated with crisis observations as evidence of non-linearity, as suggested by theoretical models such as He and Krishnamurthy (2014). However this is not correct. In He and Krishnamurthy, *both* the spread and the path of output are a non-linear function of an underlying financial stress state variable. It is not the case that output is a non-linear function of spreads, but rather that both are non-linear functions of a third variable. Since we regress output on spreads, rather than either stress or output on an underlying financial shock, the regressions need not be evidence of non-linearity.

to a financial disruption/crises and a deep recession. Then, the measured difference in long-term growth rates in these two episodes is the slow recovery that can be attributed to the financial crisis.

We try to measure this difference as follows. We have noted that crises are associated with high expected default and high risk/liquidity premia, while recessions are only associated with high expected default. If we can compare the dynamics of GDP in two episodes with the same expected default, but in one of which there are also high risk/liquidity premia, then the difference between GDP dynamics across these two events is the pure effect of a financial crisis. We use the coefficients in the spread regressions in Table 5 across crises and recessions to compute the dynamics of GDP growth in response to a shock. We consider a one-sigma shock to the spread in different events, and trace out the impulse response of this shock for GDP using our different crisis and non-crisis events.

It is likely that this approach leads to an underestimate of the crisis effect. This is because the one-sigma shock in a recession, $z_t^{recession}$, is likely larger than the shock in a crisis, z_t^{crisis}. In the crisis, the shock z_t^{crisis} increases expected default and risk premia, while the same shock in recession likely largely only increases expected default.

Figure 4 plots the evolution of GDP to a one-sigma shock to spreads. The top panel in the figure is based on recession dates, the middle panel is based on the HighCredit dates, and the bottom panel is based on the ST crisis dates. The impulse response is computed by forecasting GDP individually at all horizons from 1 to 5 years using the local projection methods in Jorda (2005). That is, we estimate (4) for $k = 1, ..., 5$ and use the individual coefficients on spreads to trace out the effect on output given a one-sigma shock to our normalized spreads. Thus the plot in Figure 4 is the difference in output paths for two events, one of which has a one-sigma higher spread. We use the Jorda methodology rather than imposing more structure as in a VAR as it is more flexible and does not require us to specify the dynamics of all variables. Comparing across the panels, we see that the crises declines are much larger than the recession declines. Figure 5 plots these impulse responses on a single graph for ease of comparison.

Our results affirm the findings of others that financial crises do result in deeper and more protracted recessions. We emphasize that we have reached this conclusion by examining the cross-section of countries rather than the mean decline across crises. Indeed the mean decline across crises plays no role in the impulse responses because the plot is of the forecast GDP path in a crisis for a 1-sigma worse crisis (or recession). The mean decline across crises is differenced out, rendering the impulse response a difference-in-difference estimate.

5.2 2008 crisis and recovery

Reinhart and Rogoff (2009a)'s mean estimate of -9.3% peak-to-trough decline in GDP in financial crises has been taken as the benchmark to compare the experience of the US after the 2008 financial crisis. We can provide a different benchmark based on our approach of examining the cross-sectional variation in crisis severity.

Figure 6 top-panel plots the actual and predicted path of output for the 2008-2013 period based on the spread in the last quarter of 2008. Our forecasts are based on estimating regression (4), with an additional regressor that takes the value of 1 in a crisis (i.e., the crisis dummy). The dummy is significant and sharpens our forecasts, but including it in regression (4) makes it harder to compare coefficients on spreads in crises versus other episodes. Figure 6 also presents the output path using the HighCredit forecast.

The actual and predicted output paths are remarkably similar, indicating that at least for this crisis, what transpired is exactly what should have been expected. The result supports Reinhart and Rogoff (2009a)'s conclusion that the recoveries from financial crises are protracted. Our forecast path is not purely from the historical average decline across crises as in Reinhart and Rogoff (2009a), but is also informed by the historical cross-section of crises severity and the spread in 2008.

In the bottom panel of 6, we plot the actual predicted path for spreads. We note that the actual reduction in spreads is faster than the reduction that would have been predicted by our regressions, while GDP growth is faster than predicted. That is, the residuals from the forecasting regressions are negatively correlated. This result could be interpreted to mean that the aggressive policy response in the recent crisis allowed for a better outcome than historical crises. Many of the historical crises in our sample come from a period with limited policy response.

6 Froth in the Pre-crisis Period

A large increase in spreads is associated with a more severe financial crisis. Is the large change in spreads from the pre-crisis period because the level of spreads pre-crisis is "too low?" That is, are crises preceded by frothy financial conditions? There has been considerable interest in this question from policy makers and academics (see Stein (2012), and Lopez-Salido *et al.* (2015)). We use our international panel of credit spreads to shed light on this question.

6.1 Spreads and credit growth

We have shown that large losses coupled with high credit growth lead to adverse real outcomes. A credit boom is observable in real time. Credit spreads reflect the risk-neutral probability of a large loss and the output effects of large loss/fragile financial sector:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \ \text{Prob}^{\mathcal{Q}}(z_t > \underline{z}) \overbrace{E_t^{\mathcal{Q}}\left[ln \ \frac{y^i_{i,t+k}}{y_{i,t}}|\text{crisis}\right]}^{\downarrow \text{ in } \mathcal{F}_{i,t}}. \tag{5}$$

Holding $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$ fixed, we would expect that as $\mathcal{F}_{i,t}$ rises before a crisis, that credit spreads also rise.

Table 8 examines this question. Columns (1) and (2) of Panel A present regressions where the left hand side is the spread at time t, and the right hand side includes a dummy for the five years before an ST crisis, as well as lagged 3-year growth in credit and lagged GDP growth. The regressions show that spreads are on average “too low” before a crisis. The coefficient on the dummy is between -0.20 and -0.36, indicating that spreads are 20-36% below what one would otherwise expect ahead of a crisis. Column (3) of Panel A shows that the reason spreads are too low is largely because spreads do not price the increase in credit growth. In these columns we include credit growth interacted with the dummy for the years before the crisis as an additional covariate. Comparing the coefficient on this covariate with that on credit growth ($\Delta Credit_{t-1}$), we see that while on average spreads and credit growth are positively correlated, in the years before a financial crisis, credit growth and spreads are negatively correlated. The coefficient on the pre-crisis dummy falls to zero in column (3), indicating that all of the “froth” in credit spreads is due to the switch in the sign on the relation between credit growth and spreads. Before a crisis, both credit grows quickly and spreads fall quickly.

In terms of equation (5), we can view this result as suggesting that investors’ risk-neutral expectations of a large loss, $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$, falls as credit growth rises, and this fall is enough to more than offset the fragility effect of credit growth. Note that such a fall could occur either through fall in the risk premium investors charge for bearing credit risk, as may occur in models with time-varying risk premia, or through a behavioral model where investors probability assessments are biased, as in the neglected risk model of Gennaioli *et al.* (2013). Our data do not allow one to distinguish between these possibilities. Finally, one caveat to this result is that it is driven by common global factors (e.g., Depression and Great Recession). Column (4) of the table reports results including a time fixed effect. Including the time fixed effect considerably weakens the explanatory power of the sign-switching credit growth covariate, although the coefficient on the dummy still indicates that credit spreads are "too low."

Panel B of Table 8 explores whether more froth is associated with more severe crises. We break the set of ST crises into mild and severe crises, splitting based on the median 3-year GDP growth in the crisis. The coefficient on the dummy for more severe crises is larger than the coefficient on the dummy for mild crises, confirming the froth-crisis relation.

Figure 8 provides a visual representation of the behavior of spreads before and during crises. The blue line in the top panel is the mean actual spread for each of the 5 years before and after a ST crisis. The red line is the fitted spread from a regression of spreads on lags of GDP growth as well as credit growth. Thus this fitted spread represents a fundamental spread based on the relation between spreads and GDP and credit growth over the entire sample. The figure shows that spreads are too low pre-crisis and jump up too high during the crisis before subsequently coming down.

6.2 Credit supply expansions and crises

Table 9 presents these results in a different way. We construct a variable, labeled "High-Froth", based on the difference between the fitted and actual lines in Figure 8. That is, our froth variable first regresses credit spreads on fundamentals (two lags of GDP and credit growth). We take the residual from this regression and compute a five year backward looking average as our measure of credit market froth. We then create a dummy for when this variable is below its median, so that spreads appear abnormally low, and label this HighFroth. The variable thus captures prolonged periods of low spreads. In the first row of Panel A, we test whether high froth periods forecast negative future GDP growth, which it does but with marginal significance. In the second row of Panel A, we likewise show that high credit (a dummy for episodes of high credit growth) also forecasts negative future GDP growth but with marginal significance. The last row interacts the froth and credit growth dummies. Episodes of low spreads *and* high credit growth are the strongest precursor to financial crises.

These results are suggestive that credit supply expansions precede crises. That is, from the work of Jorda *et al.* (2010), we know that credit growth is a predictor of crises. But credit growth can occur both with increased credit demand as well as increased credit supply. Relative to Jorda *et al.* (2010), we include information on credit spreads, which are a proxy for the price of credit. This additional information indicates that it is credit supply expansions that is associated with crises. The bottom panel of the Table presents results using a Probit regression analogous to Jorda *et al.* (2010). Again, we see that a prolonged period of low spreads and high credit growth is particularly informative for predicting financial crises.

Figure 9 shows these results graphically by plotting the cumulative probability of a crisis at each horizon when credit is low and spreads are not abnormally low and also when credit growth is high and spreads are abnormally low. Visually it is apparent that prolonged periods of low spreads and high credit growth raise the probability of a financial crisis.

It is hard to square the pre-crisis evidence with fully rational models FZ models of a financial cycle. First, in models such as Gertler and Kiyotaki (2010), He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2012), which are FZ models, a prolonged period in which fragility and leverage rises will also be coupled with an increase in spreads and risk premia, contradicting the evidence. Moreira and Savov (2014) build an FZ model with time variation in beliefs regarding a crisis. In this model, it is possible to match the evidence that severe crises are preceded by periods of low spreads where agents think a crisis is unlikely and hence increase leverage. But in their model, it also does not follow that a period of lower spreads predicts a more likely crisis as we show in Figure 9. Expectations are rational. Low spreads still indicate an unlikely crisis, it is just that if the unlikely event occurs, the crisis will be severe. Behavioral models such as Gennaioli *et al.* (2013) can capture the predictive power of froth for crises because agents' beliefs are systematically biased and this bias drives fragility and crises.

6.3 Surprise and crises

These results also suggest that "surprise" is an important aspect of crises. We have argued that spread changes correlate with the subsequent severity of a crisis because the change proxies for credit losses. Another possibility is that the change in spreads directly measures the surprise to investors, and the extent of the surprise is a powerful predictor of the severity of financial crises. Caballero and Krishnamurthy (2008) and Gennaioli *et al.* (2013) present models where this surprise element is a key feature of crises.

7 Dating Concerns and Robustness

We have presented results based on the dates of ST. Our results do depend on our choice of crisis dates. In this section, we discuss biases arising from mis-dating crises as well as the robustness of our results to alternative dates.

7.1 Peek-ahead bias

Romer and Romer (2014) note that because crisis dating is based on qualitative criteria, it has a "we know one when we see one" feel. It is easy for a crisis dating methodology that relies on qualitative criteria to peek ahead, using information on realized output losses, to date an event a financial crisis. This peek ahead problem will systematically bias researchers towards finding too large effects of financial crises on growth.

Credit spreads and credit growth are quantitative criterion that can be measured ex-ante, without referencing subsequent output growth, and thus avoid this bias. In the bottom panel of Table 7, we present results which date crises based only on credit growth and spreads, finding a significant relation between this bias-free dating of crises and the subsequent GDP contraction. Figure 5 presents impulse responses of output to a shock of 1 in the spreadnorm variable. We present results for the unconditional regression, the ST crisis, recessions, as well as the bias-free dates of HighCredit. The largest declines are using the ST dates. The results for the HighCredit episodes are smaller than for ST, but larger than for recessions or the unconditional results. The difference between ST and HighCredit may reflect the peek-ahead bias, but suggests that the conclusion that the aftermath of a crises is a deep and protracted recession is not due to this bias.

The dashed green line in Figure 6 revisits the exercise of forecasting GDP growth and spreads for the 2008-2013 period based on the spread in the last quarter of 2008, but now using information on the spread spike and credit growth, as in the HighCredit bias-free dates. The actual GDP path is in black while the blue dashed lines are the forecast based on the ST dates, where we have seen earlier that output grows faster than forecast. The green-dot line presents results based on HighCredit. Credit growth was high prior to the 2008 crisis. The forecast exercise now results in predicted GDP that is more similar to actual output. Thus, we again find that the recovery is slow and in keeping with patterns from past crises.

7.2 Alternate chronologies

For the span of data we study, there are two alternative chronologies by Bordo *et al.* (2001) and Reinhart and Rogoff (2009b) (BE and RR, respectively), and the BE, ST, and RR dates do not always agree with each other. Figure 10 presents a visual representation of the differences between ST versus RR and BE. The panel labeled ST Path, RR Path, and BE Path of the figure plots the incidence of crises in calendar time as labeled by ST, RR and BE. We have normalized $time = 0$ as the ST dating of crises, which is why the ST figure looks like a step-function: at $time = 0$, 100% of ST crises occur. The panels with the RR and BE path allows for a comparison to ST. We see that on average RR and BE date crises later than ST. Additionally, the overlap between these dates is not perfect. In the 10-year interval of the graph, RR date only 60% of the ST events as crises, while BE date about 50% of the ST events as crises. Getting the timing right matters because if the dates are too late – e.g., if we dated the recent US crisis in 2010 rather than 2008 – then the estimates of output losses in the aftermath of the crisis will be smaller. Indeed, in Table 3 we can compare statistics for the RR and BE dates to the ST dates. The declines are smaller under BE and RR's dating convention. In Table 10, we regress output declines on crisis dummy variables, and the results again show smaller declines for the BE and RR dates compared to the ST dates.

Table 11 replicates the regression forecasting the aftermath of a crisis using BE and RR dates interacted with spreads. We see that there is a statistically significant relation between the spread-crisis interaction variable, but the magnitude is much smaller than for the ST dates. So which dating is most accurate? All of ST, BE and RR date crises only based on bank failure information. Our research considers credit spreads, which is an additional piece of information to date crises. We have argued that theoretical models imply that crises begin with a large change in spreads. Table 11 shows that while the lagged value of the spread comes with the opposite sign of contemporaneous spread for both RR and BE, the statistical importance of the change is much more pronounced for the ST dates. The spread change evidence suggests that the ST dates better identify the start of a financial crisis. In unreported results, we have experimented with creating a late-crisis dummy that is one and two years ahead of the ST dates we use. We find that using this late-crisis dummy gives similar results as the RR and BE dates, suggesting that late dating is the central difference across these dates. Finally, from a theoretical standpoint, BE and RR date crises based on the actual event of bank failures. It is not at all obvious that a crisis "begins" with bank failures, as one would expect that credit will tighten anticipating actual bank failures. Our empirical results suggest that these anticipatory patterns are an important part of the output response in a financial crisis.

Table 12 replicates the pre-crisis froth regressions for the BE and RR dates. Comparing the results between ST, RR and BE, we see that that dating matters less for these regressions. We find consistently a pattern of low spreads ahead of crises, and that these low spreads arise ahead of crises due to a change in the correlation between credit growth and changes in credit spreads. The effects are also present for BE, but the results are weaker, in part because BE has many fewer crisis dates.

7.3 Robustness to post war data

We show that our main conclusions are not driven solely by the earlier data by revisiting our key interaction regressions of high credit interacted with spreads using only data from 1950 onwards. This is useful for several reasons. First, the economic environment may be different in the later part of the sample as the regulatory environment has changed (e.g., crises before the Federal Reserve may have been different). Second, our early data on bond prices collected from the Investor's Monthly Manual is noisier on some dimensions and requires more judgment in establishing spreads for each country. Table 13 shows that our main results on credit booms and the interaction of spreads are not significantly affected when considering only post 1950 data (though standard errors do increase). This suggests that the earlier data strengthen our conclusions but do not solely drive our results.

8 Conclusion

This paper studies the behavior of credit spreads and their link to economic growth during financial crises. The recessions that surround financial crises are longer and deeper than the recessions surrounding non-financial crises. The slow recovery from the 2008 crisis is in keeping with historical patterns surrounding financial crises. We have reached this conclusion by examining the cross-sectional variation between credit spreads and crisis outcomes rather computing the average GDP performance for a set of specified crisis dates. We also show the transition into a crisis begins with a large change in spreads. The severity of the subsequent crisis can be forecast by the size of credit losses ($z_{i,t}$ = change in spreads) coupled with the fragility of the financial sector ($\mathcal{F}_t^i$, as measured by pre-crisis credit growth growth). Finally, we find that spreads fall pre-crisis and are too low, even as credit grows ahead of a crisis.

These patterns of how credit cycles across a financial crisis are the stylized facts that macro-financial models of crises should seek to fit. Our paper also provides magnitudes for the dynamics of output, credit, and credit spreads across a financial crisis that quantitative models can target.

Existing theories involving financial frictions qualitatively match some of the stylized facts documented here (e.g., Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), He and Krishnamurthy (2012), Brunnermeier and Sannikov (2012), and Moreira and Savov (2014)). In particular, these theories match the non-linearities we document in terms of the "F $\times$ z" amplification facts we show here. This includes the fact that the interaction of credit losses, or spike in spreads, together with fragility in terms of high credit growth combine to forecast negative GDP events. While these theories do well to match the stylized facts on both the aftermath and transition into a financial crisis, they miss that spreads are, on average, low before a crisis as credit booms. An important exception is Moreira and Savov (2014) who show that risk premiums are on average low before a crisis even though there is typically a credit boom. However, Moreira and Savov (2014) would not match that low risk premia unconditionally predict a financial crisis. This is because risk premia are determined by rational forward looking agents in this model and as such, risk premia will unconditionally predict a crisis with a positive coefficient. A possible reconciliation of the pre-crisis froth facts is to include behavioral factors as in Gennaioli *et al.* (2013). In that paper biased expectations can imply that high sentiment is associated with an increased probability of a crisis but low observed spreads. However, these behavioral explanations typically do not speak to the amplification and non-linearities discussed above. Hence, we see a possible model that incorporates both a financial frictions view with a model that explains the pre-crisis behavior in terms of risk neutral expectations that generate low spreads as promising for explaining the stylized facts documented here.

9 Data Appendix

Credit spreads from 1869-1929. Source: Investor's Monthly Manual (IMM) which publishes a consistent widely covered set of bonds from the London Stock Exchange covering a wide variety of countries. We take published bond prices, face values, and coupons and convert to yields. Maturity or redemption date is typically included in the bond's name and we use this as the primary way to back out maturity. If we can not define maturity in this way, we instead look for the last date at which the bond was listed in our dataset. Since bonds almost always appear every month this gives an alternative way to roughly capture maturity. We check that the average maturity we get using this calculation almost exactly matches the year of maturity in the cases where we have both pieces of information. In the case where the last available date is the last year of our dataset, we set the maturity of the bond so that its inverse maturity (1/n) is equal to the average inverse maturity of the bonds in the rest of the sample. We equalize average inverse maturity, rather than average maturity, because this results in less bias when computing yields. To see why note that a zero coupon yield for a bond with face value \$1 and price p is $-\frac{1}{n}\ln p$. Many of our bonds are callable and this will have an effect on the implied maturity we estimate. Our empirical design is to use the full cross-section of bonds and average across these for each country which helps reduce noise in our procedure, especially because we have a large number of bonds. For this reason, we also require a minimum of 10 bonds for a given country in a given year for an observation to be included in our sample. Lastly, we deal with composition by requiring at least 90% of the bonds in a given year to be the same bonds as the previous year. When this is not the case, we define spread increments by looking at the change in yields of the bonds in the current year which were also available in the previous year and define the spread in the current year as last years spread plus this increment. However, we find that this situation is rare – only in about 5% of the sample do we not meet the requirement that at least 90% of the bonds in the given year were also in the previous year

US spread from 1928-2014. Source: Moody's Baa-Aaa spread. We start this series in 1928 because the US has composition issues in the IMM data in 1928-1929, hence using this spread alleviates the issues (see above).

Japan spread from 1989-2001. Source: Bank of Japan.

South Korea spread from 1995-2013. Source: Bank of Korea. AA- rated corporate bonds, 3 year maturity.

Sweden spread from 1987-2013. Source: Bank of Sweden. Bank loan spread to non-financial Swedish firms, maturities are 6 month on average.

European spreads (Ireland, Portugal, Spain, Greece) from 2000-2014. Source: Datastream. We take individual yields and create a spread in a similar manner to our historical IMM dataset.

Other spreads from 1930 onwards: For other countries we use data from Global Financial Data when available. We use corporate and government bond yields from Global Financial data where the series for each country is given as "IG-ISO-10" and "IG-ISO-5" for 5 and 10 year government yields (respectively), "IN-ISO" for corporate bond yields. ISO represents the countries three letter ISO code (e.g., CAN for Canada). We were able to obtain these for: Australia, Belgium, Canada, Germany, Norway, Sweden, the United Kingdom, and Korea. To form spreads, we take both 5 and 10 year government bond yields for each country. Since the average maturity of the corporate bond index is not given, it is not clear which government maturity to take the spread over. We solve this problem by running a time-series regression of the corporate yield on both the 5 and 10 year government yield for each individual country. We take the weights from these regressions and take corporate yield spreads over the weighted average of the government yields (where weights are re-scaled to sum to one). Therefore we define $spread = y_{corp} - (wy^5_{gov} + (1-w)y^10_{gov})$. The idea here is that the corporate yield will co-move more with the government yield closest to its own maturity. We can assess whether our weights are reasonable (i.e. neither is extremely negative) and find that they are in all countries but Sweden. The Swedish corporate bond yield loads heavily on the 5 year and negatively on the 10 year suggesting that the maturity is less than 5 years. In this case we add a 2 year government yield for Sweden (from the Bank of Sweden) and find the loadings satisfy our earlier condition. Finally, for Euro countries, we use Germany as the relevant benchmark after 1999 as it likely has the lowest sovereign risk.

GDP data. Source: Barro and Ursua (see Robert Barro's website). Real, annual per capital GDP at the country level. GDP data for Hong Kong follows the construction of Barro Ursua using data from the WDI.

Crisis dates. Source: Jorda, Schularick, and Taylor / Schularick and Taylor ("ST" dates), Reinhart and Rogoff ("RR" dates, see Kenneth Rogoff's website).

Leverage, Credit to GDP data. Source: Schularick and Taylor.

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10 Tables and Figures

Figure 1: This figure plots the behavior of credit spreads, GDP, and the quantity of credit around a financial crisis with the crisis beginning at date 0. GDP and credit are expressed in annual percentage units and are cumulative (that is, we cumulate log annual changes in these variables). Spreads are normalized by dividing by the unconditional mean consistent with our normalization in the main text. All variables are demeaned at the country level. We use crisis dates from Schularick and Taylor.

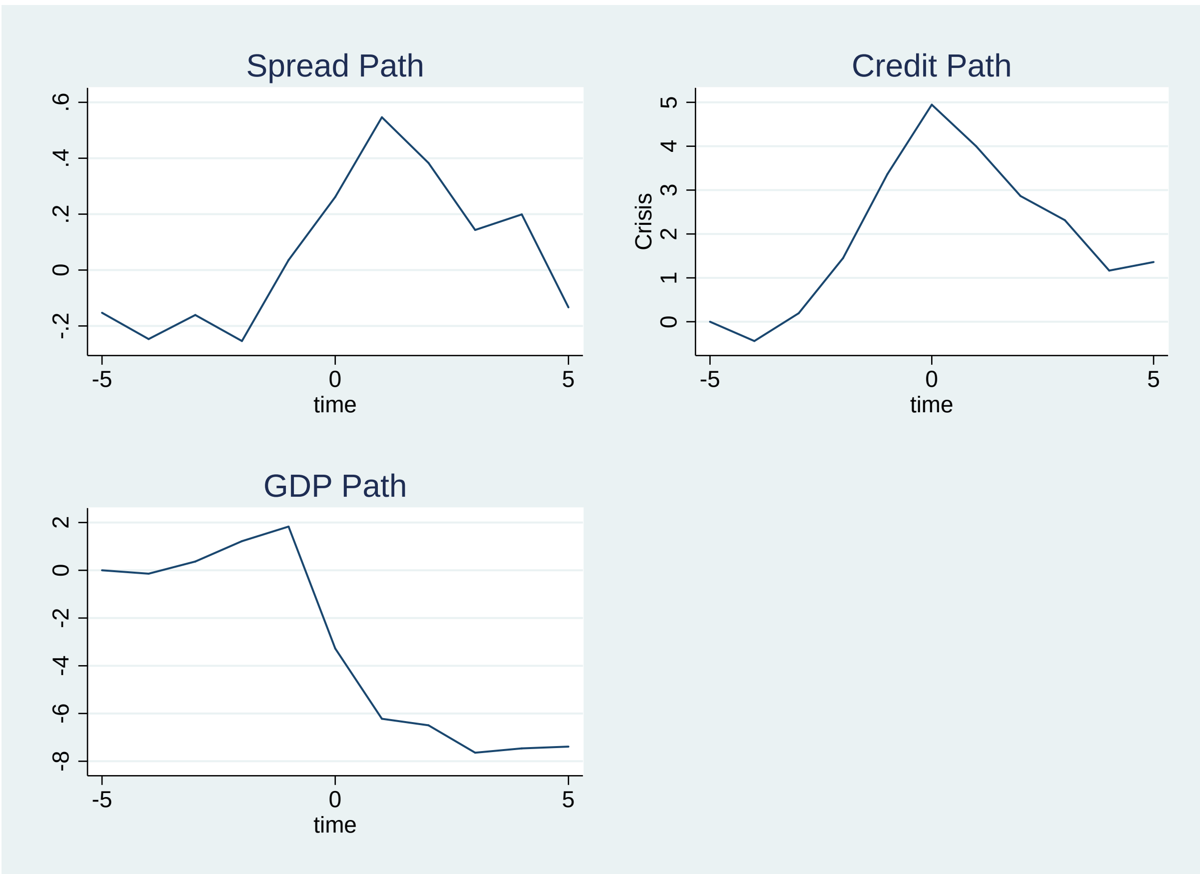

Figure 2: This figure plots the incidence of crises over time across various countries from 1870-2008. We show to total number of countries experiencing a crisis in each given year. RR denotes those measured by Reinhart and Rogoff and ST denotes those measured by Schularick and Taylor. We only plot these variables for countries and dates for which we have credit spread data to give a sense of the crises covered by our data.

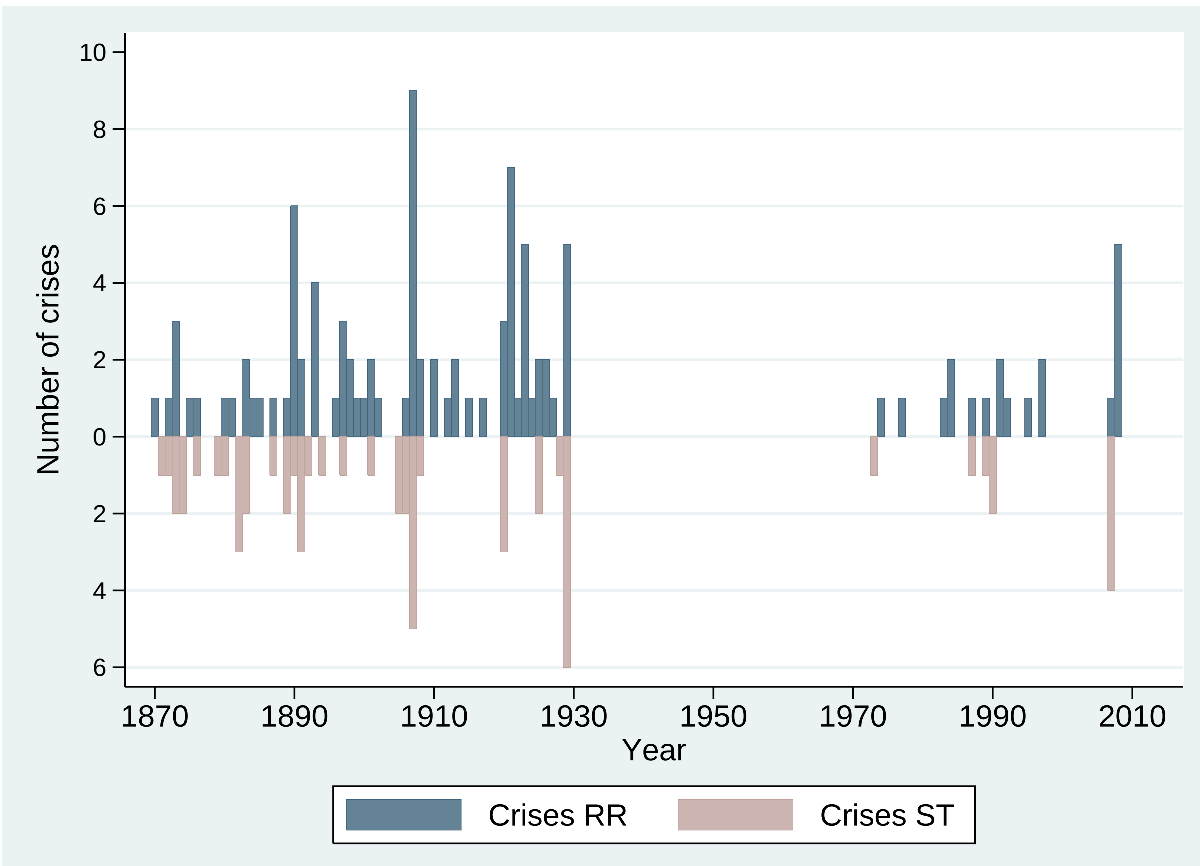

Figure 3: This figure shows the empirical distribution of outcomes in GDP across financial crises using crisis dates from Schularick and Taylor. The left panel plots peak to trough declines in GDP while the right panel plots cumulative GDP growth over a 3 year period after the start of the crisis. In both, we emphasize the significant heterogeneity in outcomes.

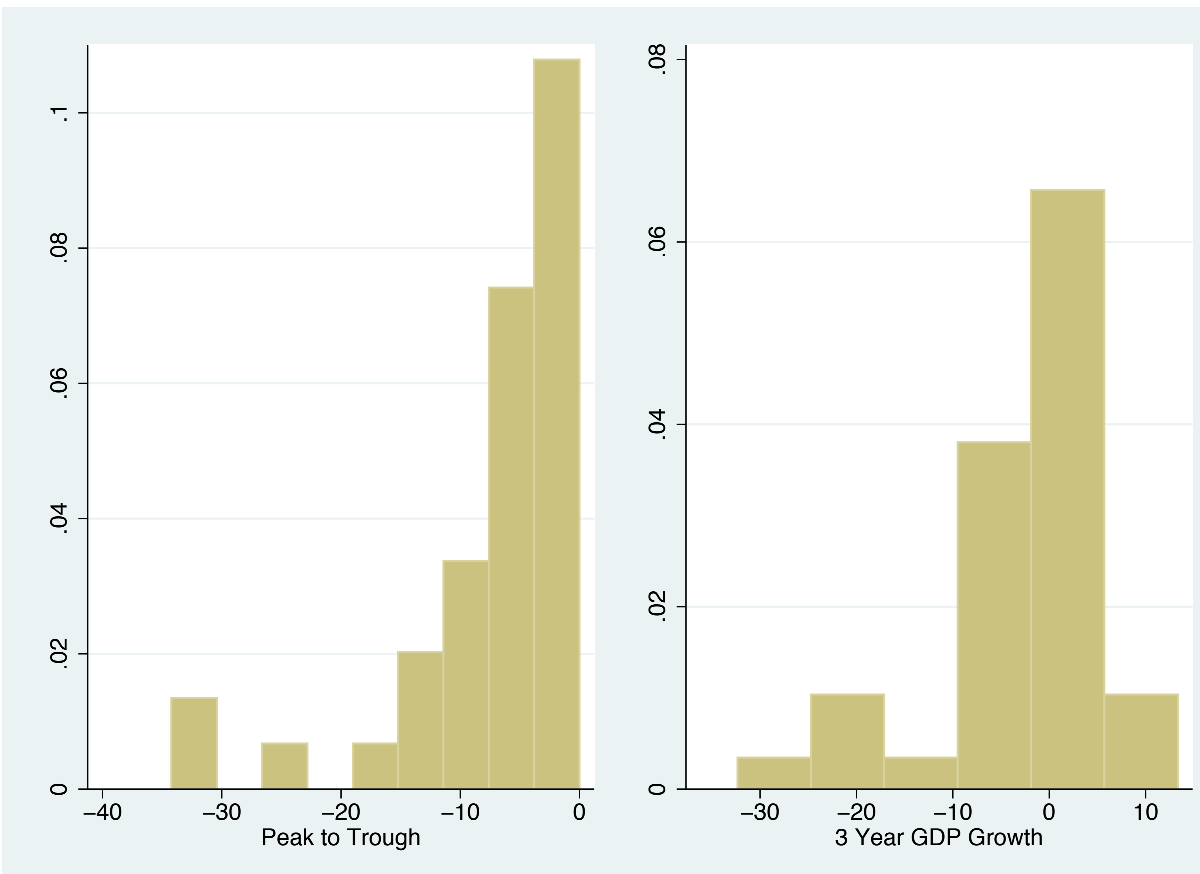

Figure 4: This figure plots the impulse responses of GDP to an innovation of one standard deviation in our spread measure (approximately equal to a unit change in spreads) during high credit growth episodes (top panel), financial crises (middle panel), and recessions (bottom panel). Impulse responses are computed using local projection measures where we forecast GDP independently at each horizon.

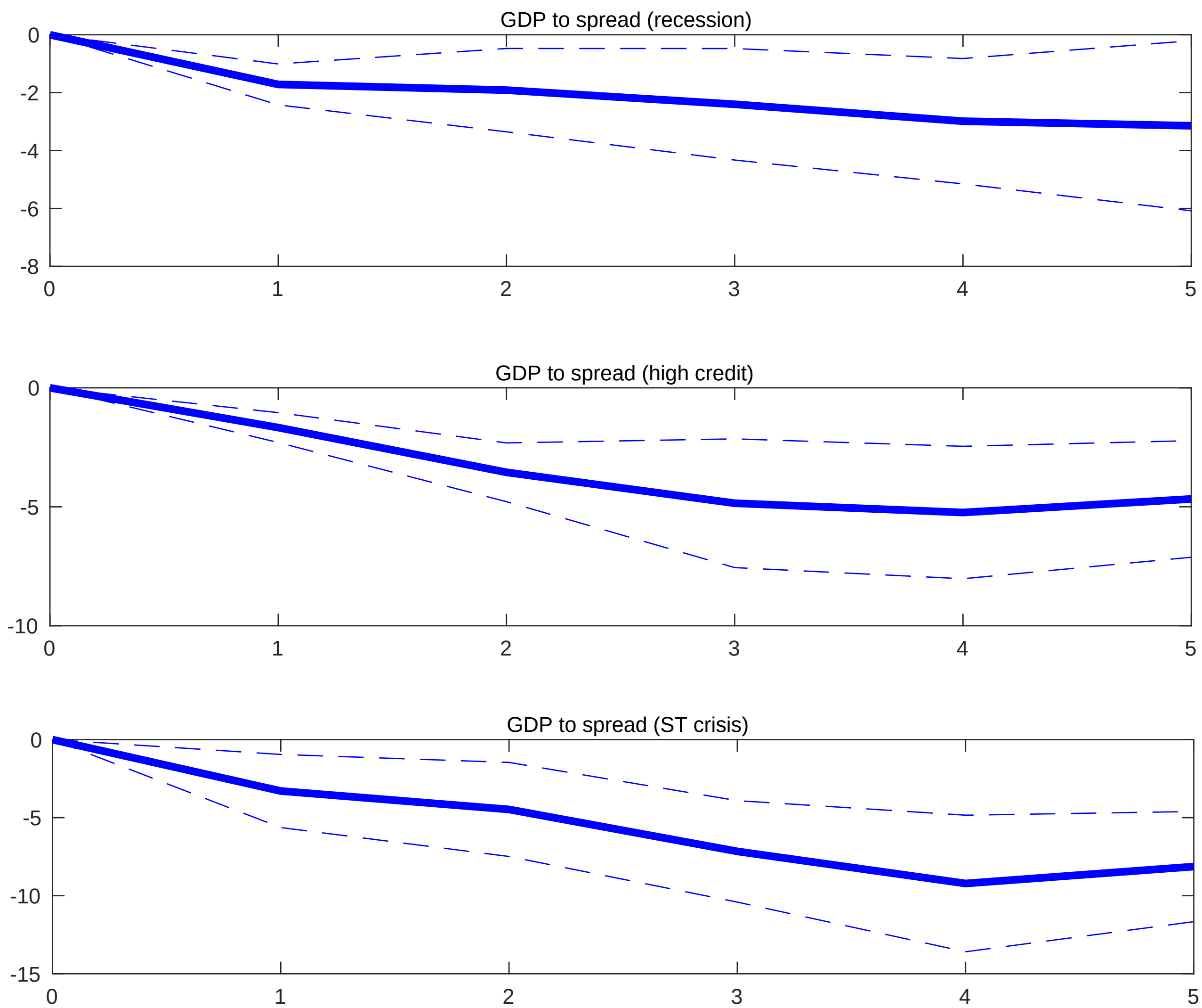

Figure 5: This figure plots impulse responses to an innovation of one (approximately one-sigma) in our spread variable. Our predicted values are then formed from the regressions based on the Schularick and Taylor crisis dates. This is done unconditionally (blue solid line), conditional on a non-financial recession (black dashed line), conditional on a financial crisis using Schularick and Taylor crisis dates (lighter dashed line), and conditional on a period of high credit growth (lighter solid line). Impulse responses are computed using local projection measures where we forecast GDP independently at each horizon.

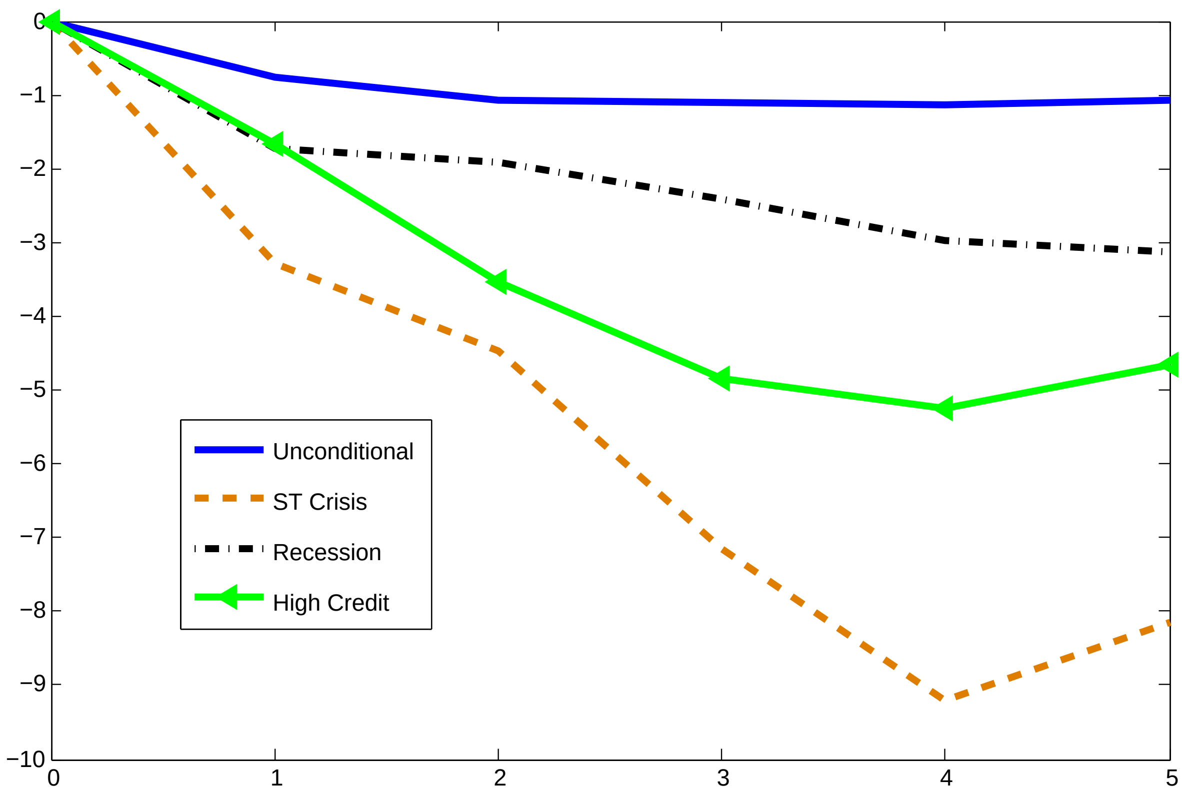

Figure 6: We predict outcomes of GDP and spreads during the 2008 US financial crisis using predicted values from our regressions and data up to 2008. We plot the actual data along with the predicted value from an interaction of spreads with financial crisis dates from Schularick and Taylor as well as an indicator for a period of high recent credit growth. The top panel, GDP, is cumulative from a base of 100 in 2008. The lower panel, spreads, uses the last quarter value of the BaaAaa spread in 2008. Our predicted value is formed using the Schularick and Taylor crisis dates.

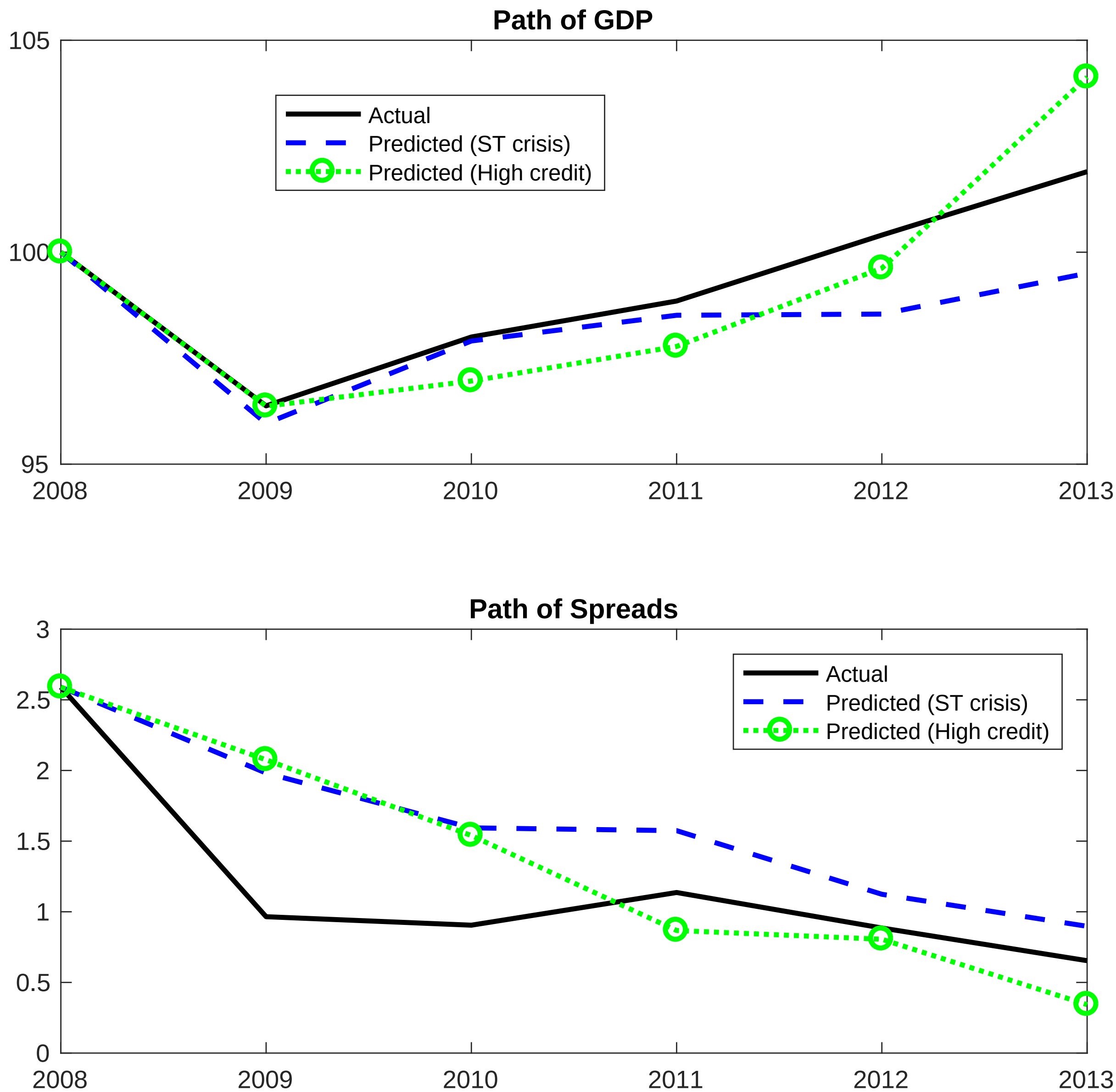

Figure 7: This figure plots the distribution of GDP growth at various horizons conditional on spreads based on a kernel density estimation. The blue solid line plots the distribution of GDP growth when spreads are in the lower 30% of their realizations, the red dashed line plots the distribution when spreads are in the highest 30% of their realizations. Analogous to our quantile regressions, the figure shows that high spreads are associated with a larger left tail in GDP outcomes.

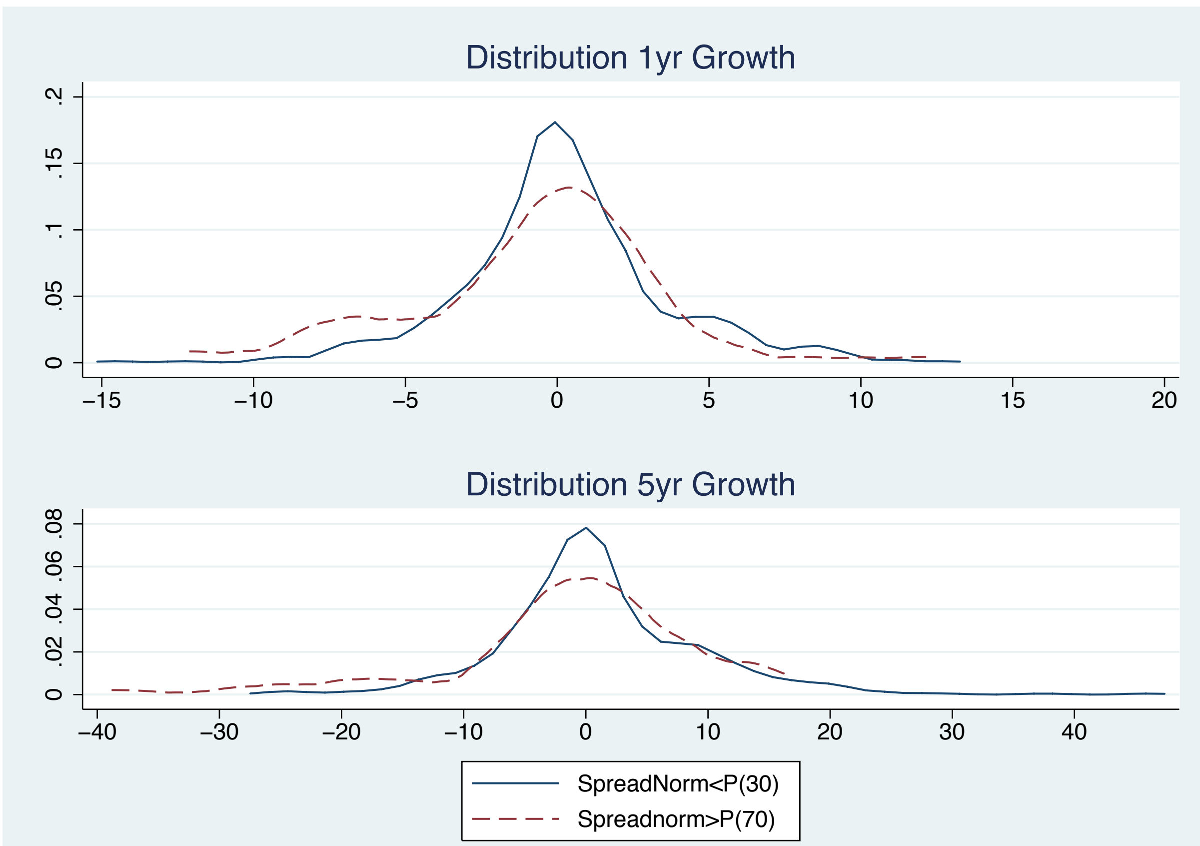

Figure 8: This figure plots the path of spreads, fundamental spreads, and cumulative credit growth in the years surrounding a financial crisis (using ST dates). The paths are formed by running regressions with dummies at various dates. "Fundamental spreads" are computed as the predicted value from a regression of spreads on fundamentals including two lags of GDP growth and the change in credit.

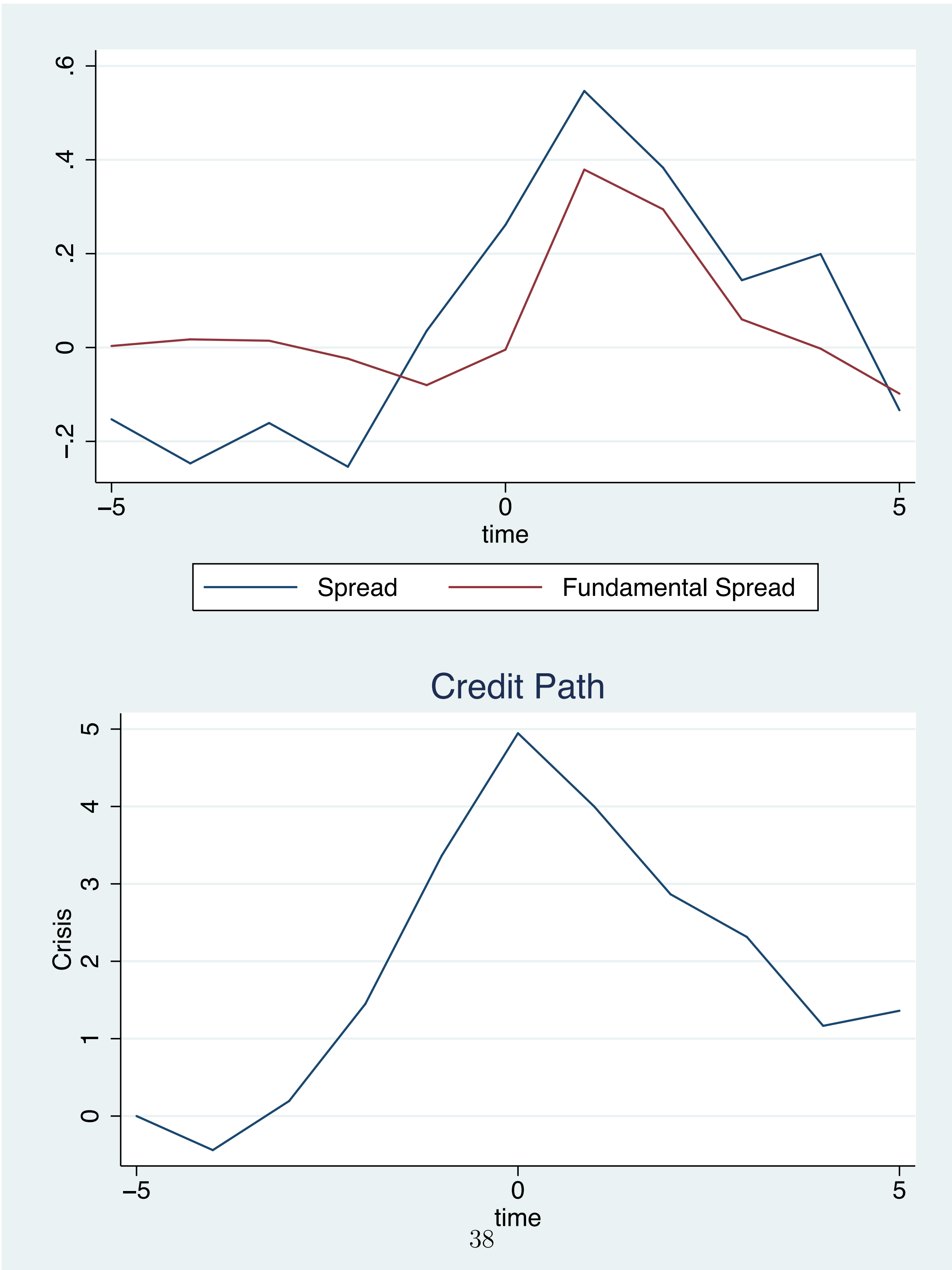

Figure 9: We plot the cumulative probability of a crisis at each horizon when we condition on credit market conditions. HC is a dummy equal to 1 if credit growth over the past 5 years has been above its median, and HF is a dummy equal to 1 if credit spreads over the last 5 years have been below their median. We compare the future probability of a crisis when credit markets appear "frothy" (HC and HF both equal 1) to when they are not (both equal to zero).

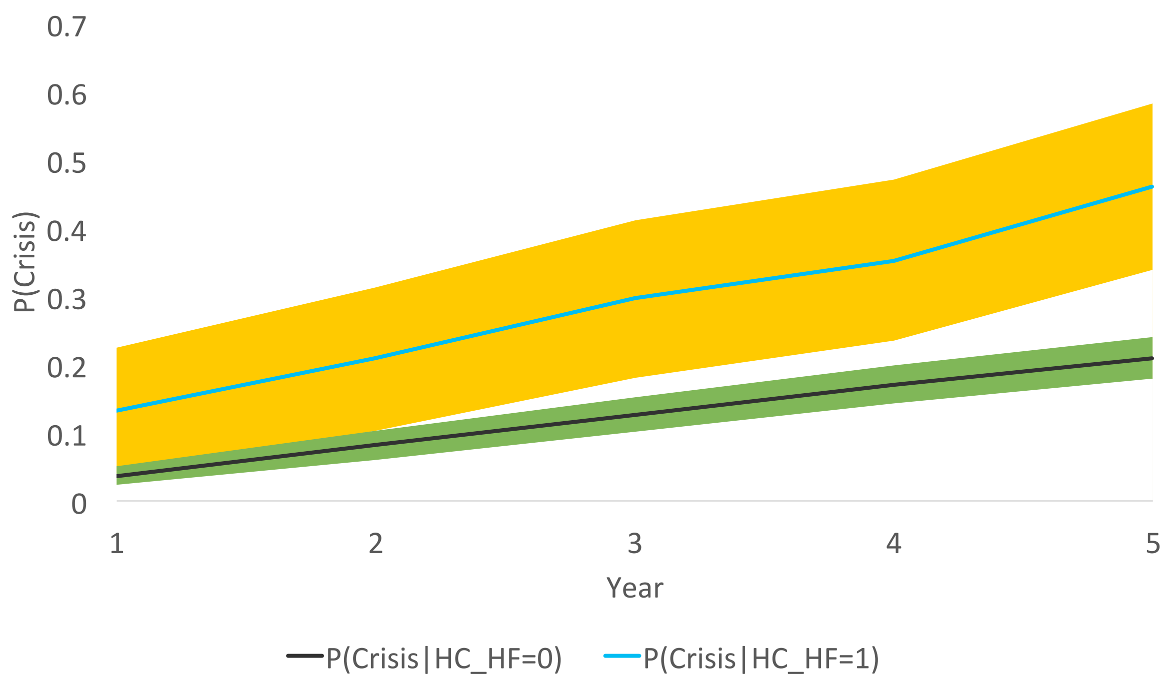

Figure 10: We plot paths of each variable with an ST crisis dated at date 0 to show the relative timing of the following variables around a crisis: GDP, credit spreads, Reinhart and Rogoff's dating convention (RR), Bordo and Eichengreen's dating convention (BE), and Schularick and Taylor's dating convention for a crisis (ST). We can see the following timeline: GDP tends to fall at the start of ST crises. Spreads rise right around when GDP falls and continue to rise slightly after. RR and BE dated crises tend to happen right around, or slightly after, those defined by Schularick and Taylor.

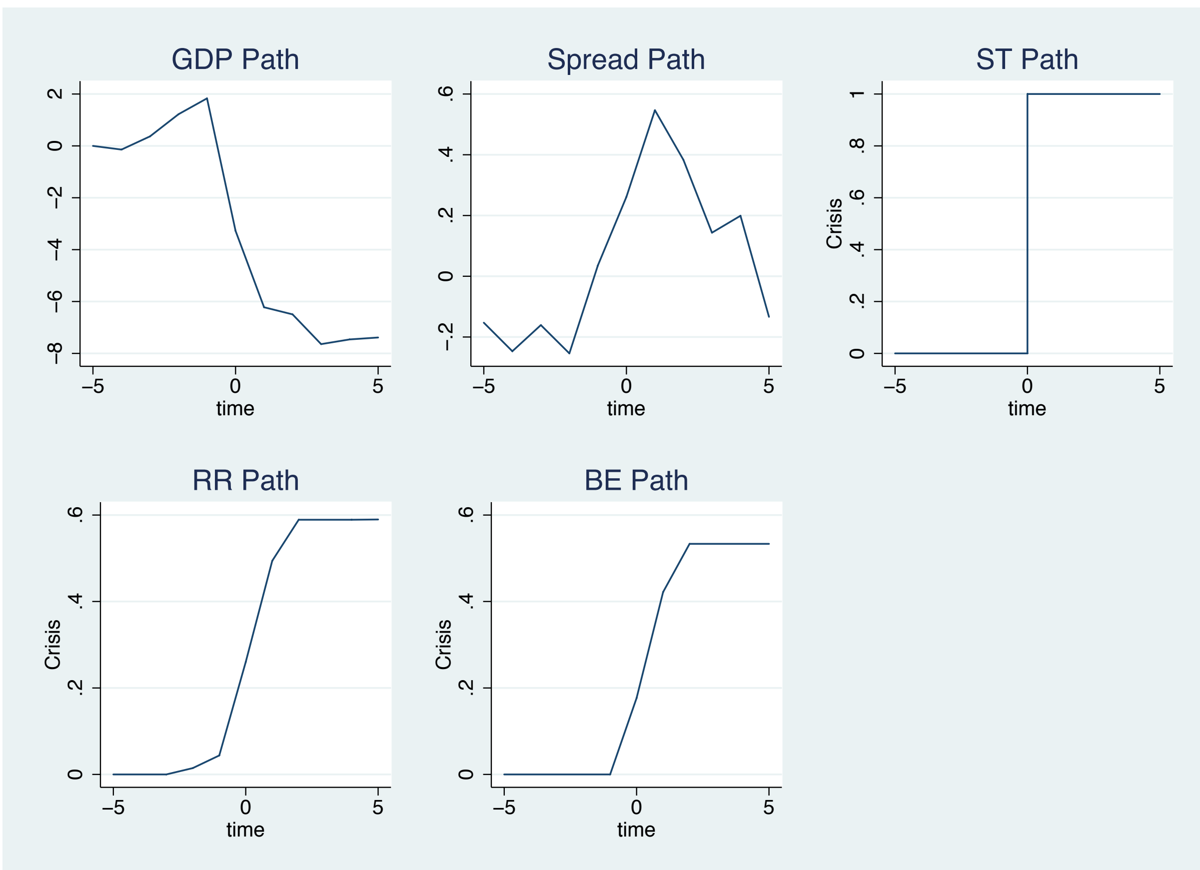

Table 1: This table provides basic summary statistics on the bonds in our sample. The top panel summarizes our historical bond data. The bottom panel documents our coverage across countries and years for the entire sample.

Panel A: Bond Statistics for 1869-1929				
Observations	Unique bonds	% Gov't	% Railroad	% Other
194,854	4,464	23%	27%	50%
Median Yield	Median Coupon	Median Discount	Avg Maturity	Median Spread
5.5%	4.2%	6%	17 years	1.9%

Panel B: Full Sample Coverage by Country				
Country	First Year	Last Year	Total Years	ST Sample
Australia	1869	2011	89	Y
Belgium	1960	2001	42	N
Canada	1869	2001	118	Y
Denmark	1869	1929	51	Y
France	1869	1929	60	Y
Germany	1871	2014	91	Y
Greece	2003	2012	10	N
Hong Kong	1995	2014	20	N
Italy	1869	1929	60	Y
Japan	1870	2001	70	Y
Korea	1995	2013	19	N
Netherlands	1869	1929	60	Y
Norway	1876	2003	97	Y
Portugal	2007	2012	6	N
Spain	1869	2012	72	Y
Sweden	1869	2011	85	Y
Switzerland	1899	1929	29	Y
United Kingdom	1869	2014	117	Y
United States	1869	2014	145	Y

Table 2: This table provides regressions of future 1 year GDP growth on credit spreads where we consider different normalizations of spreads. The first column uses raw spreads, the second normalizes spreads by dividing by the unconditional mean of the spread in each country, the third also divides by the mean but does so using only information until time t-1 so does not include any look ahead bias. We refer to this as the out of sample (OOS) normalization. The fourth and fifth columns compute a z-score of spreads and percentile of spreads by country. Each of these normalizations captures relative percentage movements in spreads in each country. Controls include two lags of GDP growth and both country and year fixed effects. Standard errors clustered by country.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Raw	MeanNorm	OOSMean	Zscore	Percentile
Spread	-0.08				
	(0.06)				
Lag Spread	0.07				
	(0.05)				
Spread/Mean		-0.74			
		(0.25)			
Lag Spread/Mean		0.47			
		(0.26)			
Spread/MeanOOS			-0.18		
			(0.08)		
Lag Spread/MeanOOS			0.01		
			(0.04)		
Z-score Spread				-0.79	
				(0.30)	
Lag Z-score Spread				0.47	
				(0.22)	
Percentile Spread					-1.33
					(0.79)
Lag Percentile Spread					0.31
					(0.65)
Observations	900	900	882	900	900
R-squared	0.35	0.37	0.36	0.36	0.35
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table 3: This table provides summary statistics for peak to trough declines in GDP around crisis episodes as well as the 3 year growth rate in GDP. ST, RR, and BE use dates from Jorda *et al.* (2010) and Jordà *et al.* (2013), Reinhart and Rogoff (2009b) and Bordo *et al.* (2001), respectively.

Distribution of declines in GDP across episodes

Financial Crises (ST dates)

	Mean	Median	Std Dev	P 10th	P 90th	N
Trough	-6.8	-4.1	7.6	-14.2	-0.7	44
3 year	-2.6	-0.8	8.5	-12.9	5.5	39

Financial Crises (RR dates)

	Mean	Median	Std Dev	P 10th	P 90th	N
Trough	-3.8	-1.9	5.9	-9.8	0	48
3 year	1.7	1.4	7.9	-5.9	10.7	47

Financial Crises (BE dates)

	Mean	Median	Std Dev	P 10th	P 90th	N
Trough	-3.9	-1.6	5.9	-14.2	0	27
3 year	2.0	1.9	7.9	-5.9	10.7	27

Table 4: This table shows the forecasting power of credit spreads for the severity of financial crises in terms of the peak to trough declines in GDP. We use the Jorda *et al.* (2010) and Jordà *et al.* (2013) dates that mark the start of recessions with financial crises and regular non-financial recessions. We include the level of spreads, lagged spreads, and 3 year growth in the credit/GDP ratio from Jorda *et al.* (2010). Standard errors in parenthesis.

$$decline_{i,t} = a + b_1 \widehat{s}_{i,t} + b_2 \widehat{s}_{i,t-1} + c\Delta credit_{i,t} + \varepsilon_{i,t}$$

VARIABLES	(1) ST Crisis	(2) ST Crisis	(3) ST Crisis	(4) ST Crisis	(5) ST Crisis	(6) Recess	(7) Recess
$\widehat{s}_{i,t}$	-1.73	-5.44		-4.50	-6.78	-1.55	-1.97
	(0.76)	(1.69)		(1.32)	(1.44)	(0.49)	(1.10)
$\widehat{s}_{i,t-1}$		4.53		6.72	5.18		0.21
		(1.85)		(2.20)	(1.63)		(1.23)
$\Delta\widehat{s}_{i,t}$			-5.42				
			(1.69)				
$\Delta credit_{i,t}$					-4.89		
					(4.17)		
Observations	44	44	44	39	34	100	100
Drop Depression				Y			
R-squared	0.09	0.19	0.18	0.24	0.47	0.07	0.06
Variation in Realized Severity $\sigma(decline)$	7.6	7.6	7.6	4.8	8.3	7.2	7.2
Variation in Expected Severity $\sigma(E_t[decline])$	2.5	3.6	3.4	2.5	5.8	2.0	2.0

Table 5: This table provides regressions of future cumulative GDP growth $\Delta lny_{t+k,i}$ on credit spreads at the 3 and 5 year horizon. We include interactions with crisis or recession dummies. Controls include two lags of GDP growth, the 3 year growth in credit/GDP, and both country and year fixed effects. Standard errors clustered by country in parenthesis.

Panel A: 3 year GDP growth

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{s}_{i,t}$	-1.06						
	(0.34)						
$\widehat{s}_{i,t-1}$	0.78						
	(0.51)						
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-1.56	-0.49				
		(1.19)	(0.90)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$			-6.25				
			(1.50)				
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$				-0.49			
				(0.23)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$					-0.48		
					(0.25)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$						-1.88	-1.63
						(0.89)	(0.75)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$							-0.35
							(1.30)
Observations	641	641	641	641	641	641	641
R-squared	0.54	0.55	0.55	0.55	0.55	0.54	0.55

Panel B: 5 year GDP growth

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{s}_{i,t}$	-1.16						
	(0.40)						
$\widehat{s}_{i,t-1}$	1.64						
	(0.79)						
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-1.87	-0.05				
		(1.24)	(1.13)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$			-8.13				
			(1.60)				
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$				-0.47			
				(0.28)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$					-0.18		
					(0.23)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$						-2.06	-1.30
						(1.41)	(0.92)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$							-2.35
							(3.22)
Observations	634	634	634	634	634	634	634
R-squared	0.53	0.52	0.54	0.55	0.55	0.52	0.54

Table 6: Quantile Regressions. We run quantile regressions of future output growth over the next year on spreads and lagged spreads for different quantiles. Controls include two lags of GDP growth. Our main result is that increases in spreads are particularly informative for lower quantiles of GDP growth. Standard errors in parenthesis.

Quantile Regressions: GDP growth on lagged spread change					
	(1)	(2)	(3)	(4)	(5)
	Q 90th	Q 75th	Q Median	Q 25th	Q 10th
$\Delta\widehat{s}_{i,t}$	-0.53	-0.70	-0.71	-1.06	-1.32
	(0.26)	(0.14)	(0.13)	(0.18)	(0.28)
Observations	898	898	898	898	898
Country FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Pseudo R2	0.09	0.06	0.05	0.08	0.12

Table 7: Which spread crises turn out badly? We run regressions where the left hand side is GDP growth at various horizons. In the top panel, the right hand side contains a dummy labeled LargeLoss which is equal to one if the change in spreads (credit losses) in a given period is above the 92nd percentile. This cutoff means that there will be the same number of times this dummy is equal to one as we have financial crisis events, making the dummy coefficient comparable to the crisis dummies. It then splits these LargeLoss episodes into two equal buckets based on whether credit growth was high or low (i.e., conditional on spread crisis, whether credit growth is above or below median within the spread crisis sample). The lower panel instead interacts spreads with a dummy for when credit growth is high, defined based on the 92nd percentile of credit growth over the entire sample. This cutoff is chosen so that the number of high credit growth episodes matches the number of financial crises in our sample based on Schularick and Taylor dates. The table shows that high spreads are bad news for output on average, but are particularly bad and long lasting when leverage is high. Controls include two lags of GDP growth. Standard errors in parenthesis.

When is an increase in spreads particularly bad for GDP?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	1yr	1yr	2yr	2yr	3yr	3yr	4yr	4yr	5yr	5yr
LargeLoss	-3.11		-4.11		-4.48		-3.99		-2.51	
	(0.69)		(0.94)		(1.22)		(1.48)		(1.71)	
(LargeLoss) x		-2.02		-4.92		-6.60		-7.44		-4.83
(HighCredit)		(0.67)		(1.19)		(2.50)		(2.82)		(3.22)
Observations	393	356	390	353	387	350	384	347	381	344
R-squared	0.63	0.62	0.70	0.68	0.71	0.69	0.69	0.68	0.60	0.68
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

	(1)	(2)	(3)	(4)	(5)
VARIABLES	1yr	2yr	3yr	4yr	5yr
(HighCredit) x	-1.67	-3.55	-4.85	-5.24	-4.67
$\widehat{s}_{i,t}$	(0.32)	(0.63)	(1.38)	(1.42)	(1.25)
(HighCredit) x	1.34	2.85	3.67	4.48	4.51
$\widehat{s}_{i,t-1}$	(0.46)	(0.79)	(1.57)	(1.50)	(1.42)
Observations	647	644	641	638	634
R-squared	0.04	0.09	0.12	0.12	0.10
Controls	Y	Y	Y	Y	Y

Table 8: Are spreads before a crisis too low? We run regressions of our normalized spreads on a dummy which takes the value 1 in the 5 years before a financial crisis (labeled $1_{t-5,t-1}$) in order to assess whether spreads going into a crisis are low. We show the univariate results, as well as the results controlling for time fixed effects. We then add changes in credit growth and GDP to control for fundamentals that could drive spreads. Panel B splits this result by severe versus mild crises based on the median drop in GDP in a crisis. It thus asks whether spreads are especially low before crises which are particularly severe. Standard errors clustered by time in parenthesis.

Panel A: Spreads before a crisis

	(1)	(2)	(3)	(4)
$1_{t-5,t-1}$	-0.24	-0.36	-0.00	-0.32
	(0.11)	(0.14)	(0.18)	(0.20)
$(\Delta Credit_{t-1})$ X			-2.83	-0.51
$1_{t-5,t-1}$			(1.15)	(1.18)
$\Delta Credit_{t-1}$	0.88	0.90	1.27	0.97
	(0.48)	(0.58)	(0.52)	(0.62)
ΔGDP_{t-1}	-2.70	-0.16	-2.68	-0.18
	(1.74)	(1.68)	(1.73)	(1.68)
Observations	621	621	621	621
R-squared	0.06	0.40	0.07	0.40
Country FE	Y	Y	Y	Y
Year FE	N	Y	N	Y

Panel B: Spreads before severe vs. mild crises

	(1)	(2)
$1_{t-5,t-1}$ X	-0.29	-0.43
Severe	(0.26)	(0.20)
$1_{t-5,t-1}$ X	-0.20	-0.18
Mild	(0.13)	(0.11)
Observations	621	621
R-squared	0.06	0.40
Country FE	Y	Y
Year FE	N	Y
Controls	Y	Y

Table 9: Credit market froth and fragility. We explore whether low spreads can lead to negative outcomes both by negatively forecasting GDP and by positively forecasting a crisis. We compute a five year backward looking average of spreads as our measure of credit market froth. We then create a dummy for when this variable is below its median, so that spreads have been recently low, and label this "High Froth." This is meant to capture prolonged periods of low spreads. In Panel A, we test whether high froth periods forecast future GDP growth. We also interact high froth with periods of high credit growth, as this captures episodes where credit is booming but spreads are falling and may lead to fragility. Panel B uses these same variables to forecast a financial crisis (using financial crisis dates from Schularick and Taylor). We run probit regressions on the cumulative crisis indicator at various horizon (e.g., we predict whether a crisis occurs in any of the next K years and vary K from 1 to 5).

Panel A: High Froth and GDP Growth by Horizon

	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
HighFroth	-0.52	-0.54	-0.27	-0.32	-0.63
	(0.40)	(0.69)	(0.95)	(1.18)	(1.33)
HighCredit	-0.84	-1.39	-0.96	-0.17	1.37
	(0.56)	(0.98)	(1.17)	(1.31)	(1.35)
(HighFroth)×(HighCredit)	-0.50	-0.98	-2.36	-3.25	-4.12
	(0.81)	(1.29)	(1.41)	(1.63)	(1.79)
Observations	567	564	561	558	554
R-squared	0.06	0.09	0.10	0.09	0.10

Panel B: Probit, Does High Froth Predict a Crisis?

	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
(HighFroth)×(HighCredit)	0.03	0.07	0.12	0.16	0.21
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Observations	567	564	561	558	554

Panel C: Credit Supply and Crises

	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
Credit Supply	0.05	0.08	0.09	0.08	0.08
	(0.03)	(0.04)	(0.04)	(0.04)	(0.08)
Observations	567	564	561	558	554

Table 10: Additional Results: This table provides regressions of future GDP growth on event dummies. Controls include two lags of GDP growth, the 3 year growth in credit/GDP from Schularick and Taylor, as well as both country and year fixed effects. Standard errors clustered by country in parenthesis.

	(1)	(2)	(3)
VARIABLES	3yr	3yr	3yr
$1_{crisisST,i,t}$	-5.26		
	(2.12)		
$1_{crisisRR,i,t}$		-2.09	
		(1.35)	
$1_{crisisBE,i,t}$			-2.16
			(1.49)
Observations	641	641	641
R-squared	0.43	0.41	0.41
Country FE	YES	YES	YES
Year FE	YES	YES	YES

	(1)	(2)	(3)
VARIABLES	5yr	5yr	5yr
$1_{crisisST,i,t}$	-5.54		
	(2.40)		
$1_{crisisRR,i,t}$		-0.74	
		(1.93)	
$1_{crisisBE,i,t}$			-1.39
			(1.88)
Observations	634	634	634
R-squared	0.40	0.39	0.39
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Table 11: Additional Results: This table provides regressions of future GDP growth on credit spreads at the 5 year horizon. We include interactions with crisis or recession dummies to assess whether spreads become more informative during crisis periods. We provide estimates for three alternative sets of crisis dates: ST, RR, and BE. Controls include two lags of GDP growth, the 3 year growth in credit/GDP from Schularick and Taylor, and both country and year fixed effects. Standard errors clustered by country in parenthesis.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	5yr	5yr	5yr	5yr	5yr
$\widehat{s}_{i,t}$	-1.16				
	(0.40)				
$\widehat{s}_{i,t-1}$	1.64				
	(0.79)				
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-8.18			
		(1.17)			
$\widehat{s}_{i,t-1} \times 1_{crisisST,i,t}$		8.13			
		(1.60)			
$\widehat{s}_{i,t} \times 1_{crisisRR,i,t}$			-2.38		
			(0.80)		
$\widehat{s}_{i,t-1} \times 1_{crisisRR,i,t}$			1.69		
			(0.79)		
$\widehat{s}_{i,t} \times 1_{crisisBE,i,t}$				-1.14	
				(0.46)	
$\widehat{s}_{i,t-1} \times 1_{crisisBE,i,t}$				0.29	
				(0.94)	
$\widehat{s}_{i,t} \times 1_{recess,i,t}$					-3.14
					(1.50)
$\widehat{s}_{i,t-1} \times 1_{recess,i,t}$					0.94
					(1.17)
Observations	634	634	634	533	634
R-squared	0.53	0.54	0.53	0.54	0.54
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 12: Robustness: Are spreads before a crisis too low? We run regressions of our normalized spreads on a dummy which takes the value 1 in the 5 years before a financial crisis (labeled $1_{t-5,t-1}$) in order to assess whether spreads going into a crisis are low. We consider both RR and BE financial crisis dates for robustness, compared to the ST dates shown earlier. We show the univariate results, as well as the results controlling for time fixed effects. We then add changes in credit growth and GDP to control for fundamentals that could drive spreads. Standard errors clustered by time in parenthesis.

Panel A: Spreads before a crisis

	(1) RR	(2) RR	(3) RR	(4) RR	(5) BE	(6) BE	(7) BE	(8) BE
$1_{t-5,t-1}$	-0.30	-0.20	-0.17	-0.25	-0.24	-0.34	-0.14	-0.36
	(0.11)	(0.14)	(0.10)	(0.14)	(0.12)	(0.15)	(0.14)	(0.18)
$(\Delta Credit_{t-1})$ X			-1.77	-0.75			-1.94	0.77
$1_{t-5,t-1}$			(0.74)	(0.82)			(1.12)	(1.20)
$\Delta Credit_{t-1}$	0.86	0.86	1.22	0.70	0.27	0.21	0.71	0.78
	(0.47)	(0.57)	(0.56)	(0.63)	(0.37)	(0.41)	(0.66)	(0.68)
ΔGDP_{t-1}	-2.70	-0.32	-2.52	-0.37	-2.44	-0.60	-2.11	-0.48
	(1.75)	(1.69)	(1.75)	(1.67)	(1.82)	(1.72)	(1.80)	(1.74)
Observations	621	621	621	621	606	606	606	606
R-squared	0.07	0.39	0.07	0.39	0.05	0.39	0.05	0.39
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y

Panel B: Spreads before a severe vs. mild crises

	(1) RR	(2) RR	(5) BE	(6) BE
$1_{t-5,t-1}$ X	-0.47	-0.26	-0.43	-0.32
Severe	(0.10)	(0.15)	(0.13)	(0.21)
$1_{t-5,t-1}$ X	-0.16	0.03	0.13	0.13
Mild	(0.19)	(0.11)	(0.16)	(0.13)
Observations	621	621	606	606
R-squared	0.07	0.39	0.05	0.39
Country FE	Y	Y	Y	Y
Year FE	N	Y	N	Y
Controls	Y	Y	Y	Y

Table 13: Robustness: Credit boom interaction. We repeat our exercise showing high credit dummy interacted with spread changes using only post 1950 data. Standard errors clustered by year.

Panel A: Post 1950					
	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
$\Delta s_{i,t} \times \mathit{High\ Credit}$	-1.45	-2.12	-2.77	-2.62	-2.60
	(0.68)	(0.84)	(1.01)	(1.12)	(1.15)
$\Delta s_{i,t} \times (1 - \mathit{High\ Credit})$	-1.28	-1.33	-0.88	-0.93	-1.32
	(0.44)	(0.75)	(0.83)	(0.91)	(0.88)
Observations	292	289	286	283	276
R-squared	0.25	0.19	0.18	0.19	0.21
Country FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N

Panel B: Post 1950, Year Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
$\Delta s_{i,t} \times \mathit{High\ Credit}$	-0.24	-1.23	-1.69	-1.52	-1.30
	(0.39)	(0.61)	(0.80)	(1.00)	(0.99)
$\Delta s_{i,t} \times (1 - \mathit{High\ Credit})$	-0.12	-0.53	-0.35	-0.42	-0.42
	(0.35)	(0.19)	(0.20)	(0.21)	(0.34)
Observations	292	289	286	283	276
R-squared	0.68	0.68	0.69	0.72	0.73
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y