Credit Spreads and the Severity of Financial Crises *

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Abstract

We study the behavior of credit spreads and their link to economic growth during financial crises. We find that the recessions that accompany financial crises are severe and protracted. The severity of the 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 spreads fall in the runup too a crisis and are abnormally low, even as credit grows ahead of a crisis. This behavior of prices and quantities suggests that credit supply expansions are a precursor to crises. The result also suggests that crises involves a dramatic shift in expectations and are a surprise.

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1 Introduction

This paper answers the following questions about financial crises:

- How long and deep is the typical crisis? What should we have expected about the path of output in the US following the 2008 financial crisis?
- Are financial crisis driven recessions significantly different than noncrisis driven recessions?
- What conditions set the stage for a financial crisis?

To answer these questions we begin with a definition of a financial crisis. Theoretical models predict that crises are 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 (leverage, short-term debt financing). The shock can result 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 (2013), and Moreira and Savov (2014) for theoretical models of asset markets and crises.

Next, we identify financial crises in the data to measure how output and credit spreads behave around these events. We rely on three sets of chronologies, by Bordo, et. al., (2001), Reinhart and Rogoff (2009b), and Jorda *et al.* (2010) (henceforth BE, RR, and ST). These three chronologies are the only ones we are aware of that span the data we study. BE and RR date crises based on the year of a major bank run or bank failure. For example, Reinhart and Rogoff (2009b) state:

> We mark a banking crisis by two types of events: (1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions), that marks the start of a string of similar outcomes for other financial institutions.

We also consider a chronology based on Jorda *et al.* (2010) and Jorda, Schularick, and Taylor (2013). These authors date both the year of the bank run or failure as well as the start of the recession associated with the banking crisis, which typically occurs before the actual bank run or failure. We will argue that the ST financial recession dates provides better estimates of output losses associated with financial crises.

The choice of dates is central to crisis research. Dating as a crisis an event with small financial sector disruptions, and perhaps little output effects, will lead a researcher to conclude that crises are associated with mild real effects. On the other hand, dating only particularly severe financial events as crises, will lead to large estimates of output losses in crises. Likewise, timing matters in dating crises. Dating an event a crisis too early or too late can also lead to different estimates for output in the aftermath of a financial crisis. There are disagreements on crisis dates among researchers, with related differences regarding the real effects of financial crises.

Our research brings in information from credit spreads. Theory predicts that credit spreads should rise in financial crises, because crises are associated with high future default losses, a credit crunch, and high risk/illiquidity premia. Thus credit spreads are a signal of the severity of a financial crisis, and we use this information to better answer questions about financial crises.

To see why credit spreads are useful, consider first the issue of classifying events with varying severity as crises. Suppose that $\phi_{i,t}$ indexes the severity of a crisis, and a researcher defines a crisis by a dummy that takes the value one if $\phi_t^i > \underline{\phi}$, where $\underline{\phi}$ is a threshold a researcher uses to date a crisis. Suppose that the true relation between output growth over the next k periods and crisis severity is,

$$ln \; \frac{y_{i,t+k}}{y_{i,t}} = a_i + \beta\phi_{i,t}. \tag{1}$$

Researchers typically run the regression,

$$ln \; \frac{y_{i,t+k}}{y_{i,t}} = a_i + b1_{\phi^i_{i,t} > \underline{\phi}} + \epsilon_{i,t+k}$$

and use the estimated $\hat{b}$ to measure how different growth is in a crisis relative to a non-crisis. But it is clear that this estimate is sensitive to the choice of the cutoff $\underline{\phi}$, since,

$$\hat{b} = \beta \left(E[\phi_{i,t}|\phi_{i,t} > \underline{\phi}] - E[\phi_{i,t}|\phi_{i,t} \leq \underline{\phi}]\text{Prob}[\phi_{i,t} \leq \underline{\phi}] \right)$$

Different researchers date different events as crises, implicitly using different crisis thresholds, and thus reach different conclusions on the relation between financial crises and growth.

We can address this problem by using spreads. 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 shock occurs. Suppose that crisis severity is:

$$\phi_{i,t} = z_{i,t}\mathcal{F}_{i,t}$$

and suppose that the credit spread, which reflects expected default as well as risk/illiquidity premia, can be written as,

$$s_{i,t} = \gamma_0^i + \gamma_1 E_t\left[ln\ \frac{y_{t+k}^i}{y_{i,t}}\right] + \gamma_2\phi_{i,t} = (\gamma_1\beta + \gamma_2)\phi_{i,t} + u^i. \tag{2}$$

Then the spread in a crisis is an (imperfect) signal of crisis severity.

If instead of regression (1), we run the regression,

$$ln\ \frac{y_{t+k}^i}{y_{i,t}} = a^i + bs_{i,t}1_{\phi_t^i > \underline{\phi}} + \underline{b}s_{i,t}1_{\phi_t^i < \underline{\phi}} + \epsilon_{t+k}^i \tag{3}$$

we find that $\hat{b} \propto \beta$ and this estimate is independent of the choice of the cutoff. The regression works because it estimates off the cross-sectional variation in crisis severity and growth outcomes. Thus, even if different researchers identify different events as financial crises, as long as these events all involve a significant disruption in the financial sector, the variation within these events allows us to uncover the true relation between financial disruptions and output growth.

We show that estimating (3) identifies a statistically strong relation between crises and GDP losses 5 years after, for all three chronologies we consider (BE, RR, ST). Estimating (1) gives weak and varying estimates of the aftermath of a financial crisis. Our preferred estimates are based on the ST dates. For these dates, 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.

Thus far we have explained how using the information in spreads allows for sharper estimates of the relation between financial crises and output growth. There is a second problem with the literature's 0-1 approach to dating crises: there is enormous heterogeneity in the severity of crises. In our sample of crises, the mean peak-to-trough contraction is -6.2%, but the standard deviation of this measure is 7.3% (see Table 8). Given this variation, it is a nearly empty question to ask, what is growth following a typical crisis. Many academics and policy-makers are interested in answer the question, "How slow a recovery should we expect following the 2008-2009 financial crisis in the US?" Reinhart and Rogoff (2009a) measure the peak-to-trough contraction in crises as 9.3%, with this mean measured from a select sample 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, $E\left[ln\ \frac{y^i_{t+k}}{y_{i,t}}|\phi^i_t = 2008 \text{ conditions}\right]$ rather than $E\left[ln\ \frac{y^i_{t+k}}{y_{i,t}}|\phi_{i,t} > \underline{\phi}\right]$. 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.

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 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 $\phi_{i,t}$ is better measured using $s_{i,t} - s_{i,t-1}$ 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 from equation (2),

$$s_{i,t} - s_{i,t-1} = \gamma_1 \left(E_t \left[ln\ \frac{y_{i,t+k}}{y_{i,t}} \right] - E_{t-1} \left[ln\ \frac{y_{i,t+k}}{y_{i,t}} \right] \right) + \gamma_2 \phi_{i,t}$$

so that one would expect that the change in spreads is more directly related to changes in the expectation of output growth rather than the level of output growth. Thus the importance of changes in spreads is an additional signal of the start of a financial crises, allowing us an additional piece of information to date crises. 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. Thus this spread change evidence suggests that the ST dates better identify the start of a financial crisis.

While ST financial crises are triggered by large spread changes, do all large spread changes end in financial crises? We define events with large losses 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? The empirical answer is that large losses that are preceded by high credit growth end in crises. The result squares with theoretical models of a trigger, $z_{i,t}$, and an amplification mechanism, $\mathcal{F}_{i,t}$. Models tell us that surprises coupled with high fragility can lead to crises. High credit growth, following on Jorda *et al.* (2010), is one way to measure fragility. Thus we have two cases. A crisis as defined in the literature, $\phi_{i,t} > \underline{\phi}$, is a case where fragility is high and there a large surprise. In other cases, where there is less fragility, the surprise results in losses but does not pass through to the real sector. This 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 other, such as the 2008-2009 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.[1]

The point estimates for subsequent GDP growth following a large loss/high credit growth event are quite similar to the point estimates for GDP growth following ST crises. The result helps to resolve another debate with existing crisis dating methodologies. 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 and credit growth are quantitative criterion that can be measured ex-ante, without referencing subsequent output growth, and thus avoid this bias.

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 coupled with high credit growth lead to adverse real outcomes. Credit spreads reflect the probability of a large loss

[1] We can also think of this result in terms of the "triggers" and "vulnerabilities" dichotomy outlined in Bernanke (April 13 2012).

and the output effects of large loss/fragile financial sector:

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

We would 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' expectations of a large loss, Prob$(z_{i,t} > \underline{z})$ 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. Our results suggest that it is unusually high credit growth coupled with 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.

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, Shleifer, and Vishny (2013) present models where this surprise element is a key feature of crises.

To summarize, we show that:

1. The recessions that accompany financial crises are severe and protracted;

2. The severity of the 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); and,

3. Spreads fall pre-crisis and are too low, even as credit grows ahead of a crisis.

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, Kose and Terrones (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 (1991), Gilchrist and Zakrajsek (2012), Michael D. Bordo (2010), and Lopez-Salido, Stein, and Zakrajsek (2014). 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.* (2014) 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

Crisis dates come from three sources: Bordo, et. al., (2001), Reinhart and Rogoff (2009b), and Jorda *et al.* (2010) (henceforth BE, RR, and ST). The dates provided by Bordo, et. al., (2001) and Reinhart and Rogoff (2009b) are based on a major bank run or bank failure and contain the year the crisis itself began. The data from Jorda *et al.* (2010) date both the year of the crisis as well as the business cycle peak associated with the crisis. This typically occurs before actual bank run or bank failure. Many of the results we present are based on the ST business cycle peak date. We show robustness to all sets of dates.

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 1 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.

[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.

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

$$\ln\left(\frac{y_{i,t+1}}{y_{i,t}}\right) = a_i + a_t + b_0 \times spread_{i,t} + b_{-1} \times spread_{i,t-1} + \varepsilon_{i,t+k}. \tag{4}$$

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 (4) and holding the bs constant across countries. In the 2008-2009 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:

$$\hat{s}_{i,t} \equiv Spread_{i,t}/\overline{Spread^i} \tag{5}$$

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.

4 Result 1: Aftermath of Financial Crises

4.1 Variation within crises

Reinhart and Rogoff in their research emphasize that recessions accompanied by financial crises are particularly severe. Across a select sample of banking crises, Reinhart and Rogoff (2009a) report a mean peak-to-trough decline in output of 9.3%.

However, there is enormous variation in outcomes across the literature's defined financial crises. Figure 2 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 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.

[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)).

Focusing on the peak-to-trough decline, in the upper 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 8 provides statistics on the variation for the ST dates. The mean peak-to-trough decline is -7.2%, but the standard deviation is 8.0%. The median is -4.9%, which is smaller in magnitude than the mean, indicating that the distribution is left-skewed. The table also reports statistics for the RR and BE dates. The declines are smaller under BE and RR's dating convention because the declines are measured from the date of the crisis to the trough rather than from the previous peak. 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 3 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/

$$decline_{i,t} = a + b_0 \times \hat{s}_{i,t} + b_{-1} \times \hat{s}_{i,t-1} + c\Delta credit_{i,t} + \varepsilon_{i,t} \quad (6)$$

It is important to emphasize that the regression relates cross-sectional variation in spreads and the measure of severity. The average severity of crises is absorbed into the constant. Other papers, such as Reinhart and Rogoff, focus on the average severity in crises. In this regard, our research adds new information relative to the existing literature.

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 ST 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 next section, 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 3. The figure uses the ST dates and 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 (3) from the introduction. Given the importance of lagged spreads and credit growth, we modify (3) to estimate,

$$\begin{aligned} \ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) &= a_i + a_t + 1_{crisis,i,t}\left(b_0^{crisis} \times \hat{s}_{i,t} + b_{-1}^{crisis} \times \hat{s}_{i,t-1}\right) \\ &\quad +1_{no-crisis,i,t}\left(b_0^{no-crisis} \times \hat{s}_{i,t} + b_{-1}^{no-crisis} \times \hat{s}_{i,t-1}\right) + c'x_t + \varepsilon_{i,t+k} \end{aligned} \tag{7}$$

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.

Column (1) of Table 4 and 5 presents a baseline where we pool crises and non-crises, forcing the b coefficients to be the same across these events. This regression indicates that there is a relation between spreads and subsequent GDP growth, consistent with results from the existing literature (see, for example, Gilchrist and Zakrajsek (2012)).

Columns (2)-(5) 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 3. High current spreads forecast more severe crises. The lagged spread comes in with a positive coefficient that is significantly different than zero in many of the specifications. The effects are statistically stronger at the 3-year horizon as reported in Table 5. The effects are also strongest for the ST dates, both in terms of magnitudes and statistical significance.

The results in Tables 4 and 5 should be compared to the results in Table 6. There we run a regression to estimate 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,

$$ln\ \frac{y_{i,t+k}}{y_{i,t}} = a_i + a_t + \beta 1_{crisis,i,t} + c'x_t + \varepsilon_{i,t+k}. \tag{8}$$

which corresponds to (1) in the introduction, and what other researchers have measured. There is only weak statistical evidence of output declines based on this dummy variable approach for the RR and BE dates. The ST dates show significant output declines out to 5 years. In contrast, we find strong statistical evidence of output declines out to 5 years for all sets of dates when using spreads.

Figure 4 plots the evolution of GDP to a one-sigma shock to spreads (a shock of $\Delta\hat{s} = 1$), conditional on ST crises (top panel) and RR crises (lower panel). Focusing on the ST dates, we see that output falls, reaching a low at the 4-year horizon of -9% before recovering. The pattern is similar for the RR dates although smaller in magnitude with output falling -3%

at the 4-year horizon. The difference between ST and RR is likely due to the fact that RR date the crises typically later than ST.

The impulse responses in Figure 4 are computed by forecasting GDP individually at all horizons from 1 to 5 years using the local projection methods in Jordà (2005) (see also Romer and Romer, 2014). That is, we estimate (7) for $k = 1, ..., 5$ and use the individual coefficients on spreads to trace out the effect on output given a one-sigma shock to our normalized spreads. Thus the plot in Figure 4 is the difference in output paths for two financial crises, 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.

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.

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,

[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.

then the difference between in 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 100 basis point 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 shock in a recession, $z_t^{recession}$ that leads a 100 basis point change in spreads is likely larger than the shock, z_t^{crisis}, that leads to a 100 basis point change in spreads. In the crisis, the shock z_t^{crisis} increase expected default and risk premia, while the same shock in recession likely largely increases expected default.

Figure 10 presents the results. The top panel presents results based on unconditional regressions, i.e., a regression pooling crises and non-crises dates. We see that output declines by about 1% 5 years after a shock to spreads. The lowest panel presents results for non-financial crisis recessions. Here also we see a decline of about 3% 5 years out. The middle panels presents results for our three dating conventions. The largest effects are with the ST dates (around 9% decline), while the estimates for the RR and BE dates are around 3% decline. 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 in value-weighted 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. Thus our results are new to the literature.

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 5 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 using the (7) with spread as dependent variable. Our forecasts are based on estimating regression (7), with an additional regressor of 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 (7) 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, 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 Result 2: Losses and Crises

Theoretical models of financial crises trace the effects of losses on assets held by the financial sector (i.e., a shock $z_{i,t}$) to disruptions in financial intermediation which affects output growth. Since the financial sector primarily holds credit-sensitive assets, the change in spreads can proxy for financial sector losses. Thus we should expect that the change in spreads, more so than the level of spreads, should correlate with the subsequent severity of crisis. This section presents results consistent with this prediction.

To be more formal, suppose that spreads are:

$$s_{i,t} = \gamma_{i,0} + \gamma_1 E_t \left[ln \ \frac{y_{i,t+k}}{y_{i,t}} \right] + \gamma_2 \phi_{i,t} + l_{i,t}.$$

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, causing $z_{i,t}$ to rise. 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 terms $\gamma_1 \phi_{i,t} + l_{i,t}$ 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. 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)).

5.1 Change in spreads

In Tables 3, 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 3 regresses the peak-to-trough decline in GDP on the change 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) - (8) of Table 3. These results are consistent with crises theories which highlight the losses suffered by levered financial institutions on credit assets.

These results on the importance of the change in spreads are most visible for the ST crisis dates. For this reason we think the ST dates provide a better gauge of the recessions associated with financial crises. That is, the behavior of spreads around these dates is most consistent with theoretical crisis models. For the RR and BE dates, while the level of spreads in the year dated as a crisis is significantly related to the severity of the crisis, the lagged spread has considerably less explanatory power. We think this is because RR and BE date the crisis as the year when banks fail. Financial intermediation is likely disrupted well ahead of the actual event of bank failure, so that the ST dates provide a better gauge of the start of a crisis.

5.2 Spreads and output skewness

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

Table 7 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 6 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.

5.3 Large losses, fragility, and crises

We examine further the relation between spikes in spreads and tail outcomes. 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, SpreadCrisis defines events with widespread asset losses.

Figure 8 provides a visual representation of how SpreadCrises overlap with the ST crises. There is considerable overlap in the dates, although there are many events that are labeled "Spread Crises" that are not ST crises.

The first row of the top panel of Table 9 presents the average path of GDP conditional on a SpreadCrisis event. We see that there is reduction in output that persists for many years. These numbers are directly comparable to the numbers in Table 6 where we report average values of GDP declines following ST/BE/RR crisis. The SpreadCrisis event yields larger and more persistent declines than the BE/RR. For example, the 3-year decline is -4.45% after SpreadCrisis while it is -2.09% (RR) and -2.16% (RR). The numbers are not as large as those ST, for which the average 3-year decline is -5.26% (ST).

When do large losses 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 $\mathcal{F}_{i,t}$) leads to the crisis event. We examine this prediction in the data, by constructing a fragility indicator based on Jorda *et al.* (2010). In the second row of Table 9 we interact SpreadCrisis with a dummy for whether credit growth has been above median in the 3 years before the crisis. The average GDP declines in this subsample are larger, in line with theory, and slightly higher than the number for ST in Table 6. The bottom panel of Table 9 presents this interaction regression a different way. We interact spreads and lagged spreads with 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 Tables 4 and 5. At the 3-year horizon, the coefficient in the credit/spread crisis interaction is -4.85, which compares to the coefficient in Table 4 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 not as large as ST, but larger than BE and RR. Finally, 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.

Figure 11 presents impulse responses of output to a shock of 1 in the spreadnorm variable. We present the results in a single graph for all of the regressions we have presented in this paper. The largest declines are using the ST dates. The results for the spreadcrisis/creditgrowth episodes are smaller than for ST, but larger than the other dating conventions which all give a 5 year decline around 3% of GDP.

5.4 Peek-ahead bias

The results of this section also allay concerns about peek-ahead bias with existing crisis chronologies (see Romer and Romer, 2014). The concern is that if crisis dates are picked with knowledge about GDP outcomes, then the dates may be biased to favor the conclusion that the aftermath of crises is a deep and protracted recession. Spreads and credit growth are variables that are defined ex-ante with no knowledge of subsequent GDP growth, and our results therefore show that the peek-ahead bias is not a significant problem with existing crisis dates.

5.5 2008 crisis and recovery, V2

Figure 9 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. The upper panel plots the actual and predicted path of output for the 2008-2013 using specification (7). The actual 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 the specification of Table 9 where we condition on both spread-crises and credit growth. 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.

The lower panel presents results for the actual and predicted path of spreads. We consistently find that spreads in the recent crisis recovered faster than output.

6 Result 3: Pre-crisis Expectations

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, Stein, and Zakrajsek, 2014). 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 probability of a large loss and the output effects of large loss/fragile financial sector:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{ Prob}(z_t > \underline{z}) \overbrace{E_t \left[ln \ \frac{y^i_{i,t+k}}{y_{i,t}} |\text{crisis} \right]}^{\downarrow \text{ in } \mathcal{F}_{i,t}} . \tag{9}$$

We may expect that as $\mathcal{F}_{i,t}$ rises before a crisis, that credit spreads also rise.

Table 10 examines this question. Columns (1), (2), (5), and (6) 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 a crisis (ST crisis in (1) and (2), and RR in (5) and (6)), 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) and (7) show 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, 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 (9), we can view this result as suggesting that investors' expectations of a large loss, $\text{Prob}(z_t > \underline{z})$ falls as credit growth rises, and this fall is enough to more than offset the fragility effect of credit growth. One caveat to this result is that it is driven by common global factors (e.g., Depression and Great Recession). Columns (4) and (8) of the table report results include a time fixed effect. Including the time fixed effect considerably weakens the explanatory power of the sign-switching credit growth covariate.

Figure 12 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 11 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 12. 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 Schularick and Taylor, we know that credit growth is a predictor of crises. But credit growth can arise both with increased credit demand as well as increased credit supply. Relative to Schularick and Taylor, 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 Schularick and Taylor.

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, Shleifer, and Vishny (2013) present models where this surprise element is a key feature of crises.

7 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 that the severity of the 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.

8 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.

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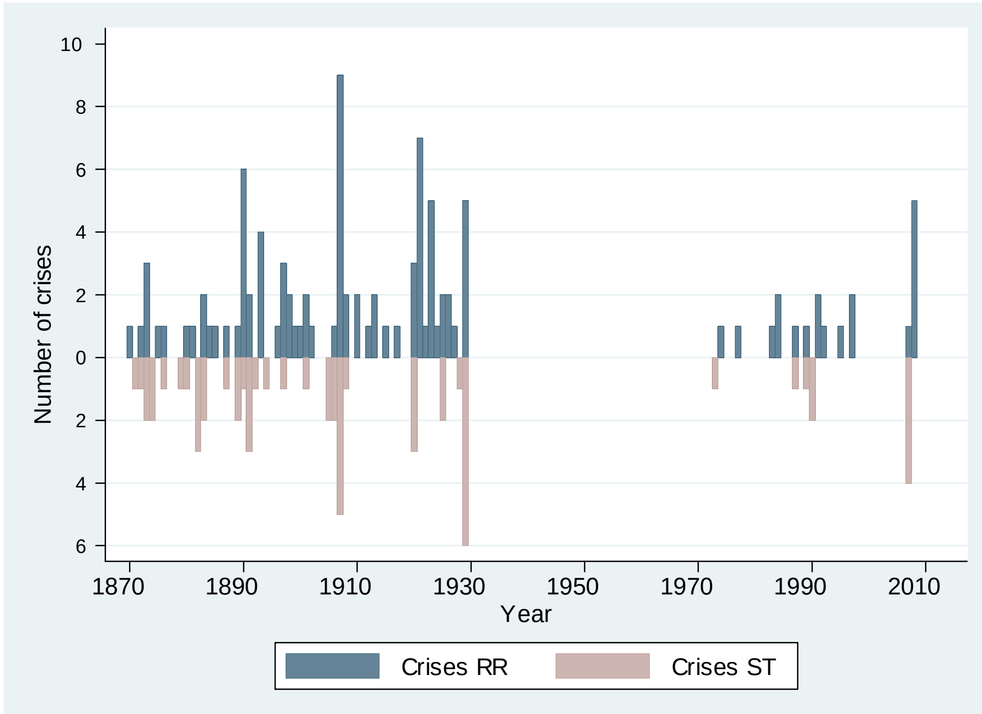

Figure 1: This figure plots the incidence of crises over time across various countries from 1870-2008. RR denotes those measured by Reinhart and Rogoff and ST denotes those measured by Schularick and Taylor. We only plot these variables for countries and dates for which we have credit spread data to give a sense of the crises covered by our data.

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9 Tables and Figures

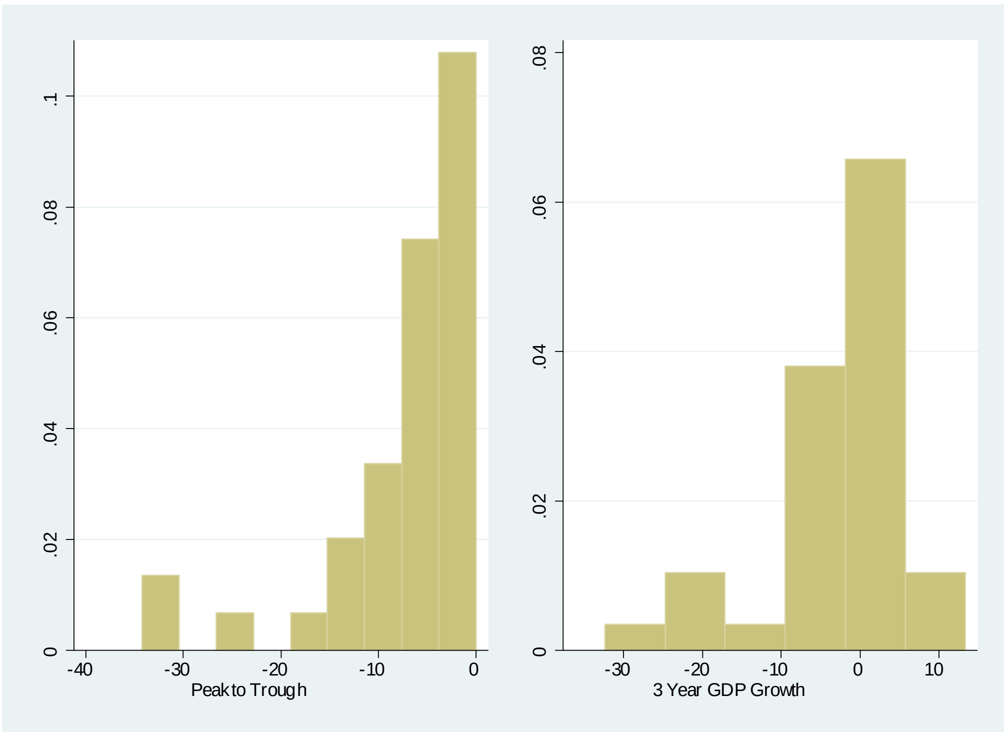

Figure 2: This figure shows the empirical distribution of outcomes in GDP across financial crises using crisis dates from Schularick and Taylor. The left panel plots peak to trough declines in GDP while the right panel plots cumulative GDP growth over a 3 year period after the start of the crisis. In both, we emphasize the significant heterogeneity in outcomes.

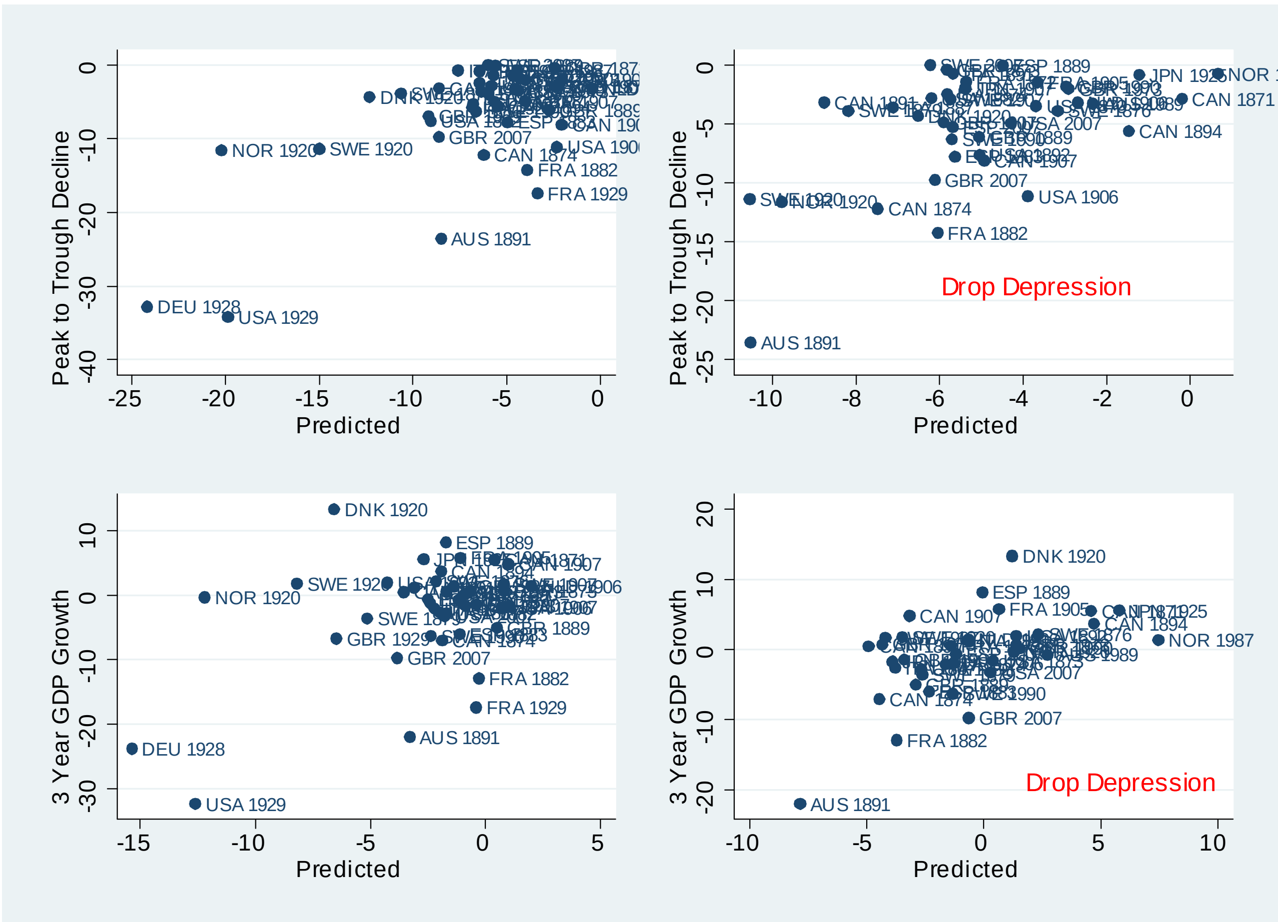

Figure 3: We plot the predicted vs actual declines in GDP in crises formed using the current and lagged spread as forecasters and using crisis dates from Schularick and Taylor. We include predicted peak to trough declines (top) as well as the predicted 3 year growth rate (bottom). The right panel re-does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

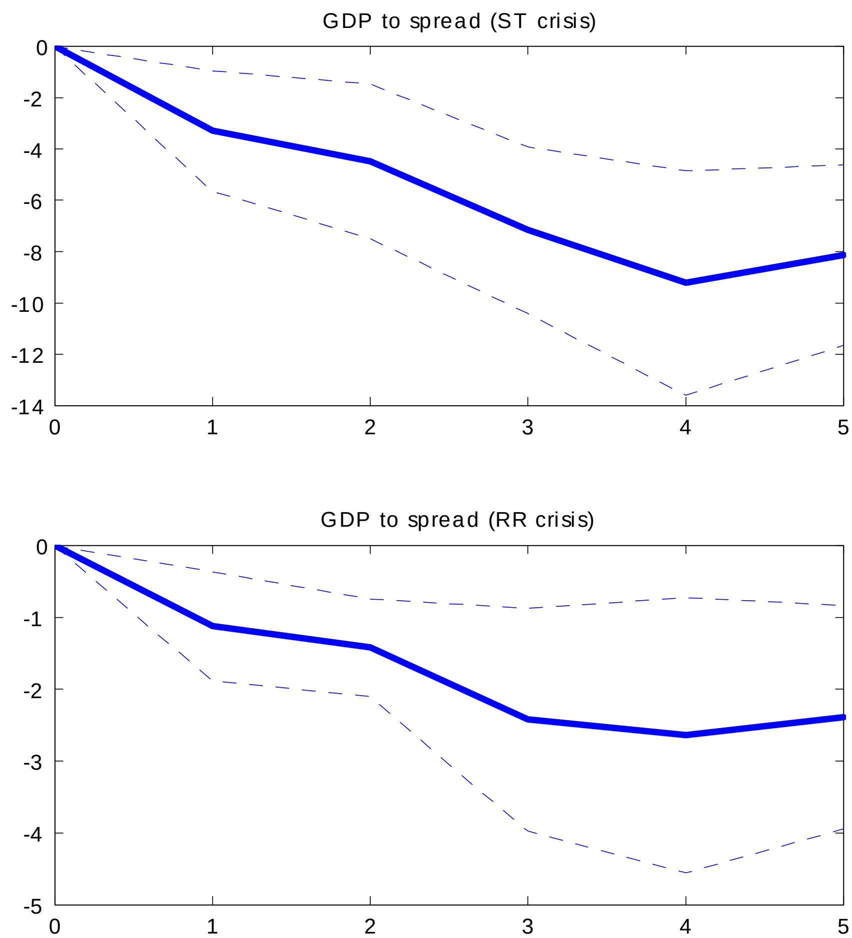

Figure 4: This figure plots the impulse responses of GDP and normalized spreads to an innovation of one (approximately one-sigma) in our spread measure during crisis episodes. We show this for Schularick and Taylor crises in the top panel (labeled ST crisis) as well as during Reinhart and Rogoff crises in the lower panel (labeled RR crisis). Impulse responses are computed using local projection measures where we forecast GDP independently at each horizon.

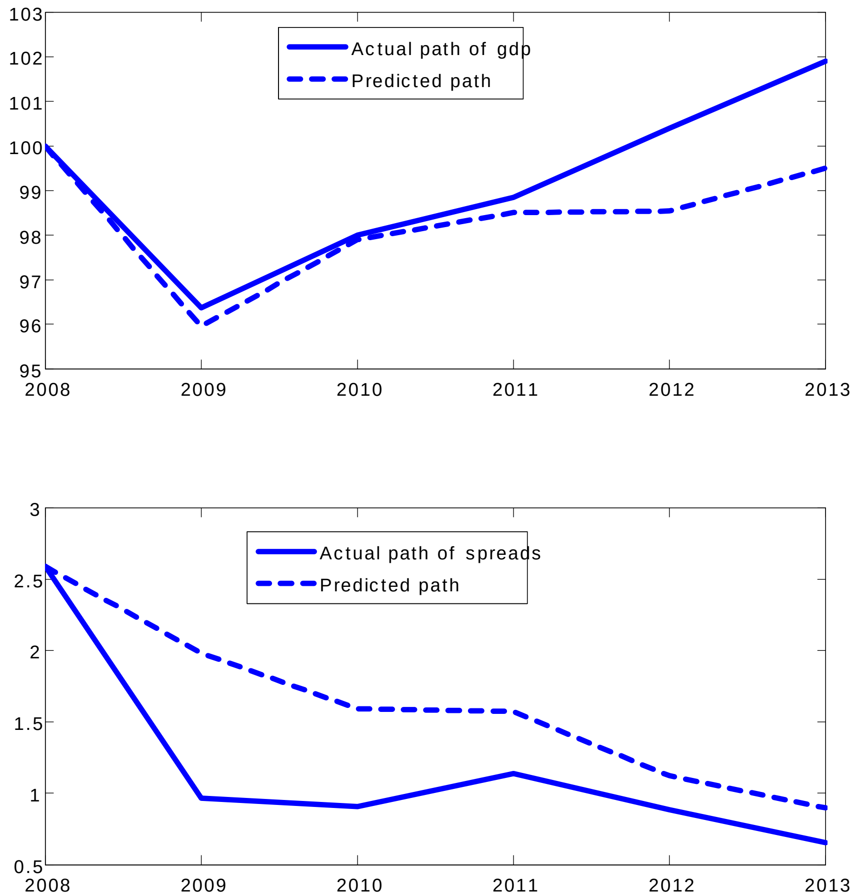

Figure 5: We predict outcomes of output and spreads during the 2008 US financial crisis using predicted values from our regressions and data up to 2008. The top panel, GDP, is cumulative from a base of 100 in 2008. The lower panel, spreads, uses the last quarter value of the BaaAaa spread in 2008. Our predicted value is formed using the Schularick and Taylor crisis dates.

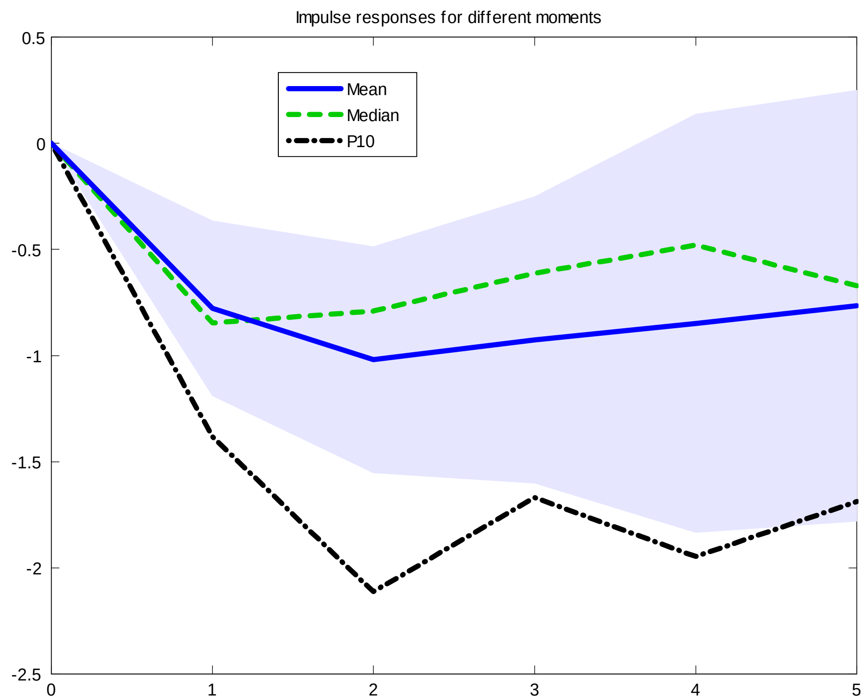

Figure 6: We plot impulse responses of GDP to an innovation of one (approximately one-sigma) in spreads for various moments: the mean, median, and 10th percentile. All impulse responses use the Jorda local projection method where we use quantile regression or OLS depending on the moment plotted. 95% confidence intervals are given in colored shaded regions.

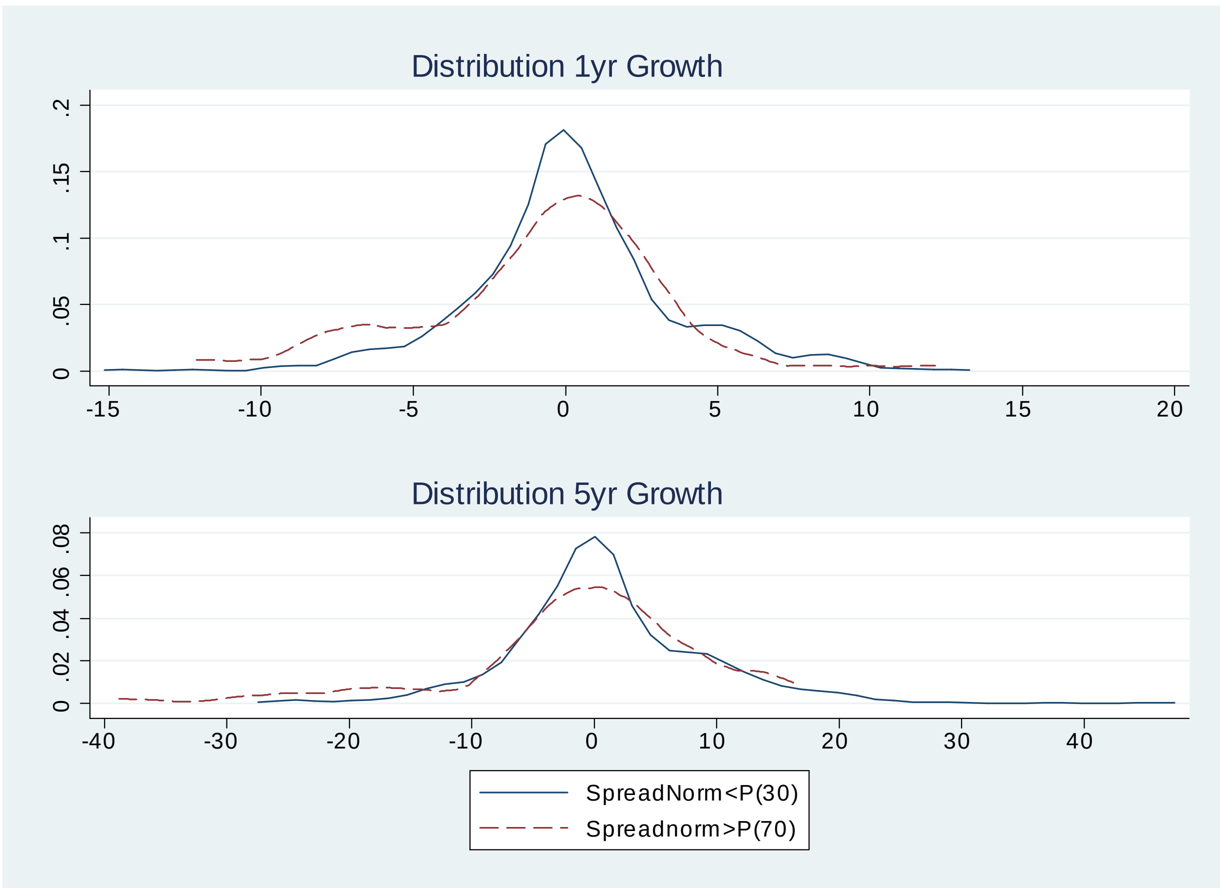

Figure 7: This figure plots the distribution of GDP growth at various horizons conditional on spreads based on a kernel density estimation. The blue solid line plots the distribution of GDP growth when spreads are in the lower 30% of their realizations, the red dashed line plots the distribution when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

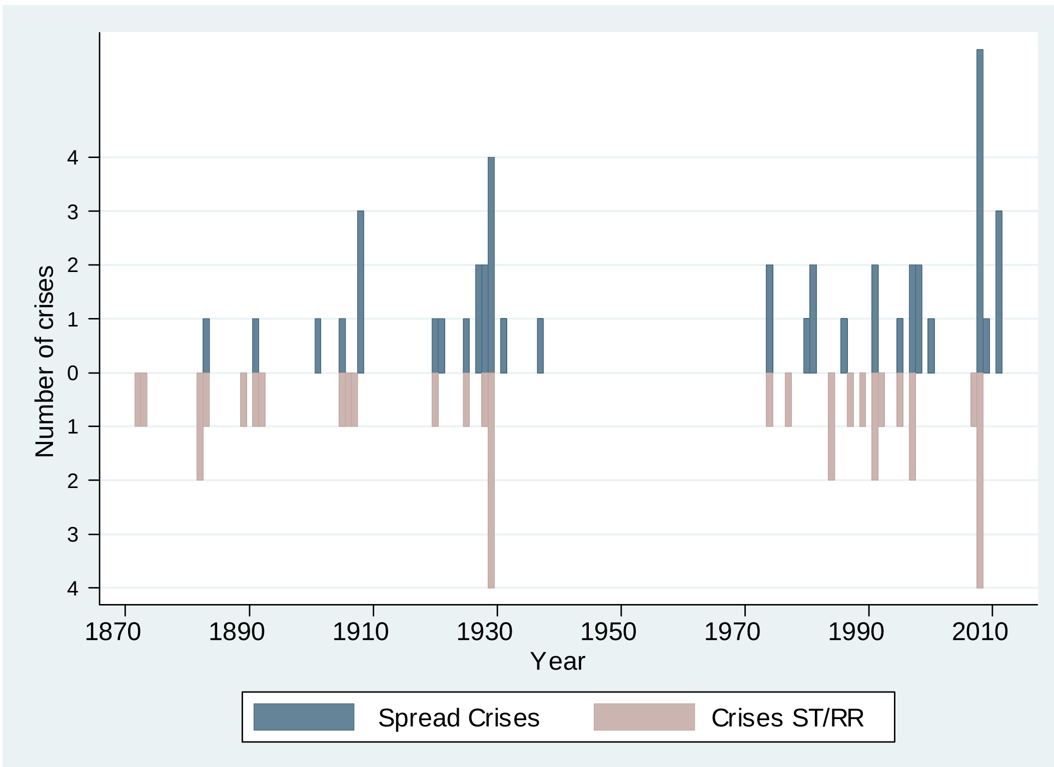

Figure 8: We plot our spread crises counts by year along with counts from Schularick and Taylor for crisis dates. Our spread crisis dates are defined as an increase in spreads above a given threshold as well as an increase in the dividend/price ratio above median. As described in the text, this threshold is chosen to give approximately the same total number of crises as Schularick and Taylor.

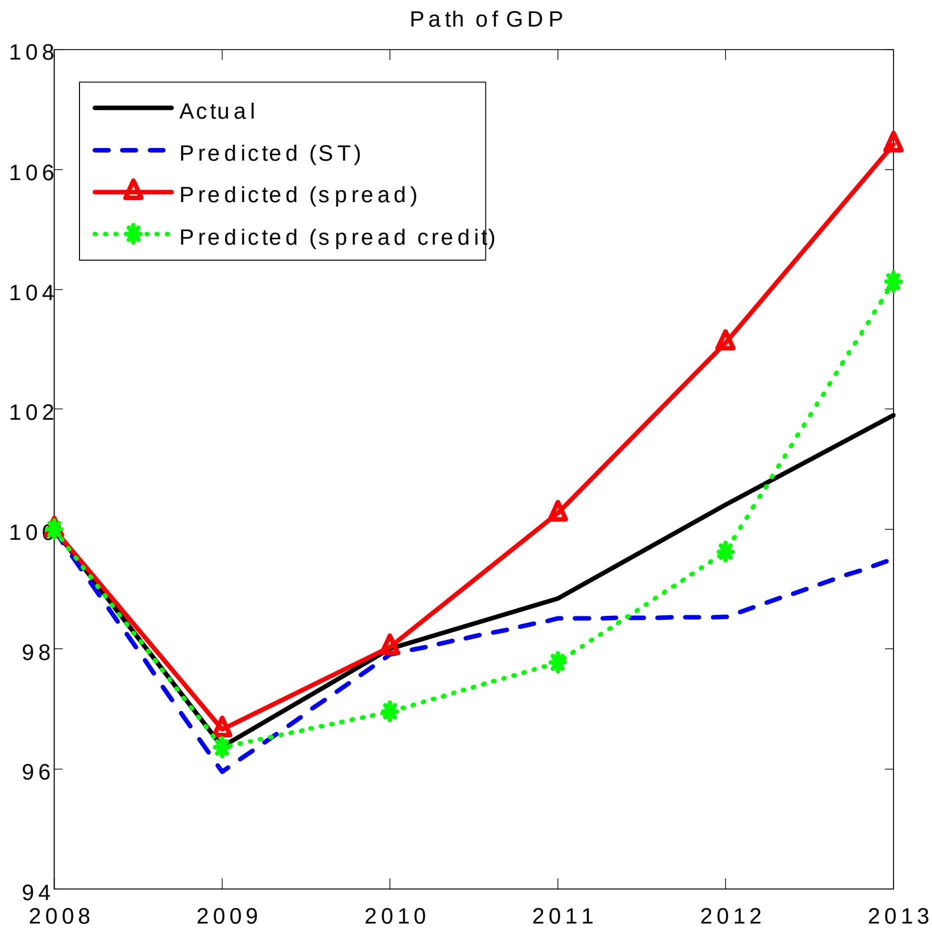

Figure 9: We predict outcomes of output and spreads during the 2008 US financial crisis using predicted values from our regressions and data up to 2008. The top panel, GDP, is cumulative from a base of 100 in 2008. The lower panel, spreads, uses the last quarter value of the BaaAaa spread in 2008.

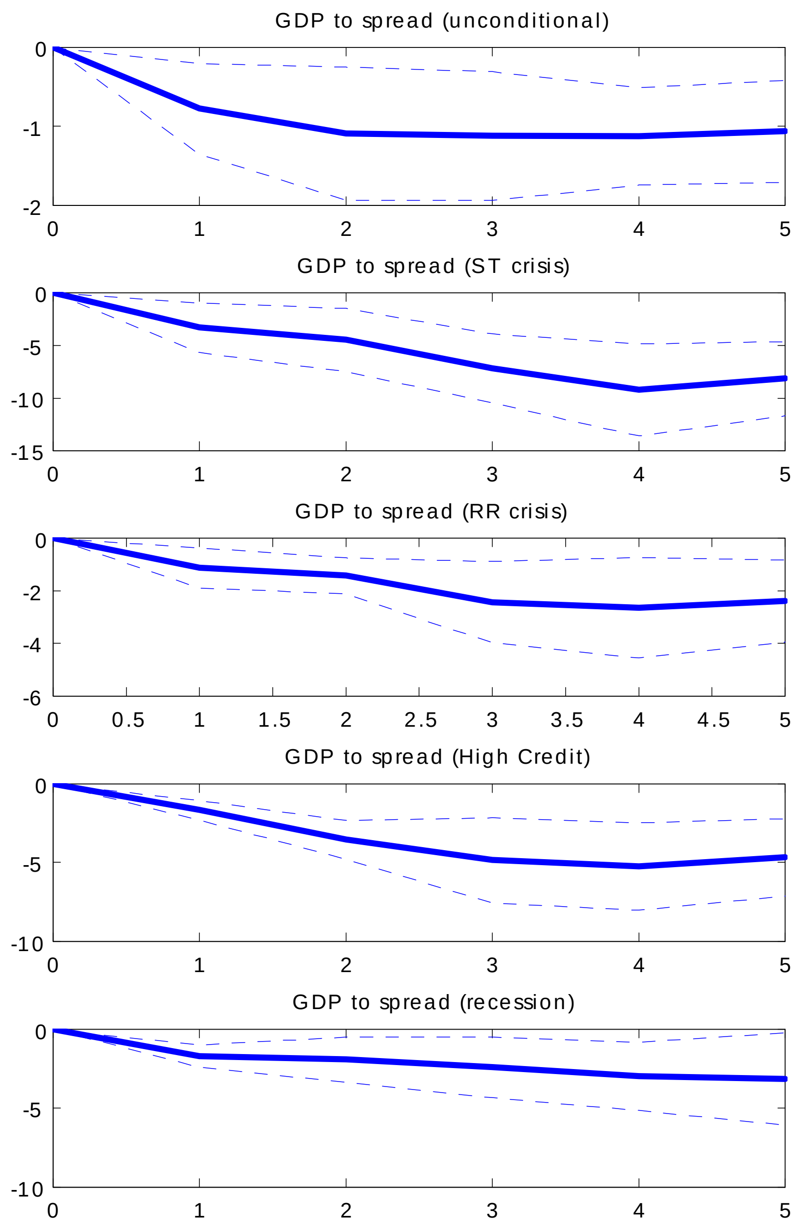

Figure 10: This figure plots the impulse responses of GDP and normalized spreads to an innovation of one (approximately one-sigma) conditional on various episodes. We show this unconditionally in the top panel as well as during crises in the lower panels, where crises are defined using Schularick and Taylor (ST), Reinhart and Rogoff (RR), or using high credit growth episodes (High Credit). The last panel gives these results using non-financial recessions defined by ST. Impulse responses are computed using local projection measures where we forecast GDP growth independently at each horizon.

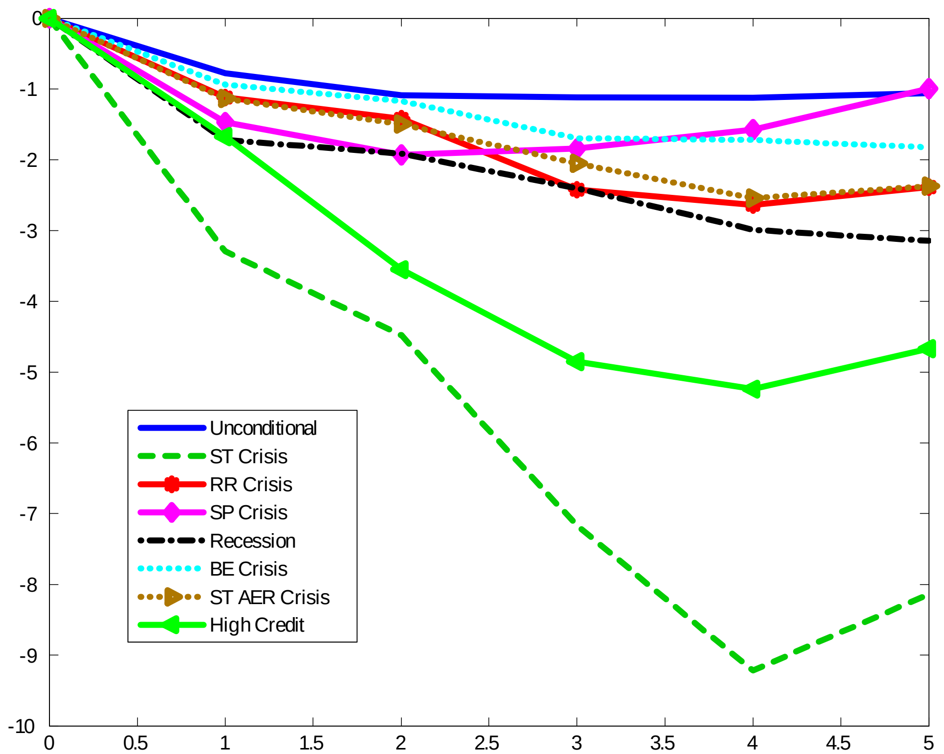

Figure 11: This figure plots impulse responses to an innovation of one (approximately one-sigma) in our spread variable. This is done unconditionally (blue solid line), conditional on a non-financial recession (black dashed line), and conditional on a financial crisis. We use many alternative dates for the financial crisis and show that in all dating conventions the impulse responses are reasonably close and are lower than both unconditional and recession estimates. See text for dating details.

Figure 12: This figure plots the path of spreads, fundamental spreads, and credit 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.

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.

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

Table 3: This table 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 Schularick and Taylor 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 credig/GDP ratio from Schularick and Taylor. Standard errors in parenthesis.

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

VARIABLES	(1) ST Crisis	(2) ST Crisis	(3) ST Crisis	(4) ST Crisis	(5) ST Crisis	(6) Recess	(7) Recess
$\widehat{s}_{i,t}$	-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 4: This table provides regressions of future GDP growth on credit spreads at the 5 year horizon (top and bottom panels, respectively). 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 from Schularick and Taylor, and both country and year fixed effects. Standard errors clustered by country in parenthesis.

VARIABLES	(1) 5yr	(2) 5yr	(3) 5yr	(4) 5yr	(5) 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 5: This table provides regressions of future GDP growth on credit spreads at the 3 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 from Schularick and Taylor, as well as both country and year fixed effects. Standard errors clustered by country in parenthesis.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	3yr	3yr	3yr	3yr	3yr
$\widehat{s}_{i,t}$	-1.16				
	(0.29)				
$\widehat{s}_{i,t-1}$	0.78				
	(0.51)				
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-7.17			
		(1.21)			
$\widehat{s}_{i,t-1} \times 1_{crisisST,i,t}$		6.26			
		(1.45)			
$\widehat{s}_{i,t} \times 1_{crisisRR,i,t}$			-2.42		
			(0.80)		
$\widehat{s}_{i,t-1} \times 1_{crisisRR,i,t}$			0.78		
			(0.51)		
$\widehat{s}_{i,t} \times 1_{crisisBE,i,t}$				-1.15	
				(0.34)	
$\widehat{s}_{i,t-1} \times 1_{crisisBE,i,t}$				0.60	
				(0.63)	
$\widehat{s}_{i,t} \times 1_{recess,i,t}$					-2.40
					(0.98)
$\widehat{s}_{i,t-1} \times 1_{recess,i,t}$					0.14
					(0.80)
Observations	641	641	641	533	641
R-squared	0.54	0.56	0.55	0.56	0.55
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 6: This table provides regressions of our normalized spread measure on lagged spreads conditional on crises and normal times. Standard errors clustered by year. 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 in parenthesis.

$$\widehat{s}_{i,t+1} = a_i + b\widehat{s}_{i,t} + cx_{i,t} + e_{i,t+1}$$

	(1)	(2)	(3)	(4)
VARIABLES				
Δlev	4.04	3.87	4.09	4.12
	(1.61)	(1.44)	(1.61)	(1.58)
$\widehat{s}_{i,t}$	0.67			
	(0.15)			
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		0.50		
		(0.33)		
$\widehat{s}_{i,t} \times (1 - 1_{crisisST,i,t})$		0.68		
		(0.16)		
$\widehat{s}_{i,t} \times 1_{crisisRR,i,t}$			0.44	
			(0.36)	
$\widehat{s}_{i,t} \times (1 - 1_{crisisRR,i,t})$			0.69	
			(0.16)	
$\widehat{s}_{i,t} \times 1_{recess,i,t}$				1.16
				(0.26)
$\widehat{s}_{i,t} \times (1 - 1_{recess,i,t})$				0.62
				(0.15)
$\widehat{s}_{i,t-1}$	0.12	0.12	0.13	0.09
	(0.14)	(0.14)	(0.14)	(0.13)
$1_{crisisST,i,t}$		0.51		
		(0.25)		
$1_{crisisRR,i,t}$			0.58	
			(0.27)	
$1_{recess,i,t}$				-0.32
				(0.23)
Observations	449	449	449	449
R-squared	0.51	0.51	0.52	0.53
Country FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Table 7: 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 8: 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 Schularick and Taylor, Reinhart and Rogoff, and Bordo and Eichengreen, 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 9: 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?

VARIABLES	(1) 1yr	(2) 1yr	(3) 2yr	(4) 2yr	(5) 3yr	(6) 3yr	(7) 4yr	(8) 4yr	(9) 5yr	(10) 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

VARIABLES	(1) 1yr	(2) 2yr	(3) 3yr	(4) 4yr	(5) 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 10: 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. We repeat this both using ST and RR crisis dates. Standard errors clustered by time in parenthesis.

VARIABLES	(1) ST	(2) ST	(3) ST	(4) ST	(5) RR	(6) RR	(7) RR	(8) RR
$1_{t-5,t-1}$	-0.24	-0.36	-0.00	-0.32	-0.30	-0.20	-0.17	-0.25
	(0.11)	(0.14)	(0.18)	(0.20)	(0.11)	(0.14)	(0.10)	(0.14)
$(\Delta Credit_{t-1})$ X			-2.83	-0.51			-1.77	-0.75
$1_{t-5,t-1}$			(1.15)	(1.18)			(0.74)	(0.82)
$\Delta Credit_{t-1}$	0.88	0.90	1.27	0.97	0.86	0.86	1.22	0.70
	(0.48)	(0.58)	(0.52)	(0.62)	(0.47)	(0.57)	(0.56)	(0.63)
ΔGDP_{t-1}	-2.70	-0.16	-2.68	-0.18	-2.70	-0.32	-2.52	-0.37
	(1.74)	(1.68)	(1.73)	(1.68)	(1.75)	(1.69)	(1.75)	(1.67)
Observations	621	621	621	621	621	621	621	621
R-squared	0.06	0.40	0.07	0.40	0.07	0.39	0.07	0.39
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	Y	N	Y	N	Y	N	Y

Table 11: 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 12: This table provides regressions of future GDP growth on event dummies. Controls include two lags of GDP growth, the 3 year growth in credit/GDP from Schularick and Taylor, as well as both country and year fixed effects. Standard errors clustered by country in parenthesis.

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

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