How Credit Cycles across a Financial Crisis *

Arvind Krishnamurthy
Stanford GSB and NBER

Tyler Muir
Yale SOM and NBER

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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). 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, are credit markets "frothy" before 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. Theory shows how the trigger 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). The shock 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 then turn to the data to identify crises. We primarily rely on a chronology based on Jorda *et al.* (2010) and Jordà *et al.* (2013). 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 and they are the primary dates we use in our study. 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). We also present our results based on these chronologies.

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.

<u>Aftermath of a crisis:</u> Using the ST dates, we characterize the dynamics of credit markets and output around financial crises. We describe our results in reverse chronology, beginning with the aftermath of a crisis. We estimate the following regression (country i, time t):

$$ln\ \frac{y^i_{t+k}}{y_{i,t}} = a_i + a_t + b \times s_{i,t} \times 1_{crisisST,i,t} + \underline{b} \times s_{i,t} \times 1_{NOcrisisST,i,t} + \epsilon^i_{t+k} \quad (1)$$

where $ln\ \frac{y^i_{t+k}}{y_{i,t}}$ is output growth over the next k periods, $s_{i,t}$ is the credit spread for country-i at time t, and $1_{crisisST,i,t}$ is a dummy for ST crisis date. The regression includes a fixed country effect that absorbs mean growth for that country, and a time effect that absorbs common global variation in output growth. We are interested in estimates of b, which describe the relation between spreads and output growth in the cross-section of crises. Note that an alternative specification which is commonly used in the literature is

$$ln\ \frac{y^i_{t+k}}{y_{i,t}} = a_i + a_t + \beta \times 1_{crisisST,i,t} + \underline{\beta} \times 1_{NOcrisisST,i,t} + \epsilon^i_{t+k} \quad (2)$$

In this regression, β is the mean output growth conditional on a crisis. But, specification (2) is sensitive to the set of crises studied, which is a significant drawback. For example, if one included in the set of crises both severe events (say the Great Depression) and minor events (say the S&L crisis), then estimates of β will reflect the average over these events. Indeed within our sample of ST crises, there is enormous heterogeneity in the severity of crises: the mean three-year output contraction is -2.6%, but the standard deviation of this measure is 8.5% (see Table 3). While crises are diverse phenomena, crisis dating is binary. Spreads are useful because they can index crisis severity to capture the diversity. Theory predicts that credit spreads should reflect high future default losses, a credit crunch, and high risk/illiquidity premia. Each of these components of spreads is an increasing function of crisis severity.[1]

We show that estimating (1) identifies a statistically strong relation between crises and GDP losses in the aftermath of crises. Estimating (2) gives weak and varying estimates of GDP losses. For our preferred estimates, a one-sigma increase in spreads (crisis severity), is associated with an 8.2% decline in 5 year cumulative GDP growth. A one-sigma increase in spreads in a non-financial recession is associated with an 3.1% decline in 5 year cumulative GDP growth.

With the continuous measure we can also offer a sharp answer to the question, "How slow a recovery should we expect following the 2008-2009 financial crisis in the US?" In a well known paper, Reinhart and Rogoff (2009a) measure the peak-to-trough contraction in crises as 9.3%, with this mean measured from a select set of financial crises. We provide a more precise answer than the mean decline across a sample of crises. Since spreads index the severity of crises, we can compare the severity the 2008 crisis to historical crises and thus provide the estimate, $E\left[ln\ \frac{y^i_{t+k}}{y_{i,t}} | \text{2008 conditions}\right]$ rather than $E\left[ln\ \frac{y^i_{t+k}}{y_{i,t}} | \text{Crisis}\right]$. We plot the predicted path of GDP in this manner. This path is remarkably close to the actual path of GDP, suggesting that the realized growth of GDP in the US is in line with what should have been expected based on past financial crises.

Transition into a crisis: Theory suggests that crises are the result of an unexpected shock, $z_{i,t}$ ($E_t[z_{i,t}] = 0$), affecting a fragile financial sector. Denote $\mathcal{F}_{i,t}$ as the fragility of the financial sector. 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 $z_{i,t} \times \mathcal{F}_{i,t}$.

In many financial crisis models, the shock $z_{i,t}$ which triggers the crisis is a paper loss on assets that banks hold. Given that bank assets are credit sensitive whose prices will

[1] A widening of spreads could cause a reduction in output, via a credit crunch, or spreads may just correlate with subsequent economic conditions. We do not take a stand on whether or not the relation between spreads and activity reflects causation or correlation. There is a large literature which examines the transmission of bank-specific shocks on credit supply and real activity. If we were attempting to determine causality, we may be more interested in measuring bank credit spreads. But as we are using the credit spread information simply as a signal, we do not go down this road.

move along with credit spreads, the change in spreads from pre-crisis to crisis will be closely correlated with bank losses. This logic suggest that crisis severity will be more correlated with $s_{i,t} - s_{i,t-1}$ rather than just $s_{i,t}$.

Consistent with this loss-trigger view of crises, we find that the change in spreads around the ST dates is closely related to the subsequent severity of financial crises. On the other hand, we find little role for lagged spreads in non-financial recessions. In these events, the level of spreads at time t is the best signal regarding future output growth, which 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)). Indeed, theoretically, 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.

While ST financial crises are triggered by large spread changes, do all large spread changes end in financial crises? We define large loss events as those where the change in spreads is in the highest 90th percentile of spread changes and the change in the stock market dividend/price ratio is above median. The set of dates with large losses is not the same as the ST set of dates. This is not just a problem of dating, but reflects deeper economics. Quantile regressions show that spread spikes are most informative for the left tail of GDP outcomes. That is, large spread spikes only mildly forecast low median GDP growth going forward, but they strongly forecast low quantiles of GDP growth going forward.

Then which large loss events do end in financial crises? Empirically we show that large losses that are preceded by high credit growth end in crises. The result provides further support for the loss/amplification models of financial crises, since high credit growth, following on Jorda *et al.* (2010), is one way to measure fragility, $\mathcal{F}_{i,t}$. 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. We find that, conditional on a large increase in spreads, episodes for which credit growth or leverage growth are high result in substantially worse real outcomes.

<u>Pre-crisis period:</u> Last, 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 a large loss/fragile financial sector:

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

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.

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.

Dating concerns and robustness: The results do depend on our choice of crisis dates. 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. The most significant difference across these dates is that the ST recession dates occur before the BE or RR crisis dates. This 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 too small. Second, there is a worry that all of these dates are subject to an ex-post bias. As Romer and Romer (2014) note, 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 help resolve these issues. First, we present results based on all three chronologies, and the results do differ across dating. But we argue that the ST dates best identify the inception of crises. 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. We find 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 primary difference between these chronologies is that we use ST dates associated with the start of a recession involving a financial crisis, while BE and RR dates are the dates of significant bank failures/runs, which is typically later than the ST dates. The spread change evidence suggests that the ST dates better identify the start of a financial crisis, as bank failures occur after a crisis starts.

Second, our approach helps to alleviate the peek-ahead bias. Credit spreads and credit growth are quantitative criterion that can be measured ex-ante, without referencing subsequent output growth, and thus avoid this bias. We introduce a new dating of crises based only on spreads and credit growth, defining crises as events with a large loss (as described earlier) which are preceded by high credit growth. The point estimates for subsequent GDP growth following a large loss/high credit growth event indicate that these events are followed by a deep recession and protracted recovery, similar to our ST-date estimates.

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, while corporate defaults do not. We find that corporate bond spreads offering an indicator of the severity of crises, and taken with the evidence that the incidence of defaults do not correlate with the severity of downturns or with credit spreads (see Giesecke *et al.* (2011)), the data suggest that it is variation in default risk premia that may be driving our findings.

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 also present results using these chronologies.

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.[2] 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.[3] This process helps to eliminate noise in our spread construction.

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 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,

$$\ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = a_i + a_t + b_0 \times spread_{i,t} + b_{-1} \times spread_{i,t-1} + \varepsilon_{i,t+k}. \tag{3}$$

[2] 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

[3] 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.

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 (3) 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:

$$\hat{s}_{i,t} \equiv Spread_{i,t}/\overline{Spread^{i}} \tag{4}$$

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 columnn (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. We use spreads simply as a (noisy) signal of the severity of a financial crisis. Thus it does not matter which component of spreads forecasts economic activity.[4] Likewise, a widening of spreads could cause a reduction in output, via a credit crunch, or spreads may just correlate with economic conditions. We do not take a stand on whether or not the relation between spreads and activity reflects causation or correlation. There is a large literature which examines the transmission of bank-specific shocks on credit supply and real activity. If we were interested in studying causality, we may be more interested in measuring bank credit spreads (or CDS). But as we are using the credit spread information simply as a signal, we do not go down this road.

4 Aftermath of a Financial Crisis

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%,

[4] On the other hand, some of our results are consistent with risk premia being an important component in forecasting crises. These results are consistent with Gilchrist and Zakrajsek (2012), who provide evidence that the informative component of spreads for future output is the default risk premium component rather than the expected default component. There is also a theoretical literature based on financial frictions in the intermediation sector, which draws a causal relation between increases in credit spreads and future economic activity (see He and Krishnamurthy (2012)).

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:

$$decline_{i,t} = a + b_0 \times \hat{s}_{i,t} + b_{-1} \times \hat{s}_{i,t-1} + c \times \Delta credit_{i,t} + \varepsilon_{i,t} \tag{5}$$

The spread has statistically and economically significant explanatory power for crisis severity. Focusing on column (1), a one-sigma change in $\hat{s}_{i,t}$ of 1 translates to a 2.5% 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 4.0%.

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 (1) and (5) corresponding to the ST crises, the variation that is picked up by the independent variables rises from 4.0% of GDP to 5.7% of GDP. 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 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 result in a much larger cross-country sample.

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. In the Section 5, we discuss in greater depth why the change in spreads is a powerful signal of crisis severity.

Last, we show in Column (4) that the predictive results are not driven solely by the Great Depression. We complement these results further by graphically plotting the fitted values from our regressions against actual values in Figure 4. The figure forecasts both peak-to-trough declines as well as a cumulative 3 year GDP growth rate and includes results that drop the Great Depression. Crises are labeled by country and year. The figures suggest that spreads do accurately capture variation in crisis severity, and this relation is not driven by the 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.

4.3 Spreads and the evolution of output

We now turn to estimating equation (1) from the introduction. Given the importance of lagged spreads and credit growth, we modify (1) to estimate,

$$\begin{aligned} \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) &= a_i + a_t + 1_{crisis,i,t}\left(b_0^{crisis} \times \hat{s}_{i,t} + b_{-1}^{crisis} \times \hat{s}_{i,t-1}\right) \\ &\quad +1_{no-crisis,i,t}\left(b_0^{no-crisis} \times \hat{s}_{i,t} + b_{-1}^{no-crisis} \times \hat{s}_{i,t-1}\right) + c'x_t + \varepsilon_{i,t+k} \end{aligned} \tag{6}$$

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

Columns (1) and (5) of Table 5 presents a baseline where we pool crises and non-crises, forcing the b coefficients to be the same across these events. Column (1) corresponds to 3-year GDP growth and (5) 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. High current spreads forecast more severe crises. The lagged spread comes in with a positive coefficient that is significantly different than zero. The effects are statistically stronger at the 3-year horizon. The coefficient on spreads for the crisis dates is also higher than those for the recession dates.

Columns (4) and (8) of Table 5 report the results from regressions estimating the mean GDP growth after a crisis, but not using any information from spreads. The comparison highlights the contribution of our research which bring spreads to bear on measuring the aftermath of a crisis. We run,

$$ln\ \frac{y_{i,t+k}}{y_{i,t}} = a_i + a_t + \beta 1_{crisis,i,t} + c' x_t + \varepsilon_{i,t+k}. \tag{7}$$

which corresponds to (2) in the introduction, and what other researchers have measured. The results indicate a mean decline in output following crises at both the 3- and 5-year horizon. However, note that the statistical significance of the spread regressions is much higher than the simple dummy regression, indicating that spreads contain important information for output. Additionally, the weakness of the simply dummy regression is that the results will be sensitive to the set of crisis dates, since the regression estimates a mean across those crises.

4.4 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).[5] We use this difference in coefficients to compare recoveries from financial crises to non-financial recessions.

[5] 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.

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 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 4/5 across crises and recessions to compute a long-run effect on growth. 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 increases expected default.

Figure 5 plots the evolution of GDP to a one-sigma shock to spreads (a shock of $\Delta\hat{s} = 1$). The top panel in the figure is based on the unconditional regressions; the middle panel is based on the ST crisis dates; and the bottom panel is based on recessions. 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) (see also Romer and Romer (2014)). That is, we estimate (6) 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 5 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 or the unconditional regression panel. Conditional on ST crises, output falls, reaching a low at the 4-year horizon of -9% before recovering. Note that since the ST dates correspond to the start of a recession accompanying a financial crisis, an apples-to-apples comparison is between the ST dates and the non-financial recession dates.

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 "diff-diff" estimate.

4.5 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. The lower panel plots the actual and predicted path of spreads for the 2008-2013 period using the (6) approach with spread as dependent variable. Our forecasts are based on estimating regression (6), 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 (6) makes it harder to compare coefficients on spreads in crises versus other episodes.

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.

We also 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.

5 Transition into a Crisis

5.1 Change in spreads at the start of a crisis

In Tables 4 and 5, we find that the level of spreads in the year of financial crisis driven recessions (as dated by ST) comes in with a positive and significant coefficient, while the lagged spread comes in with a negative and significant coefficient of almost the same magnitude as the spread in the first year of the crisis-recession. Column (3) of Table 4 regresses the peak-to-trough decline in GDP on the change in spreads, confirming that the change in spreads is a powerful indicator of the subsequent severity of the crisis. In contrast, we find that in non-financial recessions, the lagged value of the spread has little explanatory power for subsequent GDP growth. See columns (6) - (7) of Table 4. The importance of the lagged spread is also evident for the crisis dates in Table 5. Additionally, we confirm that the lagged spread has little explanatory power in the recession dates of Table 5.

The empirical importance of the change in spreads for forecasting output in crises, but not for recessions, is consistent with 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,

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

Thus, 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.[6] Our results in Tables 4 and

[6]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)).

5 confirm these predictions and the differential importance of lagged spreads in crises and recessions.

5.2 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 lowering 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 $\hat{s}_t$ is -0.85 (and is $+0.66$ on the lag), while it is -1.17 (and $+0.87$ on the lag) at the 25th quantile.

Figure 7 plots the impulse response of different moments of GDP to an innovation of 1 (roughly one-sigma) in our spread measure. We see that the median response is smaller than the mean response, indicating that high spreads are associated with skewness. The 10th percentile shows a dramatic reduction in output, roughly twice the size of the mean of the response. These results suggest that a spike in spreads increases the likelihood of a tail event that the economy will suffer a deep and protracted slump.

Figure 8 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.

5.3 Large losses, fragility, and crises

We next ask, 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 investigate whether this view of crises is consistent with the data.

We define events based on large losses:

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

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

Figure 9 provides a visual representation of how SpreadCrises overlap with the ST/RR crises. There is considerable overlap in the dates, although there are many events that are labeled "Spread Crises" that are not ST/RR crises.

The first row of the top panel of Table 7 presents the average path of GDP conditional on a SpreadCrisis 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 SpreadCrisis with a dummy 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. We see that the GDP declines in the SpreadCrisis/HighCredit events are larger than in the SpreadCrisis 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/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.

6 Pre-crisis Period

A large change in spreads is associated with a more severe financial crisis. Is the large change in spreads pre-crisis 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:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{ Prob}^{\mathcal{Q}}(z_t > \underline{z}) \overbrace{E_t^{\mathcal{Q}}\left[ln \ \frac{y^i_{i,t+k}}{y_{i,t}} | \text{crisis} \right]}^{\downarrow \text{ in } \mathcal{F}_{i,t}}. \tag{8}$$

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 (8), we can view this result as suggesting that investors' risk-neutral expectations of a large loss, $\text{Prob}^{Q}(z_t > \underline{z})$, 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 10 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 10. 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).

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 11 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.

Figure 12 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 13 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 too small. 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.

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.

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.

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.

US spread from 1930-2014. Source: Moody's Baa-Aaa spread.

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.

Hong Kong 1996-2012. Source: .

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.

References

Robert Barro, Emi Nakamura, Jon Steinsson, and Jose Ursua. Crises and recoveries in an empirical model of consumption disasters. *working paper*, 2011.

Michael D. Bordo and Joseph G. Haubrich. Credit crises, money and contractions: An historical view. *Journal of Monetary Economics*, 57(1):1 – 18, 2010.

Michael D. Bordo and Joseph G. Haubrich. Deep recessions, fast recoveries, and financial crises: Evidence from the american record. *NBER working paper*, 2012.

Michael Bordo, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria. Is the crisis problem growing more severe? *Economic policy*, 16(32):51–82, 2001.

Markus K Brunnermeier and Yuliy Sannikov. A macroeconomic model with a financial sector. *Working Paper*, (236), 2012.

Ricardo J Caballero and Arvind Krishnamurthy. Collective risk management in a flight to quality episode. *The Journal of Finance*, 63(5):2195–2230, 2008.

Valerie Cerra and Sweta Chaman Saxena. Growth dynamics: The myth of economic recovery. *The American Economic Review*, 98(1):439–457, 2008.

Stijn Claessens, M Ayhan Kose, and Marco E Terrones. The global financial crisis: How similar? how different? how costly? *Journal of Asian Economics*, 21(3):247–264, 2010.

Benjamin M. Friedman and Kenneth N. Kuttner. Money, income, prices, and interest rates. *The American Economic Review*, 82(3):pp. 472–492, 1992.

Nicola Gennaioli, Andrei Shleifer, and Robert W. Vishny. A model of shadow banking. *The Journal of Finance*, 68(4):1331–1363, 2013.

Mark Gertler and Nobuhiro Kiyotaki. Financial intermediation and credit policy in business cycle analysis. *Handbook of monetary economics*, 3(3):547–599, 2010.

M Gertler and CS Lown. The information in the high-yield bond spread for the business cycle: evidence and some implications. *Oxford Review of Economic Policy*, 15(3):132–150, 1999.

Kay Giesecke, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev. Corporate bond default risk: A 150-year perspective. *Journal of Financial Economics*, 102(2):233 – 250, 2011.

Kay Giesecke, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev. Macroeconomic effects of corporate bond default crises: A 150-year perspective. *working paper*, 2012.

Simon Gilchrist and Egon Zakrajsek. Credit spreads and business cycle fluctuations. *The American Economic Review*, forthcoming, 2012.

Zhiguo He and Arvind Krishnamurthy. Intermediary asset pricing. *The American Economic Review*, forthcoming, 2012.

Oscar Jorda, Moritz Schularick, and Alan M. Taylor. Financial crises, credit booms, and external imbalances: 140 years of lessons. *NBER working paper*, 2010.

Òscar Jordà, Moritz Schularick, and Alan M Taylor. When credit bites back. *Journal of Money, Credit and Banking*, 45(s2):3–28, 2013.

Oscar Jorda. Estimation and inference of impulse responses by local projections. *The American Economic Review*, 95(1):pp. 161–182, 2005.

Nobuhiro Kiyotaki and John Moore. Credit cycles. *Journal of Political Economy*, 105(2):pp. 211–248, 1997.

David Lopez-Salido, Jeremy C Stein, and Egon Zakrajsek. Credit-market sentiment and the business cycle. *working paper*, 2015.

Atif Mian, Amir Sufi, and Emil Verner. Household debt and business cycles world wide. *working paper*, 2016.

Frederic S Mishkin. Asymmetric information and financial crises: a historical perspective. *National Bureau of Economic Research*, 1990.

Alan Moreira and Alexi Savov. The macroeconomics of shadow banking. *working paper*, 2014.

Thomas Philippon. The bond market's q. *The Quarterly Journal of Economics*, 124(3):1011–1056, 2009.

Carmen M. Reinhart and Kenneth S. Rogoff. The aftermath of financial crises. *American Economic Review*, 99(2):466–72, 2009.

Carmen M. Reinhart and Kenneth S. Rogoff. *This time is different: Eight centuries of financial folly*. Princeton University Press, Princeton, NJ, 2009.

Christina D. Romer and David H. Romer. New evidence on the impact of financial crises in advanced countries. *working paper*, 2014.

Jeremy C Stein. Monetary policy as financial stability regulation. *The Quarterly Journal of Economics*, 127(1):57–95, 2012.

10 Tables and Figures

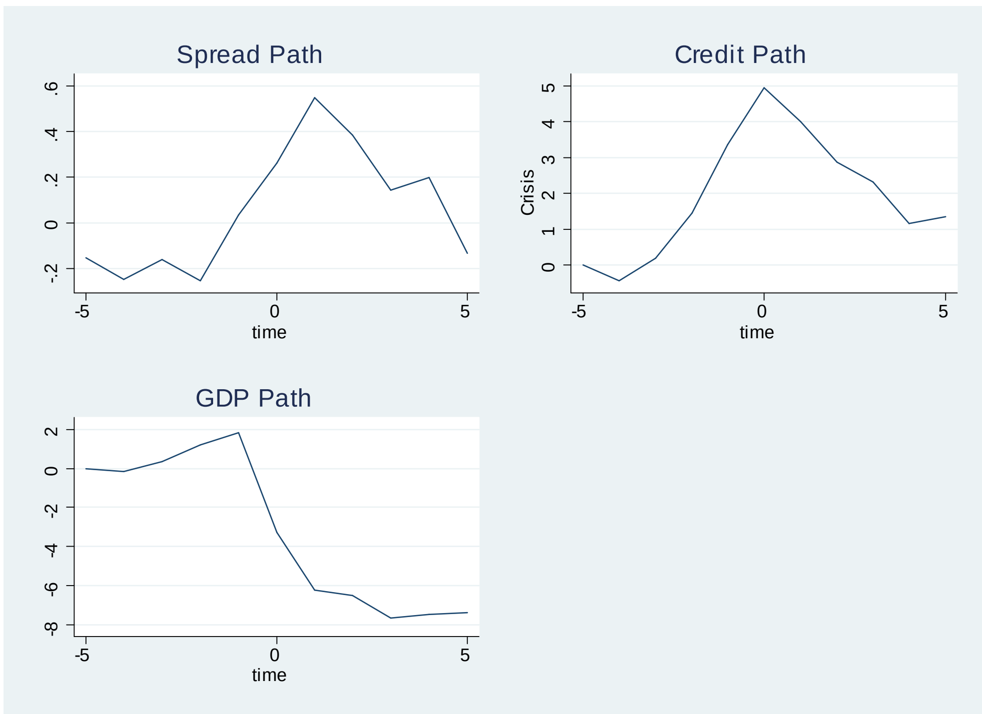

Figure 1: This figure plots the behavior of credit spreads, GDP, and the quantity of credit around a financial crisis with the crisis beginning at date 0. We use crisis dates from Schularick and Taylor.

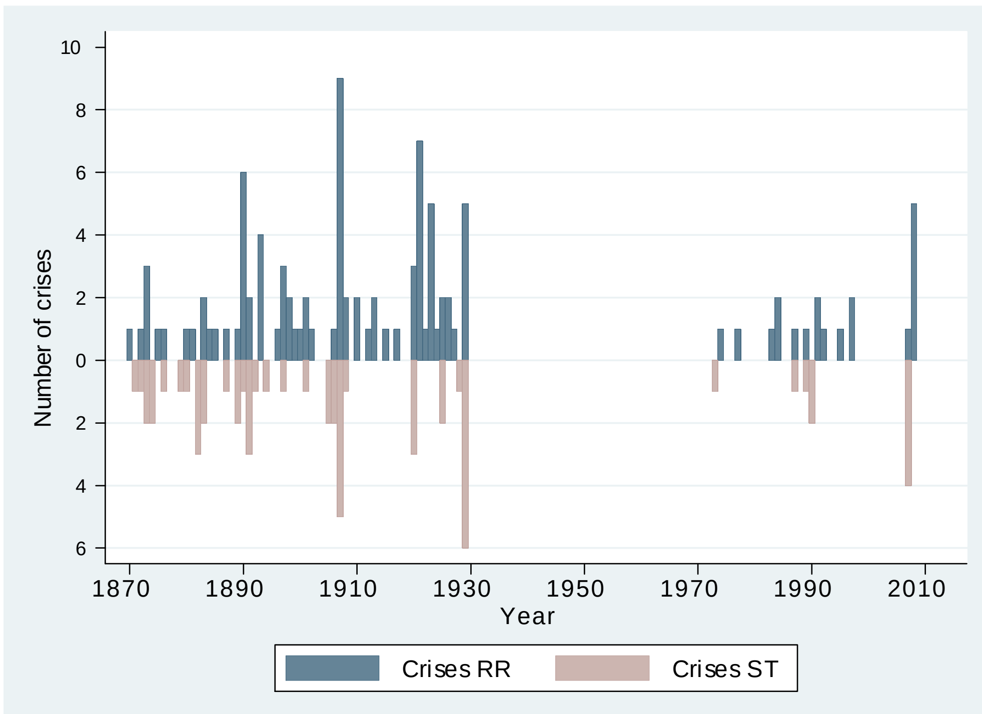

Figure 2: This figure plots the incidence of crises over time across various countries from 1870-2008. RR denotes those measured by Reinhart and Rogoff and ST denotes those measured by Schularick and Taylor. We only plot these variables for countries and dates for which we have credit spread data to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

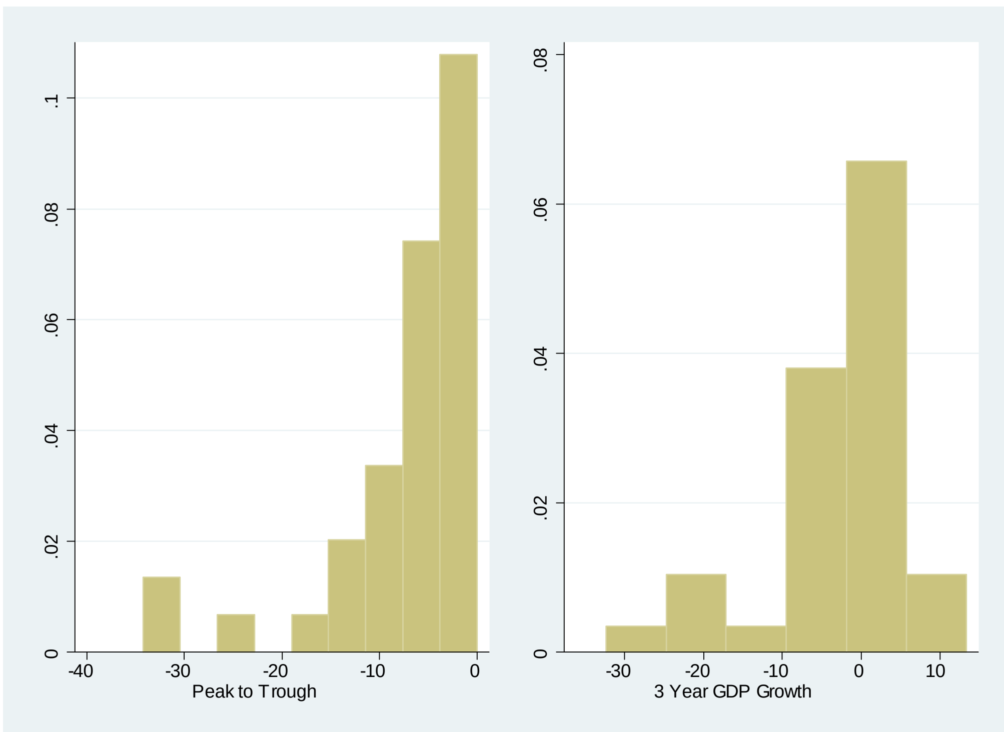

Figure 3: This figure shows the empirical distribution of outcomes in GDP across financial crises using crisis dates from Schularick and Taylor. The left panel plots peak to trough declines in GDP while the right panel plots cumulative GDP growth over a 3 year period after the start of the crisis. In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

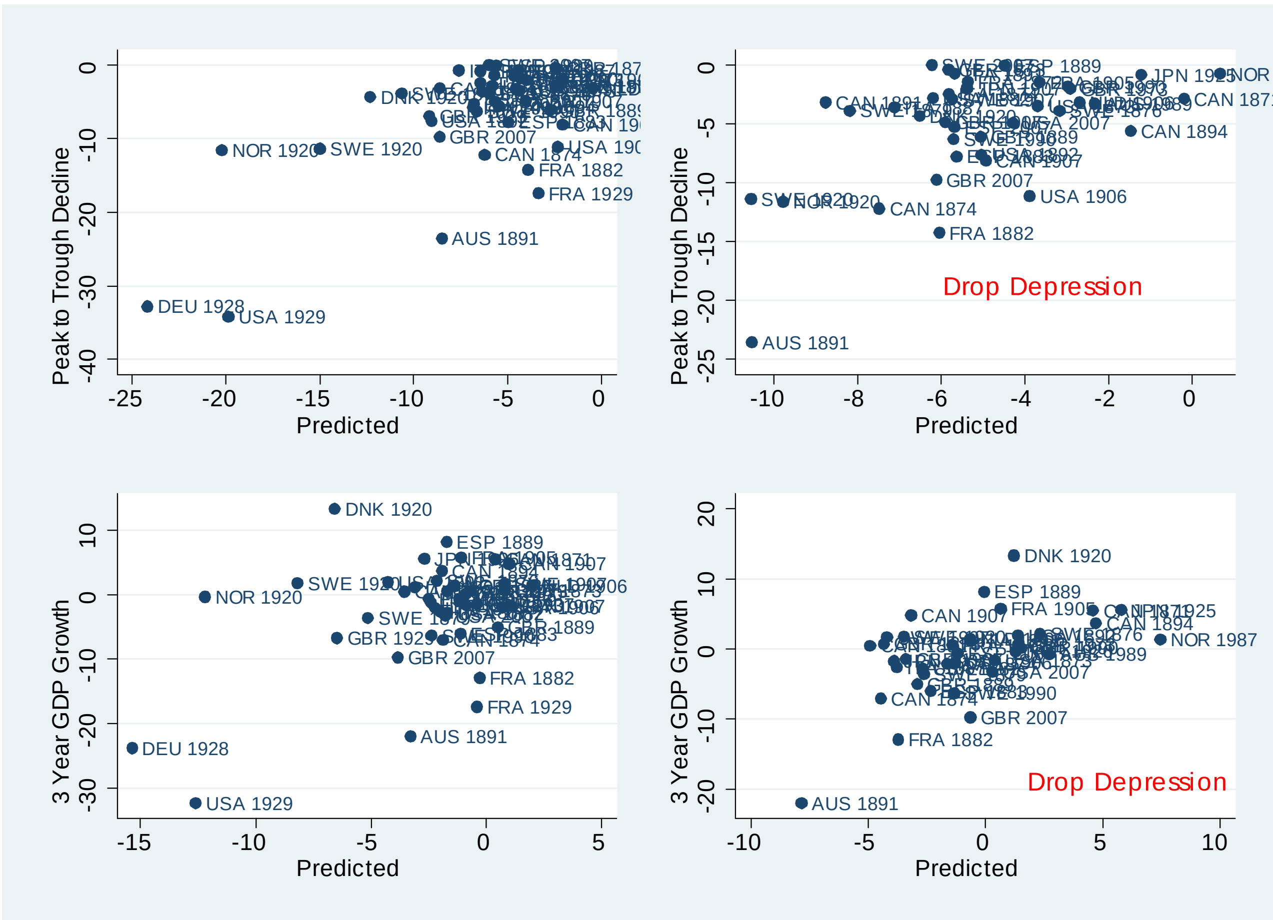

Figure 4: We plot the predicted vs actual declines in GDP in crises formed using the current and lagged spread as forecasters and using crisis dates from Schularick and Taylor. We include predicted peak to trough declines (top) as well as the predicted 3 year growth rate (bottom). The right panel re-does our forecast excluding the Great Depression years.

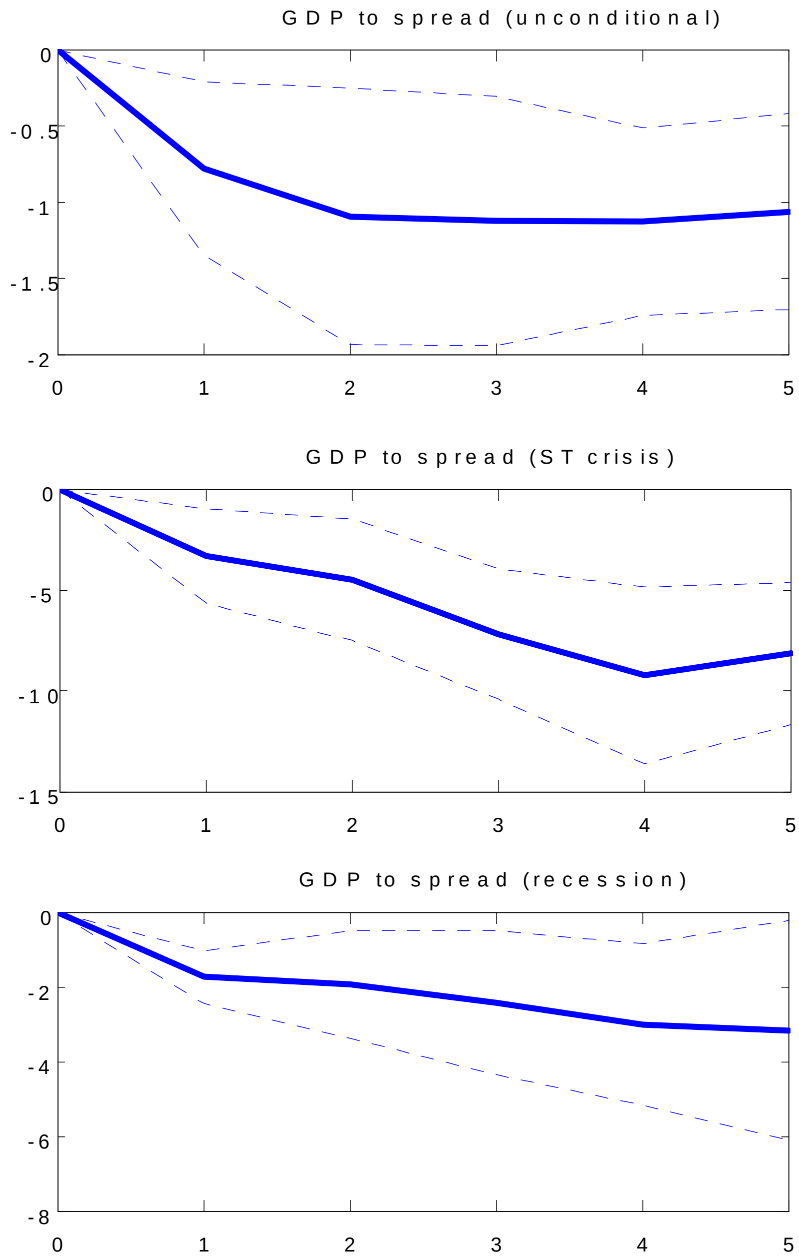

Figure 5: This figure plots the impulse responses of GDP to an innovation of one (approximately one-sigma) in our spread measure during normal times (top panel), financial crises (middle panel), and recessions (bottom panel). Impulse responses are computed using local projection measures where we forecast GDP independently at each horizon.

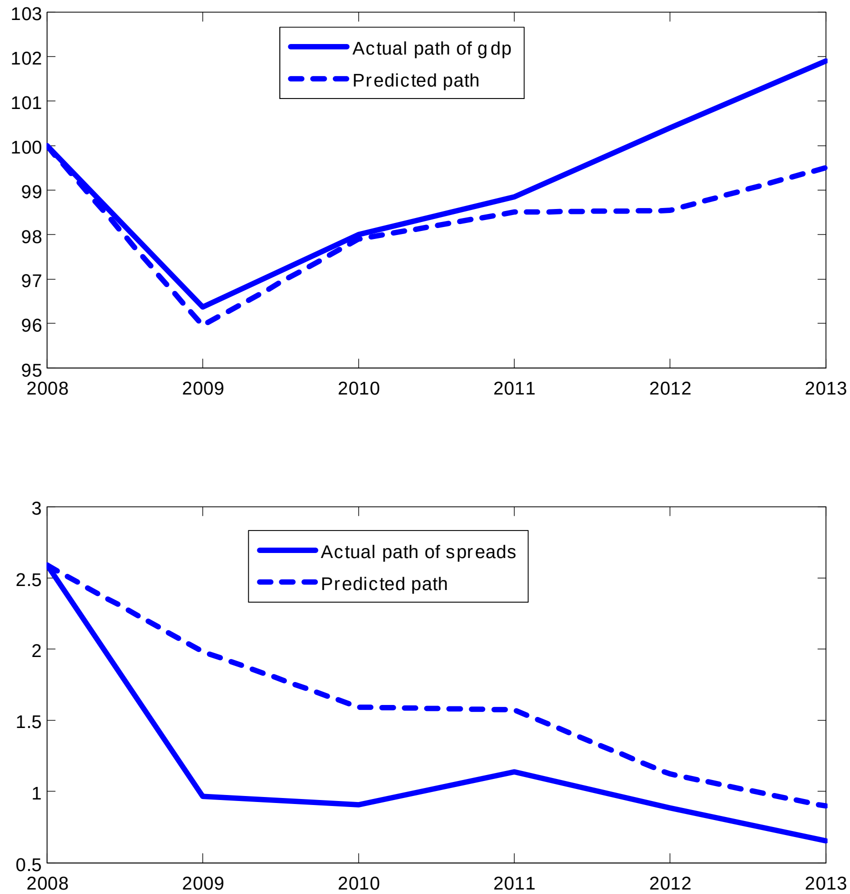

Figure 6: We predict outcomes of output and spreads during the 2008 US financial crisis using predicted values from our regressions and data up to 2008. The top panel, GDP, is cumulative from a base of 100 in 2008. The lower panel, spreads, uses the last quarter value of the BaaAaa spread in 2008. Our predicted value is formed using the Schularick and Taylor crisis dates.

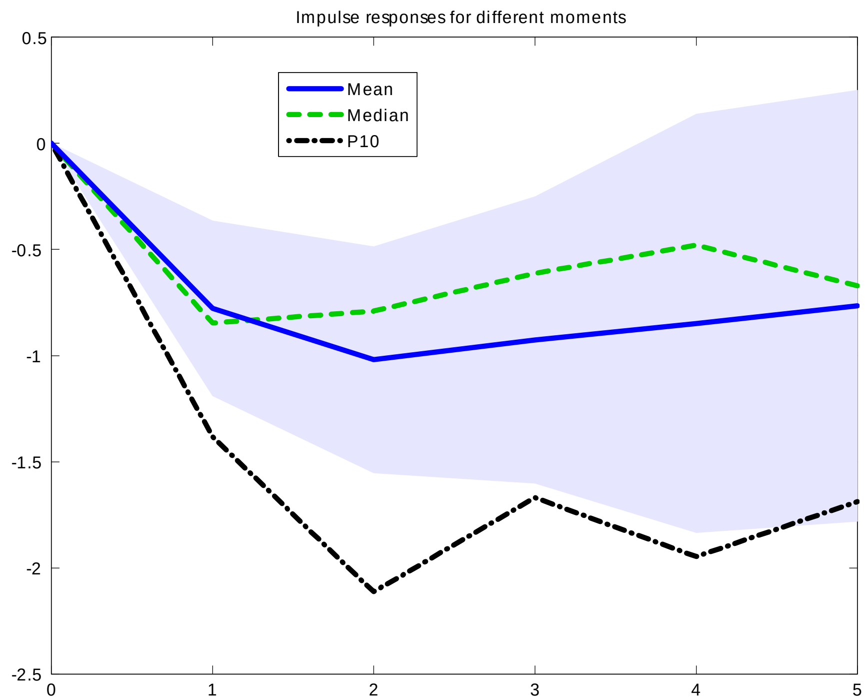

Figure 7: We plot impulse responses of GDP to an innovation of one (approximately one-sigma) in spreads for various moments: the mean, median, and 10th percentile. All impulse responses use the Jorda local projection method where we use quantile regression or OLS depending on the moment plotted. 95% confidence intervals are given in colored shaded regions for the mean response.

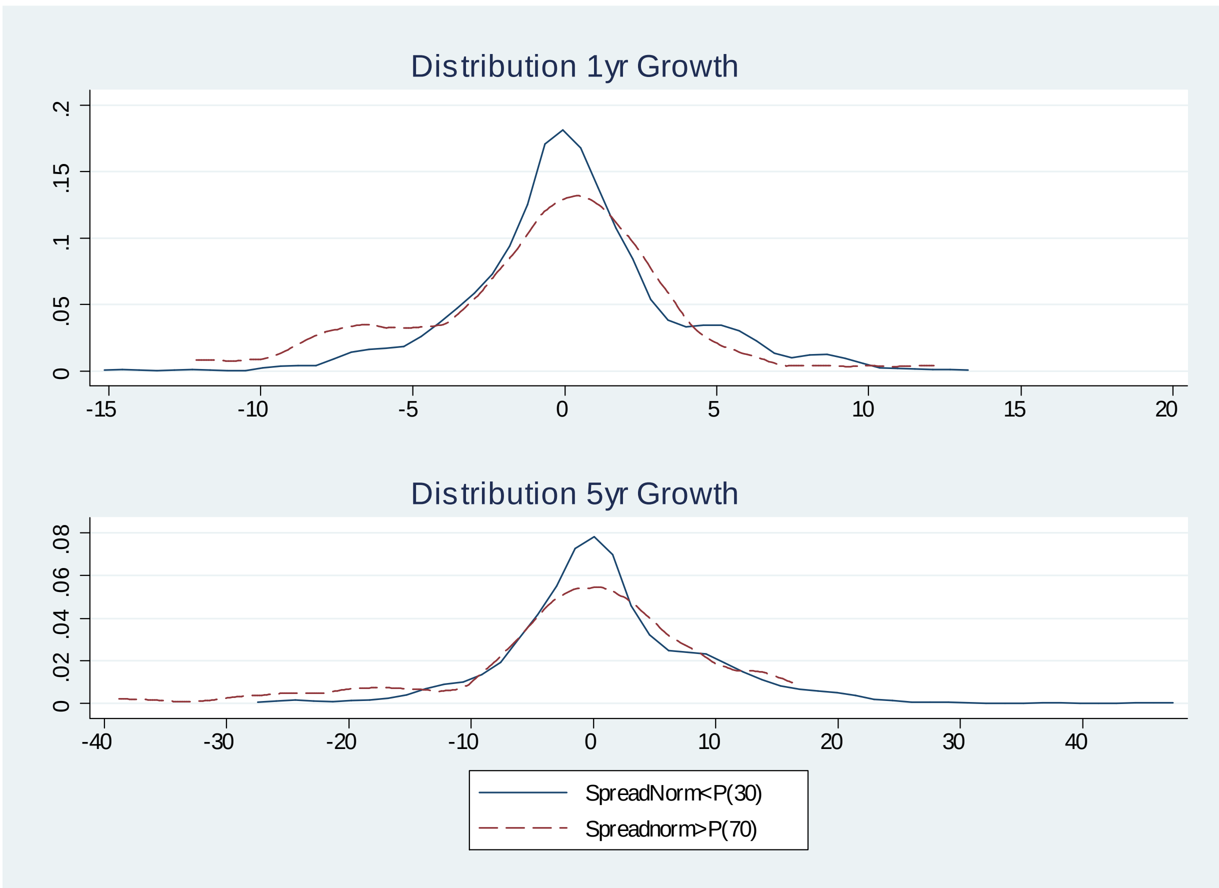

Figure 8: This figure plots the distribution of GDP growth at various horizons conditional on spreads based on a kernel density estimation. The blue solid line plots the distribution of GDP growth when spreads are in the lower 30% of their realizations, the red dashed line plots the distribution when spreads are in the highest 30% of their realizations. Analagous to our quantile regressions, the figure shows that high spreads are associated with a larger left tail in GDP outcomes.

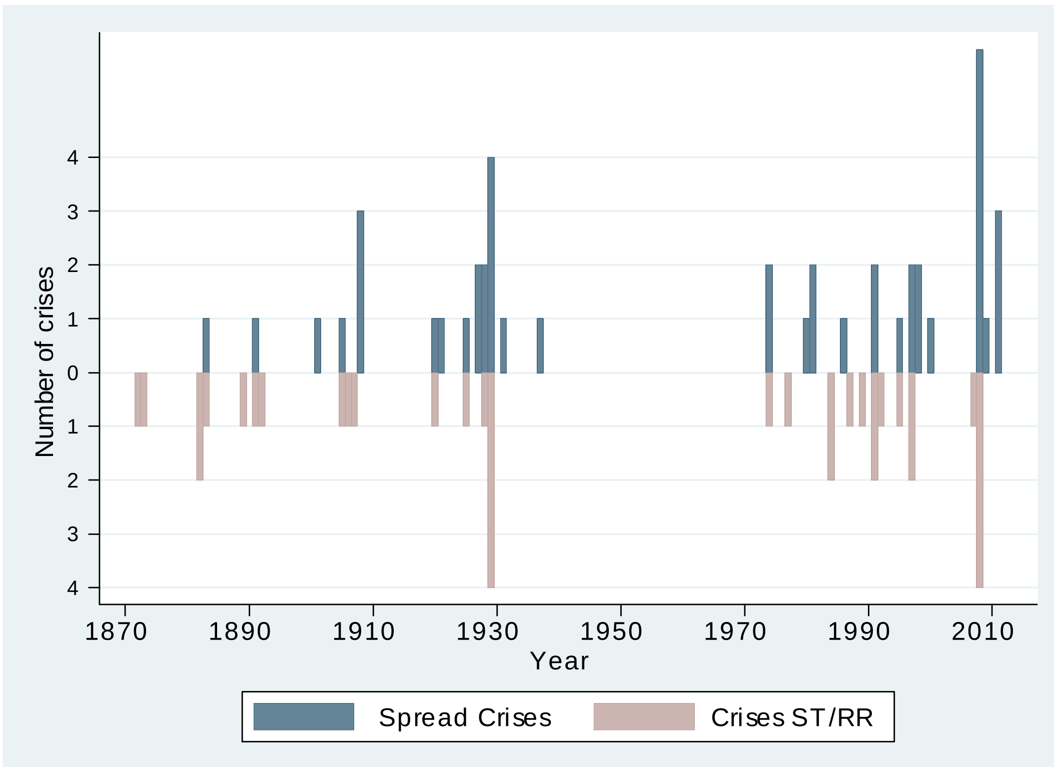

Figure 9: We plot our spread crises counts by year along with counts from Schularick and Taylor for crisis dates. Our spread crisis dates are defined as an increase in spreads above a given threshold as well as an increase in the dividend/price ratio above median. As described in the text, this threshold is chosen to give approximately the same total number of crises as Schularick and Taylor.

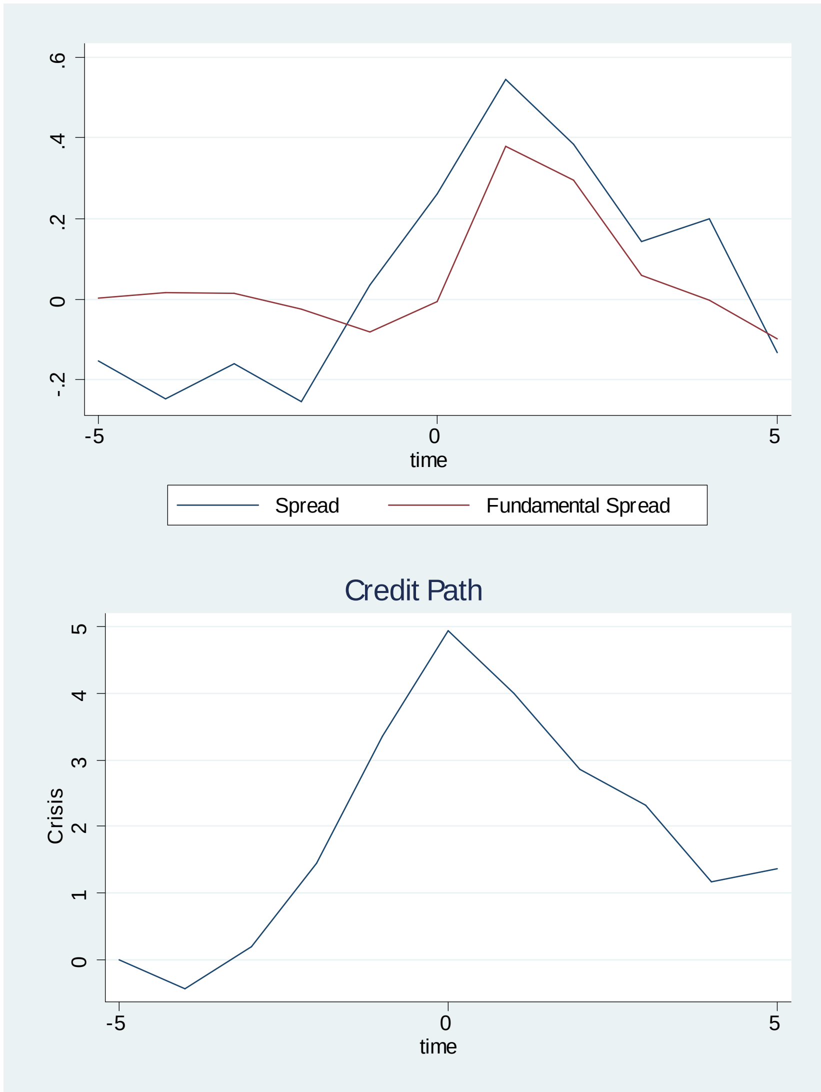

Figure 10: This figure plots the path of spreads, fundamental spreads, and cumulative credit growth in the years surrounding a financial crisis (using ST dates). The paths are formed by running regressions with dummies at various dates. “Fundamental spreads” are computed as the predicted value from a regression of spreads on fundamentals including two lags of GDP growth and the change in credit.

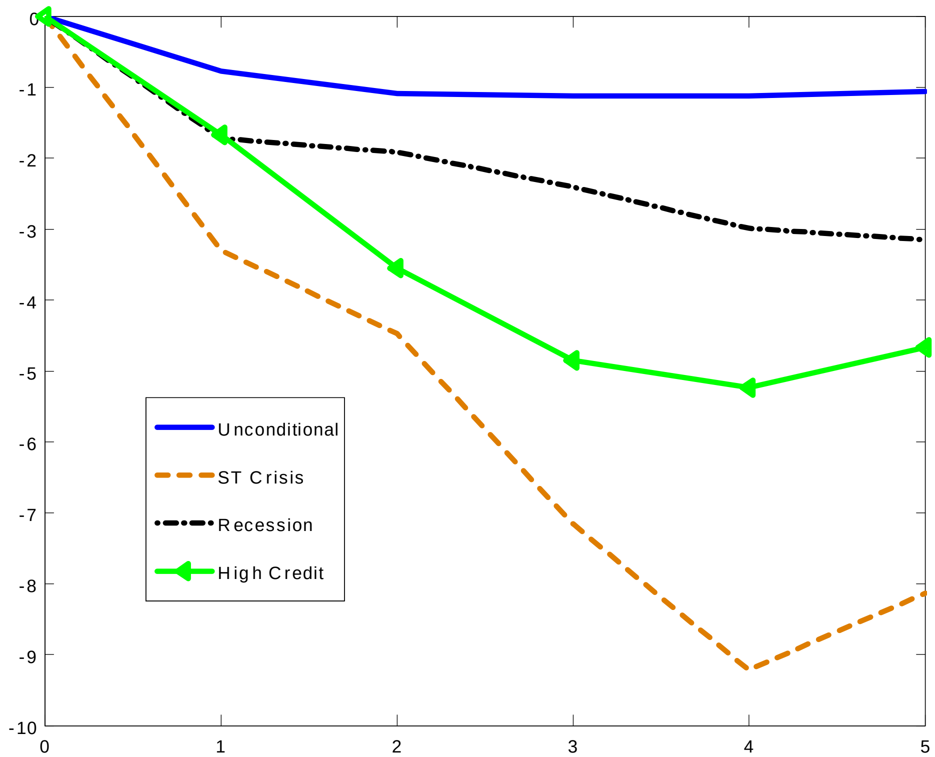

Figure 11: This figure plots impulse responses to an innovation of one (approximately one-sigma) in our spread variable. This is done unconditionally (blue solid line), conditional on a non-financial recession (black dashed line), conditional on a financial crisis (lighter dashed line), and conditional on a period of high credit growth (lighter solid line). See text for dating details.

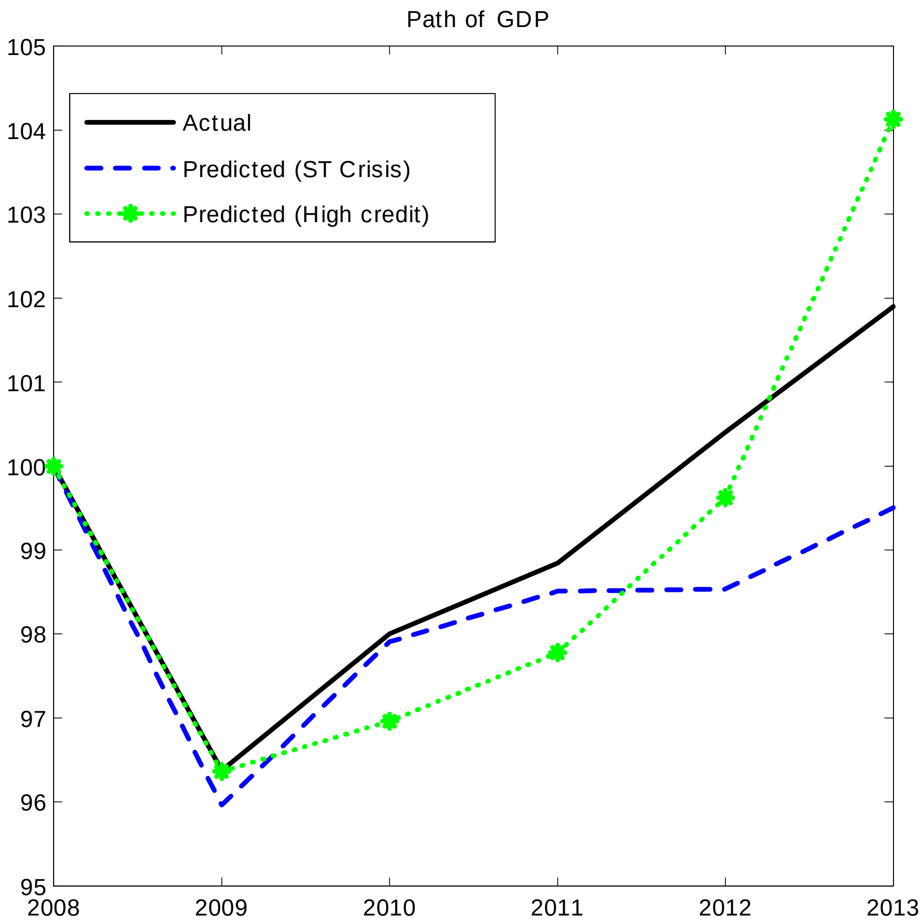

Figure 12: We predict outcomes of GDP during the 2008 US financial crisis using predicted values from our regressions and data up to 2008. We plot the actual data along with the predicted value from an interaction of spreads with financial crisis dates from Schularick and Taylor as well as an indicator for a period of high recent credit growth.

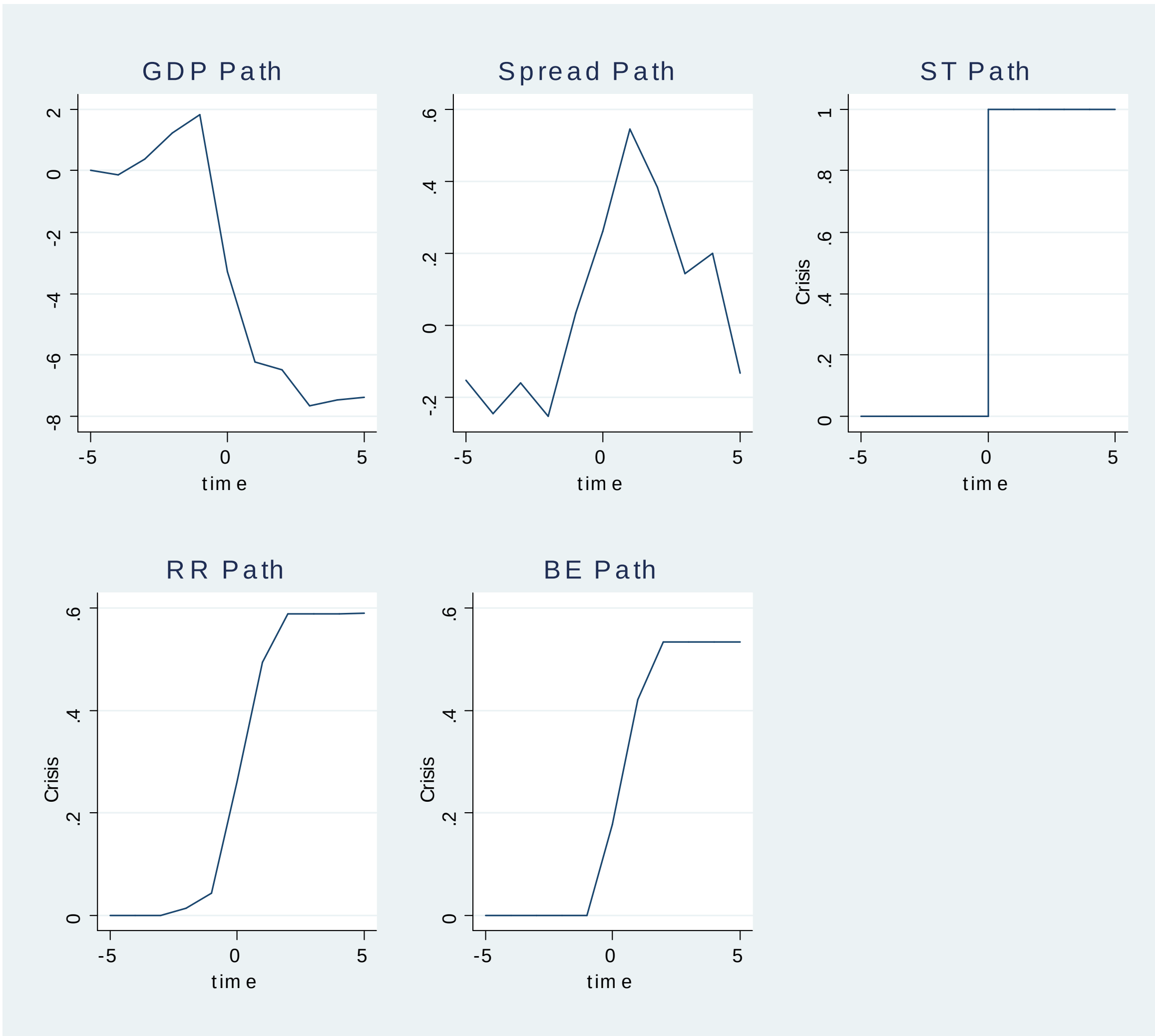

Figure 13: We plot paths of each variable with an ST crisis dated at date 0 to show the relative timing of the following variables around a crisis: GDP, credit spreads, Reinhart and Rogoff's dating convention (RR), Bordo and Eichengreen's dating convention (BE), and Schularick and Taylor's dating convention 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 movments in spreads in each country. Controls include two lags of GDP growth and both country and year fixed effects. Standard errors clustered by country.

VARIABLES	(1) Raw	(2) MeanNorm	(3) OOSMean	(4) Zscore	(5) 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	ST Crisis	ST Crisis	ST Crisis	ST Crisis	ST Crisis	Recess	Recess
$\widehat{s}_{i,t}$	-2.52	-6.42		-4.50	-6.78	-1.55	-1.97
	(0.62)	(1.40)		(1.32)	(1.44)	(0.49)	(1.10)
$\widehat{s}_{i,t-1}$		4.88		6.72	5.18		0.21
		(1.60)		(2.20)	(1.63)		(1.23)
$\Delta\widehat{s}_{i,t}$			-6.75				
			(1.47)				
$\Delta credit_{i,t}$					-4.89		
					(4.17)		
Observations	44	44	44	39	34	100	100
Drop Depression				Y			
R-squared	0.27	0.39	0.32	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 $\sigma(E_t[decline])$	4.0	4.9	4.4	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 to assess whether spreads become more informative during crisis periods. Controls include two lags of GDP growth, the 3 year growth in credit/GDP, and both country and year fixed effects in all regressions. Standard errors clustered by country in parenthesis.

VARIABLES	(1) 3yr	(2) 3yr	(3) 3yr	(4) 3yr	(1) 5yr	(2) 5yr	(3) 5yr	(4) 5yr
$\widehat{s}_{i,t}$	-1.15				-1.16			
	(0.29)				(0.40)			
$\widehat{s}_{i,t-1}$	0.78				1.64			
	(0.51)				(0.79)			
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-7.17				-8.18		
		(1.21)				(1.17)		
$\widehat{s}_{i,t-1} \times 1_{crisisST,i,t}$		6.26				8.13		
		(1.45)				(1.60)		
$1_{crisisST,i,t}$			-5.26				-5.54	
			(2.12)				(2.40)	
$\widehat{s}_{i,t} \times 1_{recess,i,t}$				-2.40				-3.14
				(0.98)				(1.50)
$\widehat{s}_{i,t-1} \times 1_{recess,i,t}$				0.14				0.94
				(0.80)				(1.17)
Observations	641	641	641	641	634	634	634	634
R-squared	0.53	0.54	0.54	0.54	0.53	0.53	0.54	0.53

Table 6: Quantile Regressions. We run quantile regressions of output growth 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					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Q 90th	Q 75th	Q Median	Q 25th	Q 10th
$\widehat{s}_{i,t}$	-0.40	-0.45	-0.85	-1.17	-1.39
	(0.26)	(0.16)	(0.14)	(0.18)	(0.30)
$\widehat{s}_{i,t-1}$	0.85	0.75	0.66	0.87	0.99
	(0.30)	(0.18)	(0.16)	(0.20)	(0.34)
Observations	898	898	898	898	898
Country FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Pseudo R2	0.10	0.07	0.05	0.09	0.13

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 for whether there was a crisis according to our spread variable. It then splits these spread crisis 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
SpreadCrisis	-3.11		-4.11		-4.48		-3.99		-2.51	
	(0.69)		(0.94)		(1.22)		(1.48)		(1.71)	
(SpreadCrisis) 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. 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 "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).

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	-0.30	-0.42	-0.17	-0.53	-1.30
	(0.42)	(0.72)	(0.99)	(1.23)	(1.42)
HighCredit	-0.44	-0.81	-0.60	0.24	1.30
	(0.61)	(1.05)	(1.23)	(1.34)	(1.36)
(HighFroth)×(HighCredit)	-1.09	-1.58	-2.89	-3.86	-4.25
	(0.90)	(1.32)	(1.52)	(1.71)	(1.82)
Observations	527	524	521	518	514
R-squared	0.07	0.08	0.09	0.10	0.10

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

	(1)	(2)	(3)	(4)	(5)
HighFroth	0.32			0.09	0.14
	(0.23)			(0.27)	(0.30)
HighCredit		0.68			0.20
		(0.18)			(0.38)
(HighFroth)×(HighCredit)			0.70	0.65	0.45
			(0.24)	(0.28)	(0.48)
Observations	539	647	527	527	527

Table 10: 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.

VARIABLES	(1) 3yr	(2) 3yr	(3) 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

VARIABLES	(1) 5yr	(2) 5yr	(3) 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: 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