How Credit Cycles across a Financial Crisis*

Arvind Krishnamurthy
Stanford GSB and NBER

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

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*emails: a.krishnamurthy@stanford.edu and tyler.muir@anderson.ucla.edu. We thank Michael Bordo, Gary Gorton, Robin Greenwood, Francis Longstaff, Emil Siriwardane, Jeremy Stein, David Romer, Chris Telmer, Alan Taylor, Egon Zakrajsek, and seminar/conference participants at Arizona State University, AFA 2015 and 2017, Chicago Booth Financial Regulation conference, NBER Monetary Economics meeting, NBER Corporate Finance meeting, FRIC at Copenhagen Business School, Riksbank Macro-Prudential Conference, SITE 2015, Stanford University, University of Amsterdam, University of California-Berkeley, University of California-Davis, UCLA, USC, Utah Winter Finance Conference, and Chicago Booth Empirical Asset Pricing Conference. We thank the International Center for Finance for help with bond data, and many researchers for leads on other bond data. We thank Jonathan Wallen and David Yang for research assistance.

1 Introduction

We characterize the dynamics of credit markets and output across a financial crisis cycle, contributing to a literature that examines the empirical links between credit and the macroeconomy. This literature has sought answers to two main questions: (1) What is the aftermath of a financial crisis, and in particular, what factors lead to a more protracted post-crisis recession? See papers by Bordo *et al.* (2001), Cerra and Saxena (2008), Reinhart and Rogoff (2009), Claessens *et al.* (2010), Bordo and Haubrich (2012), Jordà *et al.* (2011), Schularick and Taylor (2012), Romer and Romer (2014). (2) What does the run-up to a crisis look like, and what credit variables help to predict a crisis? See papers by Schularick and Taylor (2012), Jordà *et al.* (2011), Baron and Xiong (2017), López-Salido *et al.* (2017), Mian *et al.* (2017).

We revisit these questions with new data. In particular, our research brings in information from credit spreads, i.e., the spreads between higher and lower grade bonds within a country, while much of the research cited above has focused on quantity data such as credit-to-GDP. 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 López-Salido *et al.* (2017)). However, the US has only experienced two significant financial crises over the last century. We collect information on credit spreads internationally dating back 150 years and across 19 countries, and thus more comprehensively examine the relation between credit and financial crises.[1]

We summarize our findings as follows:

- A large increase in credit spreads presages the economy's transition into a financial crisis. Crises involve a sudden shift in investors' expectations and, therefore, are a surprise.

- The severity of a financial crisis, in terms of the decline in output, is informed by the size of the increase in credit spreads coupled with the extent of the pre-crisis growth in credit.

- Crises are preceded by unusually high credit growth and unusually narrow credit spreads; that is, frothy credit-market conditions.

- Frothy credit market conditions help to forecast the incidence of crises.

[1] In work that was begun contemporaneously, Mian *et al.* (2017) examine credit spreads in international data going back to the 1970s.

The first two findings describe what happens in a crisis and what factors are associated with worse crises, which is question (1) that prior research has addressed. This work, in particular Schularick and Taylor (2012), demonstrates that growth in credit-to-GDP in the years before a crisis presages a worse crisis. We complement this result by showing that the extent of the rise in credit spreads at the start of a crisis – loosely, the size of the shock – coupled with pre-crisis credit growth better describes the aftermath of a crisis than either the shock or the credit-growth run up, separately. As we discuss below, this interaction result conforms well to existing theoretical models of financial crises.

The second two findings describe the preconditions for a financial crisis, which is question (2) of prior research. Our answer is froth, consistent with Baron and Xiong (2017), Schularick and Taylor (2012). Relative to this work, we show that low credit spreads and high credit growth offer the sharpest signal of a coming crisis. Prior work has shown that each of these signals separately has contains information for predicting crises. We replicate this finding in our data, adding the new result that a combined signal has the most information for predicting cries. We also show that these signals do not forecast recessions. The information is special to crises. Finally, we run out-of-sample regressions where we construct our signals using data only upto time t and use the signal to forecast a crisis after date t. While the statistical significance of our results are weakened in this exercise, our basic finding continue to hold. Our results support narratives where credit supply expansions play an important role in the run-up to a crisis.

While we find a strong association between froth and crises, we find a much weaker association between froth and average future declines in output. Moreover, out-of-sample, the sign on the relationship changes and is not statistically different than zero. Our results indicate that froth is associated with a greater likelihood of the left-tail crisis event, but not especially a change in mean output realizations. This result is inconsistent with that reported in López-Salido *et al.* (2017), Mian *et al.* (2017). On the other hand, these papers do not especially study financial crises and study smaller samples than we do.

Our results shed light on theories of financial crises. Theoretical models describe crises as the result of a shock or trigger (losses, defaults on bank loans, the bursting of an asset bubble) that affects a fragile financial sector. Denote these losses as $z_{i,t}$ ($E_t[z_{i,t}] = 0$, for country-i, time t). Theory shows how the shock is amplified, with the extent of amplification driven by the fragility of the financial sector (low equity capital, high leverage, high short-term debt financing). Denote $\mathcal{F}_{i,t}$ as the fragility of the financial sector. Then models suggest that the severity of the crisis should depend on $\mathcal{F}_{i,t} \times z_{i,t}$. A sizable shock to a fragile financial sector results in a financial crisis with bank runs as well as a credit crunch, i.e., a decrease in loan supply and a rise in lending rates relative to safe rates. Asset market risk premia also rise as investors shed risky assets. All of this leads to a rise in credit spreads a reduction in the quantity of credit and a deep recession. See Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), He and Krishnamurthy (2012), Brunnermeier and Sannikov (2012), Moreira and Savov (2014), and Krishnamurthy and Li (2020) for theoretical models of credit markets and crises. We label this theoretical characterization of financial crises as the "FZ" model of crises.

The FZ model is supported by our empirical evidence. Jordà *et al.* (2011) show that growth in credit-to-GDP helps forecast the occurrence of a crisis as well as the severity of the crisis. Growth in credit from the banking sector is largely funded by bank debt issues and hence through increased leverage of the banking sector (see Krishnamurthy and Vissing-Jorgensen (2015)). This suggests that growth in credit-to-GDP can measure the increase in fragility of the financial sector ($\mathcal{F}_{i,t}$). We show that a jump in spreads, which can represent the shock $z_{i,t}$, coupled with fragility best characterizes the severity of a crisis. 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. Our answer is that in the former case, fragility was not particularly high, while in the latter case, fragility was high.

Additionally, the evidence indicates that the relevant spread information is embedded in the change in spreads rather than the level of spreads. The result is consistent with the FZ model. Bank assets are credit sensitive whose prices will move along with credit spreads. Thus the change in spreads from pre-crisis to crisis will be closely correlated with bank losses, and measure the z-shock in the FZ model. The result is also inconsistent with other models of the relation between spreads and subsequent GDP outcomes. Spreads may be passive forecasters of GDP outcomes because they are forward looking measures of expected default by corporations. But under this passive forecast model, the level of spreads at time t, $s_{i,t}$, should be the best signal regarding future output growth. Indeed we find that in non-financial recessions, the level of spreads at time t rather than the change in spreads better predicts output declines. This is the common finding in the literature examining the forecasting power of credit spreads for GDP growth (see Friedman and Kuttner, 1992, Gertler and Lown, 1999, Philippon, 2009, Gilchrist and Zakrajsek, 2012). Under this passive-forecast model, one would expect that the change in spreads is more directly related to the change in the expectation of output growth rather than the level of output growth. Thus our finding on the importance of the change in spreads appears most consistent with the FZ model.

Our second set of results relating froth to crises are consistent with narratives in which expansions in credit supply are an important precursor to crises. Kindelberger (1978) is a prominent reference for this narrative, which has been taken up more recently by a number of studies (see Jordà *et al.*, 2011, 2013, Baron and Xiong, 2017, Mian *et al.*, 2017). Jordà *et al.* (2011) 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.

Credit spreads reflect the risk-neutral probability (true probability times risk-premium adjustment, denoted $\mathcal{Q}$), of a large loss and the (risk-neutral) expectation of output declines following a crisis:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{ Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{crisis}]$$

where, $\text{Loss}_{i,t}$ is increasing 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. 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 two sets of results, describing the evolution of crises based on fragility × losses and describing the runup to crises in terms of froth, are our main findings. They provide guidance for theories of financial crises. Models such as Gertler and Kiyotaki (2010), He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2012) are FZ models and are the types of models that can match the evolution and aftermath of a crisis. However, these models will not match the pre-crisis spread evidence. In the models, a prolonged period in which fragility and leverage rises will also be coupled with an increase in spreads and risk premia. That is, the logic of these models is that asset prices are forward looking and will reflect the increased risk of a crisis as fragility grows. The spread evidence is more consistent with models of belief formation in which agents discount the likelihood of a crisis. In Moreira and Savov (2014), severe crises are preceded by periods of low spreads where agents think a crisis is unlikely and hence increase leverage. In this case, if an unlikely large negative shock occurs, the crisis will be severe. In behavioral models such as Gennaioli *et al.* (2013) and Bordalo *et al.* (2018), agents' beliefs are systematically biased and this bias is a driver of fragility and crises. Krishnamurthy and Li (2020) evaluate the rational, diagnostic, and FZ model of crises in a unified framework. Finally, models of agent beliefs such as Caballero and Krishnamurthy (2008), Moreira and Savov (2014), Gennaioli *et al.* (2013) and Bordalo *et al.* (2018) also imply that crises will be triggered by a large "surprise." We have discussed how spread changes correlate with the subsequent severity of a crisis because the change proxies for credit losses. Another possibility is that the change in spreads directly measures the surprise to investors, and is thus consistent with these theories.

The rest of this paper is organized as follows. Sections 2 and 3 describe our data. Section 4 presents our result on patterns during a crisis and its aftermath. Section 5 describes pre-crisis patterns. Section 6 explores the robustness of our results to pre- and post-war data as well as alternative dating conventions. An appendix detailing the data sources is in Section A.

2 Data and Definitions

In order to describe patterns around financial crises, we need to know what is a financial crisis. We primarily use crisis dates from Jordà *et al.* (2011) as well as Jordà *et al.* (2013) (henceforth, JST). The data from Jordà *et al.* (2011) 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 JST business cycle peak dates. Reinhart and Rogoff (2009) and Baron *et al.* (2019) offer two other prominent crisis chronologies covering our sample. We discuss these alternative chronologies in Section 6.

[Table 1 about here.]

Our data on credit spreads come from a variety of sources. Table 1 details the data coverage. Much 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. Lastly, we deal with compositional changes in the sample by requiring at least 90% of the bonds in a given year to be the same bonds as the previous year. Our data appendix describes the construction of spreads during this period in more detail.

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

Figure 1 plots the incidence of crises as dated by JST over our sample (i.e. the intersection of their sample and our sample that contains 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

[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 Jordà *et al.* (2011) 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.

Gilchrist and Zakrajsek (2012)). 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. Almost all of the prior 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,

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

where $y_{i,t}$ is real per capita GDP in country i at time t. 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. Driscoll-Kraay standard errors with 8 lags are reported in parentheses. We use this error structure for all of the panel data regressions we present. We have also checked our results when double clustering standard errors. The results are broadly similar. Given that we have a relatively small cross-section of countries, we think that double clustering is not appropriate and hence report Driscoll-Kray standard errors (see, e.g., Petersen (2008) on computing standard errors when there are few clusters).

[Table 2 about here.]

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

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

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

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

The rest of the columns report other normalizations. The mean normalization is based on the average spread from the full sample, which may be a concern. In column (3) we instead normalize the year t spread by the mean spread up until date $t-1$ for each country. That is, this normalization does not use any information beyond year t in its construction. In column (4), we report results from converting the spread into a Z-score for a given country, while in columns (5) we convert the spread into its percentile in the distribution of spreads for that country. All of these approaches do better than the non-normalized spread, both in terms of the R^2 and the t-statistics in the regressions. But none of them does measurably better than the mean normalization. Finally, our approaches to normalization are implicitly making a homogeneity assumption that countries with on average higher spreads (or higher spread volatility) are no different than countries with on average lower spreads. In other words, the information content for crisis-outcomes is contained in the deviations of the spread at a given time from the average spread for that country. We check this assumption by splitting the sample into high spread countries and low spread countries and then running regressions within each subsample. These results are reported in columns (6) and (7). The coefficient estimates on the normalized spreads are economically and statistically the same across these samples validating our homogeneity assumption. 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.

4 Crisis and Aftermath

Figure 2 provides a first look at our data on credit, spreads, and output. Date 0 on the figure corresponds to the date of a JST-dated crisis. The top-left panel plots the path of the mean across-country normalized spread, relative to the mean normalized spread for country-i, from 5-years before the crisis to 5-years after the crisis. We see that spreads are 20% below their average value in the years before the crisis. Note that a one-sigma of the normalized credit spread is very near one, so that the spreads are equivalently 0.2sigma's below their mean value. They rise in the crisis, going as high as 50% over their mean value in the year after the JST crisis date, before returning over the next 5 years to the mean value. The top-right panel plots the path of the quantity of credit. The credit variable is expressed as the average across-country percentage change in the quantity of credit from 5-years before the crisis to a given year, after demeaning by the sample growth rate in credit for country-i. That is, positive values imply that credit growth since time -5 has been faster than average. We see that credit grows faster than average in the years leading up to the crisis at time zero. After this point, credit reverses so that by time $+5$ the variable is back near the country average. The bottom-left panel plots GDP, again as average percentage change from 5-years before the crisis, after demeaning by the sample growth rate in GDP for country-i. GDP grows slightly faster than average in the years preceding the crisis. GDP falls in the crisis below trend and remains low up to 5 years after the crisis.

[Figure 2 about here.]

These patterns in credit and output are consistent with prior evidence, in particular the work of Jordà *et al.* (2013). The magnitudes as reflected in Figure 2 are also in line with that paper. The panel on spreads is new simply because prior work examining historical crisis dates lacked data on spreads. But the pattern documented in the figure should not be surprising and is consistent with the prior work on spreads we have cited. Spreads rise in a crisis when default risk, risk premia, and liquidity premia rise and then fall as these components fall.

4.1 Credit and crisis intensity

The patterns in Figure 2 reflect the average behavior across all JST crisis dates. There is considerable heterogeneity within these crises. Table 3 presents statistics. Across the 39 JST crisis dates in our sample, the mean decline in GDP over the 3 years subsequent to the date of the crisis is -2.6%, but the standard deviation is 8.5%. Our paper delves into the cross-section, examining the variation within crises and asking what factors are associated with a worse crisis. Prior research, in particular Schularick and Taylor (2012), demonstrates that growth in credit-to-GDP in the years before a crisis presages a worse crisis.

[Table 3 about here.]

Figure 3(a) presents a histogram of 5 year GDP growth around a crisis as dated by Jordà *et al.* (2013). Both GDP losses and spread spikes are skewed. Figure 3(b) presents a scatter plot of the spread changes against future 5 year GDP growth for the financial crisis dates. There is a clear negative relation, and the rest of this section explores this negative relation in greater detail.

[Figure 3 about here.]

We estimate variants of the following specification:

$$\ln\left(\frac{y_{i,t+k}}{y_{i,t}}\right) = a_i + a_t + 1_{crisis,i,t} \times b'_{crisis} Z_{i,t} + 1_{no-crisis,i,t} \times b'_{no-crisis} Z_{i,t} + c' x_t + \varepsilon_{i,t+k} \tag{3}$$

The dependent variable is per-capita GDP growth from t to $t+k$. The variables $Z_{i,t}$ include the normalized credit spread as well as credit growth in country$-i$ at time t. This is a panel data regression that includes both crisis and non-crisis dates. We are particularly interested in the coefficient b_{crisis} on the credit variables interacted with the crisis dummy. Note that the regression conditions on the occurrence of a crisis at time t. By definition, output will be low in the years after t. Thus b_{crisis} measures the relation between credit variables in the year when the crisis starts and the subsequent severity of the crisis, within the set of crisis dates. Our regressions also include a country fixed effect and a year fixed effect. We also include two lags of annual GDP growth in x_t to control for GDP trends that may not be accounted for by the time and country dummies.

We start with a baseline where we pool crises and non-crises, forcing the b coefficients to be the same across these events. Columns (1) of Table 4 presents these results, with panel A for 3-year growth and panel B for 5-year growth. We note that a high spread at time t forecasts lower GDP growth going forward at both the 3 and 5 year horizons.

Column (2) presents the main result of this section. We include both the spread at date t as well as the change in the spread from $t-1$ to t, both interacted with the crisis dummy. We see that the change in the spread helps to explain subsequent GDP growth. We return to a discussion of why the change in the spread matters more than the level of the spread in the next section. The standard deviation of spread changes is approximately one, so that a one-sigma increase in spreads forecasts about a 7% drop in GDP over the next 3-years. At the 5-year horizon, a one-sigma increase in spreads forecasts about an 8% decrease in GDP.

We note that the result reported in column (2) describes variation across crisis episodes. That is, there is a mean decline in output in JST crises as illustrated in Figure 2. The result in column (2) indicates that if spreads spike one-sigma more than the average spike in spreads of around 0.5, then output falls by an additional $6-7\%$ relative to the mean path of Figure 2.

[Table 4 about here.]

Next, we consider the importance of credit growth which is the variable that Jordà *et al.* (2013) have found to correlate with crisis outcomes. Column (3) of the table includes $\Delta cred_{i,t}$ which measures credit growth in the 3-years preceding the crises and is normalized to have unit standard deviation. We see that credit growth also helps to explain the intensity of crises. The coefficient estimate of -0.60 means that a one-sigma change in credit growth leads to a lowering in crisis GDP growth of about 0.60% (this is similar to Jordà *et al.* (2013)'s result that a one-sigma increase in credit growth leads to a lowering in crisis GDP growth of about 1%).[4] Another point of reference is Mian *et al.* (2017), who show that a one-sigma increase in private debt-to-GDP growth over the last 3 years is associated with a 2.1% decline in output over the next 3 years. The Mian *et al.* (2017) results are from a more recent sample, beginning in 1970, and do not explicitly condition on crises.

Comparing columns (2) and column (3), we see that the coefficient on spread changes is not appreciably altered with the introduction of the credit growth variable. That is, spreads and credit growth have independent forecasting power for output growth. This latter result is similar to Greenwood and Hanson (2013) who find that a quantity variable that measures the credit quality of corporate debt issuers deteriorates during credit booms, and that this deterioration forecasts low returns on corporate bonds even after controlling for credit spreads. Greenwood and Hanson (2013)'s finding is in U.S. data, while our result derives from a larger cross-country sample.

To provide a sense of the importance of credit spreads and credit growth in explaining crisis outcomes, we run a regression of output growth on the credit variables but restricting the sample to the 39 JST dates. The standard deviation of 3-year GDP growth across these crisis episodes is 8.5%. If we only consider the credit spread change as independent variable (along with a constant), the standard deviation of the predicted 3-year GDP growth from the regression is 3.5%. If we only consider the credit growth variable, the standard deviation is 2.8%. If we consider both of these variables, as well as their interaction, the standard deviation is 6.0%. That is, the two variables, credit spread changes and credit growth account for the bulk of the across-crisis variation in 3-year GDP growth. Similar statistics apply for the 5-year GDP growth case. Results are available upon request.

The regressions in columns (2) and (3) report coefficients on the independent variable of interest interacted with a crisis dummy. Crises are episodes where GDP declines. One may be concerned that the coefficients reflect these declines in a mechanical way. To deal with this concern, in column (4) we include a JST crisis dummy separately. The coefficient on

[4] If we omit changes in spreads from this regression we find a coefficient of around -1% on the credit growth term, consistent with Jordà *et al.* (2013).

the spread change is not appreciably altered.

4.2 Credit spread spikes versus levels

The result in column (2) of Table 4 indicates that changes in spreads rather than the level of spreads helps to explain GDP outcomes in crises. In column (5), we report a regression where we only include the spread in the year of the crisis and not the spread change. It is apparent that there is important information in the spread change that is not contained in the level of the spread.

Columns (6) - (9) present results showing that the association between spread spikes and worse crises is a crisis-specific result. In columns (6) and (7) we consider dates that are not crisis dates. We focus on the set of dates for which JST crises do not occur in any of the next 5 years. We see from comparing (6) and (7), and noting that the coefficient estimates are nearly the same, that information in spreads is contained in the spread at date t rather than in the change from date $t-1$ to t. Columns (8) and (9) focus on recession dates, as dated by JST. Here also we see that there is a statistically strong relation between spreads and subsequent GDP growth, but not especially between spread changes and subsequent GDP growth.

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

To be more formal, suppose that spreads are:

$$s_{i,t} = \bar{\gamma}_i + \gamma_1 E_t[\text{Loss}_{i,t}] + l_{i,t}.$$

where $\text{Loss}_{i,t}$ are expected default losses which we would expect to be decreasing in expected output growth, $E_t\left[ln\ \frac{y_{i,t+k}}{y_{i,t}}\right]$, $l_{i,t}$ is an illiquidity component of spreads, and $\bar{\gamma}_i$ is the mean value of the spread.

In a crisis, illiquidity/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 $\gamma_1 E_t[\text{Loss}_{i,t}]$ 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,

$$s_{i,t} = \bar{\gamma}_i + \gamma_1 E_t[\text{Loss}_{i,t}].$$

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

4.3 Crisis triggers and amplifiers

The start of a crisis is associated with a spike in spreads and larger spikes in spreads are associated with worse crises. These results were derived from examining JST dated crises. We next ask what information is contained in spread spikes without conditioning on the occurrence of a JST crisis. Table 5 presents quantile regressions of output growth over the next year on $\Delta\hat{s}_{i,t}$. Standard errors are clustered by year (Parente and Silva, 2016). We see that the forecasting power of spreads for output increases as we move to the lower quantiles of the output distribution. At the median, the coefficient on $\Delta\hat{s}_t$ is around -0.7, while it is around -1.1 at the 25th quantile. These results indicate that a spike in spreads shifts down the conditional distribution of output growth, fattening the left tail.

[Table 5 about here.]

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

[Table 6 about here.]

To explore this possibility we construct a financial-sector fragility indicator. We create a variable (HighCredit_t) that counts the number of years in the past 5 years that annual credit growth has exceed its full sample median. We divide this count by 5, so that if $\text{HighCredit}_t = 1$ then credit growth has been above median in each of the last 5 years.

[5] 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)).

Jordà *et al.* (2011) show that 5 lags of annual credit growth has explanatory power for crises. Our variable is motivated by their findings, with our discrete dummy approach more apt to describe non-linearities in the data as the FZ theory would suggest. We interact this HighCredit variable with the change in spreads, $\Delta\widehat{s}_{i,t}$, thus tracing out the impact of a shock, $z_{i,t}$, when the financial sector is fragile. We see that an increase in the spread at date t when $\text{HighCredit}_t = 1$ substantially reduces the path of output. The coefficient in column (3) of the upper panel of Table 6 is -2% which is directly comparable to the coefficient on spreads in the unconditional regression of column (1) of Table 4 of -1.06%. Then, when credit growth has been continuously above median, the association between a change in spreads and future output is about twice as large.

We summarize these findings graphically in Figure 4. We plot the path of output conditional on an increase in the spread of one-sigma (one unit) at year 0. The top panel plots the unconditional path of output conditional to an increase in spreads. That is, the plot indicates how much lower output would be relative to average if spreads are one unit higher at year 0. We see that output is lower by about 1% out to 5 years. The dashed lines indicate two-standard deviation bands. The bottom panel is the same experiment but conditional on the high credit dummy being one at year 0. That is, this panel indicates the interaction effect of spreads and leverage of the FZ theory. We see that the output path is lowered by about 2.5% out to 5 years. The middle panel is for the JST crisis dates. The effects for the JST dates are larger, with output declines of 7% out to 5 years. The larger effect for the JST dates could indicate that the JST dates are subject to an ex-post dating bias. That is, since these dates are based on qualitative information, it possible that they implicitly condition on a subsequent GDP decline. See Romer and Romer (2014) for a further discussion of this point. In this case, our middle panel, which is based entirely on quantitative information and has no look-ahead bias, is a better indicator of the GDP decline in a crisis. On the other hand, it is also possible that the qualitative information used in choosing the JST dates brings in a dimension that is absent from our high credit dummy and this information better picks out crisis dates.[6]

The bottom panel of Table 6 presents these results in a different way, using a simple interaction of credit growth and changes in spreads. Note that the regressions in the top panel implicitly condition on the entire sample since the *HighCredit* variable is defined relative to the full-sample median of credit growth. The results in the bottom panel are

[6]We note that the results in the middle panel of Figure 5 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.

free of this look-ahead bias. We focus on 3-year credit growth here rather than 5-year credit growth. The results are broadly similar but somewhat stronger when using 3-year credit growth as the fragility metric. We also control for credit growth and the change in spreads on their own, so the interaction term tells us the marginal effect on output when both spreads increase and credit growth is high. At the 3 year horizon the coefficient is -0.64, meaning a one-standard deviation increase in the interaction term suggests an extra marginal effect of 0.64% lower growth at this horizon. This result is consistent with the FZ view that an increase in spreads together with high fragility is associated with larger output declines.

We have discussed our results through the lens of the FZ trigger-and-amplifier model. We interpret the spike in spreads as proxying for a large loss to financial intermediaries. A second interpretation of the spread spike result is in terms of the "surprise" to investors. In Caballero and Krishnamurthy (2008), Gennaioli *et al.* (2013), Moreira and Savov (2014), and Krishnamurthy and Li (2020) the extent of the surprise is a key feature of crises. In these models, larger surprises are associated with more severe financial crises. But it is important to note that a theory that seeks to explain crises solely based on shifts in investor beliefs is not consistent with the data. One needs a theory which involves the interaction of the surprise and leverage. Moreira and Savov (2014) and Krishnamurthy and Li (2020)'s models deliver this interaction result.

[Figure 4 about here.]

5 Pre-crisis Period

We next turn our attention to the pre-crisis period. A large increase in spreads is associated with a more severe financial crisis. Is the large change in spreads from the pre-crisis period because the level of spreads pre-crisis is "too low?" That is, are crises preceded by frothy financial conditions? There has been considerable interest in this question from policy makers and academics (Stein, 2012, López-Salido *et al.*, 2017). We use our international panel of credit spreads to shed light on this question.

5.1 Pre-crisis 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:

$$s_{i,t-1} = \gamma_{i,0} + \text{Prob}^{\mathcal{Q}}(z_t > \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{crisis}] \tag{4}$$

where, $\text{Loss}_{i,t}$ is increasing in $\mathcal{F}_{i,t}$. We have shown that $\mathcal{F}_{i,t}$ is high before a crisis and that higher $\mathcal{F}_{i,t}$ is associated with larger output losses in the crisis. By itself, this factor would cause spreads to rise. Yet, we have noted that spreads are low before a crisis, suggesting that the term $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$ is low and moreover offsets the fragility-loss component of spreads. We investigate this further.

[Table 7 about here.]

In Table 7, 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 JST crisis, as well as lagged 3-year growth in credit and lagged GDP growth. Importantly, we control for a post-crisis dummy as well which is equal to one in the three years after a crisis (when spreads typically peak). This means the pre-crisis dummy should be judged relative to other "normal times" and is not mechanically low because spreads during crises are high. The coefficient on the dummy is -0.34, indicating that spreads are 34% "too-low" pre-crisis (or 0.34 sigma's lower than the normal time mean). Column (2) of Table 7 explores whether unusually low spreads are associated with more severe crises. We break the set of JST 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 low-spread/worse-crisis relation.

An important point is that spreads are low ahead of a crisis despite the fact that credit growth is high before a crisis (as shown in Jordà *et al.* (2011)). Column (3) of the table makes this clear. We include an interaction of credit growth with the dummy for the 5 years ahead of the crisis. One can see that in the full sample credit growth and spreads are positively correlated (coefficient of 0.98 in column 1). The feature that appears unique to the pre-crisis period is that both spreads are low and credit growth is high (coefficient on interaction of -1.42).

Figure 5 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 JST 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.

[Figure 5 about here.]

In terms of equation (4), we can view these results as suggesting that investors' risk-neutral expectations of a large loss, $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$, falls as credit growth rises, and this fall is enough to more than offset the fragility effect of credit growth. Note that such a fall could occur either through a fall in the risk premium investors charge for bearing credit risk, as may occur in models with time-varying risk premia, or because investors pre-crisis rationally believe that a crisis is unlikely, as in Moreira and Savov (2014), or through a behavioral model where investors' probability assessments are biased, as in the neglected risk model of Gennaioli *et al.* (2013) or the diagnostic expectations model of Bordalo *et al.* (2018). The regressions in Table 7 do not allow one to distinguish between these possibilities in part because they condition on a crisis occurring at time t. That is, these regressions do not establish that low spreads forecast crises, they only establish that crises are preceded by low spreads (i.e., it is possible that there are non-crisis events that justify investors' low $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$ assessment).

Finally, column (4) of Table 7 examines the behavior of spreads before recessions. The coefficient on spreads is negative (-0.13), but not statistically different than zero. There is froth before a crisis but not necessarily a recession.

5.2 Credit supply expansions predict crises

In Table 8 we construct a variable, labeled "HighFroth," based on the difference between the fitted and actual lines in Figure 5. That is, our froth variable first regresses credit spreads on fundamentals (two lags of GDP and credit growth). We set a dummy$=1$ if this froth variable is below its median. We then take a 5-year average of this dummy variable and label this HighFroth. The variable construction is analogous to the HighCredit variable construction we have used earlier. This variable thus captures an episode where spreads have been persistently low.[7]

[Table 8 about here.]

Table 8, Panel A, presents results using a Probit regression analogous to Jordà *et al.* (2011). Column (1) uses only our HighFroth measure. We see that HighFroth meaningfully predicts a crisis. Column (2) is based on credit growth (the HighCredit variable defined earlier). There is an association between high credit growth and crises, although our results

[7] We have also run regressions with the froth variable constructed in a simple manner: HighFroth$=1$ if the average spreads over the last 5 years is below the median. The results are qualitatively similar but not as sharp as those we present in the text.

are not as strong as those reported in Schularick and Taylor (2012).[8] Columns (3) and (4) forecasts crises using the interaction of HighFroth and HighCredit. We see that episodes of low spreads *and* high credit growth are the strongest signals of a future crisis.

In Panel B of Table 8 we repeat the forecasting exercise for recessions. There is a weak negative relation between these measures and the incidence of recessions. That is, high credit growth and low spreads do not precede recessions and, if at all, precedes booms. This is the natural business cycle correlation one would expect. In US data from 1929 to 2015, López-Salido *et al.* (2017) find that low spreads are a precursor to economic downturns. This is a sample where most downturns are recessions and not financial crises. Thus our results, from a large data sample, do not confirm their findings.

In Panel C of Table 8 we ask whether the HighFroth and HighCredit interaction forecasts declines in GDP and not just the occurrence of crises. We have seen that HighFroth/HighCredit conditions forecast crises strongly and forecast booms weakly. The question is whether the crisis effect outweighs the boom effect. We find that episodes of low spreads and high credit growth are precursors to GDP declines, suggesting that the crisis effect indeed outweighs the boom effect. As expected, since crises are unlikely events, the results are not as strong as for the crisis regressions of Panel A. Additionally, Mian *et al.* (2017) in a sample of OECD countries from 1970 onwards document an economically and statistically strong relation between episodes of high credit growth and subsequent GDP growth. In our data, which extends back much further, the relation is considerably weaker.

[Table 9 about here.]

Table 9 repeats the forecasting regressions of Table 8 using a Logit specification. In the Probit model, the fitted values do not have to lie on the unit interval and thus are hard to interpret as probabilities. We thus shift to a Logit specification. The results reveal the same strong association between low spreads and high credit growth and subsequent crises but not recessions. Figure 6 presents these Logit results graphically by plotting the cumulative probability of a crisis at each horizon when credit growth is low (HighCredit=0)and spreads are not abnormally low (HighFroth=0) and also when credit growth is high (HighCredit=1) and spreads are abnormally low (HighFroth=1). Visually it is apparent that prolonged

[8] We define HighCredit based on the dummy approach rather than the continuous 3-year credit growth variable used by Schularick and Taylor (2012). We also use a smaller sample then they do since our regressions utilize both spreads as well as credit growth, and we report standard errors clustered by country and year. In our sample, if we replace the HighCredit variable with lagged 3-year growth in credit and run the Probit regression of Table 8, the t-statistic on credit growth is 1.65.

periods of low spreads and high credit growth raise the probability of a financial crisis substantially.

[Figure 6 about here.]

[Table 10 about here.]

The results in Table 8 are based on regressions over the full sample so that the froth variable uses future data in its construction. This raises the question of whether our froth variable can predict crises out-of-sample. Table 10 presents the out-of-sample evidence. We construct the froth and credit growth variables in a rolling manner, beginning 20 years after the start of our sample. Panel A of the Table reports the crisis prediction regressions. There is a positive relation between the independent variables and the occurrence of crises, although the results are considerably weakened in the out-of-sample regressions. The recession results of Panel B are similar to that of Table 8. In the GDP results of Panel C, the sign of the association changes to now reveal a weak positive association between HighFroth/HighCredit and subsequent GDP growth.

Overall, these results are supportive of the view that credit supply expansions precede crises. That is, from the work of Jordà *et al.* (2011) and Baron and Xiong (2017), 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 Jordà *et al.* (2011), 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. These results are strongly present in Table 8 but are weaker in the out-of-sample tests.

On the other hand, our data does not reveal a robust relation between credit supply expansions and mean GDP downturns. The strongest results are that the tail event of a crisis is more likely following a credit supply expansion. We also note that there is little relation between credit supply expansions and future recessions. One way to understand this set of results is that froth raises the likelihood of a crisis but not a recession, and since crises are relatively low likelihood events, has little discernible effect on the mean path of future GDP.

What do these results teach us about models? First, in models such as Gertler and Kiyotaki (2010), He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2012), which are FZ models, a prolonged period in which fragility and leverage rises ($\mathcal{F}_{i,t}$ rises) will also be coupled with an increase in spreads and risk premia, contradicting the evidence. Moreira and Savov (2014) and Krishnamurthy and Li (2020) build an FZ model with time variation in beliefs regarding a crisis. In this model, it is possible to match the evidence that severe crises are preceded by periods of low spreads where agents think that risk is low and hence drive an expansion in credit supply. That is $\mathcal{F}_{i,t}$ could rise while $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$ falls so that on net spreads fall before a crisis. It is additionally possible as behavioral models such as Gennaioli *et al.* (2013) and Bordalo *et al.* (2018) argue that the fall in $\text{Prob}^{\mathcal{Q}}(z_t > \underline{z})$ is more than under a rational benchmark. The only evidence that points clearly in favor of this model is Panel C of Table 8 where the credit supply expansion precedes a mean decline in GDP. However, as noted, this result is among the weakest associations we report in our study.

6 Robustness

This section reports the robustness of our results to different cuts of the data. We tackle two main issues. Our sample runs from the 1870s to the present, which has also seen considerable economic and financial development. Thus a natural question to ask is whether our results change substantially across this sample. We thus run our regressions on the post-World War II sample and compare the results to our main full-sample results. Second, we have presented a number of results based on the dates of Jordà *et al.* (2013). Our results do depend on crisis dating methodology. Here we also present results using Reinhart and Rogoff (2009) and Baron *et al.* (2019).

6.1 Robustness to post-war data

We show that our main conclusions are not driven solely by the earlier data by revisiting our key interaction regressions of high credit interacted with spreads using only data from 1950 onwards. This is useful for several reasons. First, the economic environment may be different in the later part of the sample. Second, our early data on bond prices collected from the Investor's Monthly Manual is noisier on some dimensions and requires more judgment in establishing spreads for each country.

Table 11 shows that our results on crises, GDP outcomes and their interaction with spreads are not significantly affected when considering only post-1950 data (although standard errors do increase). This table should be compared to Table 4. Table 12 relates the interaction between credit booms and spread spikes to subsequent GDP outcomes. Results are in line with the full-sample results of Table 6. Finally, in Table 13 we investigate the stability of the coefficient estimates in the output prediction regressions of Table 6 across the pre- and post-war samples. We fit our regressions in pre-war data and then compare the mean-squared forecast errors out-of-sample in post-war data using the coefficients from the earlier exercise. There are 288 postwar observations across the countries in our sample. The column labeled Baseline uses two lags of GDP growth, country fixed effects, and the change in interest rates. Spread uses only data from spreads in the regression, Credit uses only credit growth. Both uses spreads and credit individually, and Interaction uses the interaction term between credit and spreads. In panel A, we use the High Credit dummy defined earlier to represent credit growth, while in panel B we take the growth in credit as a continuous measure. These results indicate the relationships we document are stable pre- and post-war.

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

6.2 Alternate chronologies

We investigate the robustness of our results to the alternative crisis chronologies by Reinhart and Rogoff (2009) (RR) and Baron *et al.* (2019) (BVX). There are three tables where crisis-dating affects the results: Tables 4, 7, and 8. In Table 14 we investigate the relationship between spikes in spreads and subsequent GDP growth using the alternate dating, revisiting the main result of Table 4. The coefficient on the relationship falls for the BVX dates relative to the JST dates but remains statistically significant. The relationship for the RR dates is weak. This appears to occur because RR date the crisis later on average than either BVX or JST. Getting the timing right matters because if the dates are too late – e.g., if we dated the recent US crisis in 2010 rather than 2008 – then the estimates of output losses in the aftermath of the crisis will be smaller. BVX date crises using declines in bank equity values which, because they are based on forward looking asset prices, will occur before an actual banking panic. Baron *et al.* (2019) discuss these timing concerns of RR in greater depth.

[Table 14 about here.]

Table 15 revisits the pre-crisis froth regressions of Table 7 for the BVX and RR dates. Comparing the results between JST, RR and BVX, we see that dating matters less for these regressions. We consistently find a pattern of low spreads ahead of crises. The extent of the low spread is diminished for the RR dates, likely because RR date crises later than other dating conventions, at a time when spreads have already risen. The point estimates for the BVX and the JST dates are very similar, although the standard errors for the BVX dates are larger.

[Table 15 about here.]

Table 16 presents regressions forecasting crises using the froth and credit variables, based on RR and BVX's alternative crisis dates. Panel A reports result for the RR dates, and we see that the results are much weaker than our main JST results. This finding is not surprising given the timing concerns with the RR dates we have noted above. Panel B presents the BVX dates. These results are surprisingly weak. Recall that BVX date crises based on large reductions in bank equity values, while JST date crises based on realized bank runs or bank closures. Our finding is that the credit variables predict events which are banking panics but not bank equity market declines. Panel C probes this finding further. We focus on the set of dates where both a BVX crisis and a JST crisis occur within 5 years of each other. In our credit spread sample, there are around 40 crises using the JST dates but 56 for the BVX dates. However, only a little over half of the BVX dates are also dated as having a JST crisis occur within a 5 year window, meaning there are many instances in which bank equity declines but a banking panic does not occur. The froth and credit variables helps to predict the joint BVX and JST dates, indicating a failure to predict the events where the equity market declines but a banking panic does not ensue. Thus, a note-worthy result from this table is that the froth variables are most informative in predicting banking panics.

[Table 16 about here.]

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 the transition into a crisis begins with a large change in spreads. The severity of the subsequent crisis can be forecast by the size of credit losses ($z_{i,t}$ = change in spreads) coupled with the fragility of the financial sector ($\mathcal{F}_t^i$, as measured by pre-crisis credit growth growth). Finally, we find that spreads fall pre-crisis and are too low, even as credit grows ahead of a crisis.

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

Existing theories involving financial frictions qualitatively match some of the stylized facts documented here (e.g., Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), He and Krishnamurthy (2012), Brunnermeier and Sannikov (2012), and Moreira and Savov (2014)). In particular, these theories match the non-linearities we document in terms of the "F $\times$ z" amplification facts we show here. This includes the fact that the interaction of credit losses, or spike in spreads, together with fragility in terms of high credit growth combine to forecast negative GDP events. While these theories do well to match the stylized facts on both the aftermath and transition into a financial crisis, they miss that spreads are, on average, low before a crisis as credit booms. This latter observation suggests that agents lower their risk-neutral probability assessment of a crisis during the credit boom. Moreira and Savov (2014) build a model in which agents update their probability assessment of a crisis shock following Bayes rule. The logic of their model indicates that crises will be preceded by low spreads. Another possible reconciliation of this evidence is the diagnostic expectations model of Bordalo *et al.* (2018). In that paper, biased expectations can lead agents to reduce their assessment of the likelihood of a crisis below a rational benchmark and can thus be consistent with the pre-crisis evidence. However, a pure behavioral model cannot speak to the interaction effect we have presented: low spreads coupled with high fragility are the best signals regarding a crisis. We see a possible model that incorporates both a financial frictions view with a model that explains the pre-crisis behavior in terms of risk neutral expectations that generate low spreads as promising for explaining the stylized facts documented here. Work along these lines is in Maxted (2019) and Krishnamurthy and Li (2020).

A Data Appendix

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

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

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

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

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

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

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

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

Crisis dates. Source: Jorda, Schularick, and Taylor / Schularick and Taylor ("JST" dates), Reinhart and Rogoff ("RR" dates, see Kenneth Rogoff's website), Baron, Verner and Xiong ("BVX" dates, from Matthew Baron).

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

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List of Figures

Figure 1: This figure plots the incidence of crises over time across various countries from 1870-2008. We show to total number of countries experiencing a crisis in each given year. We use crisis dates measured by Jordà *et al.* (2013). 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.

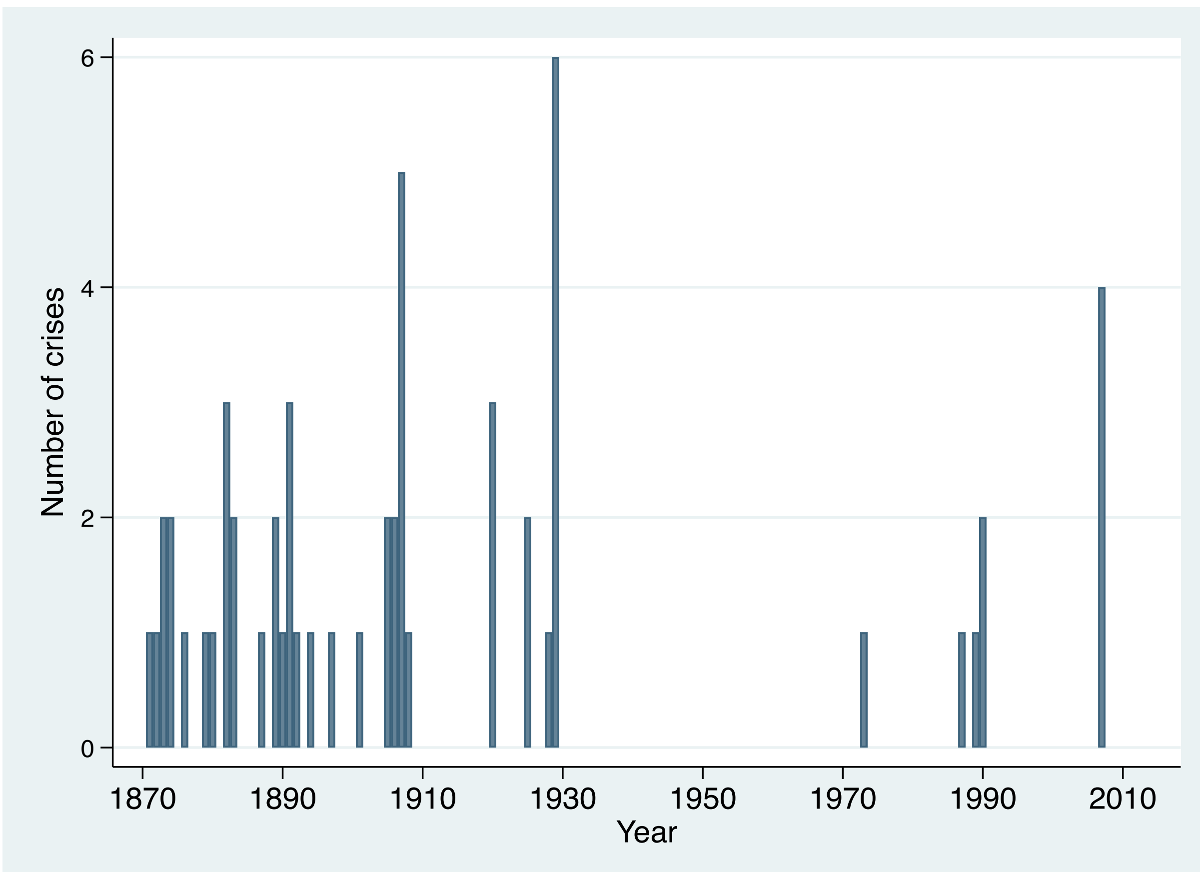
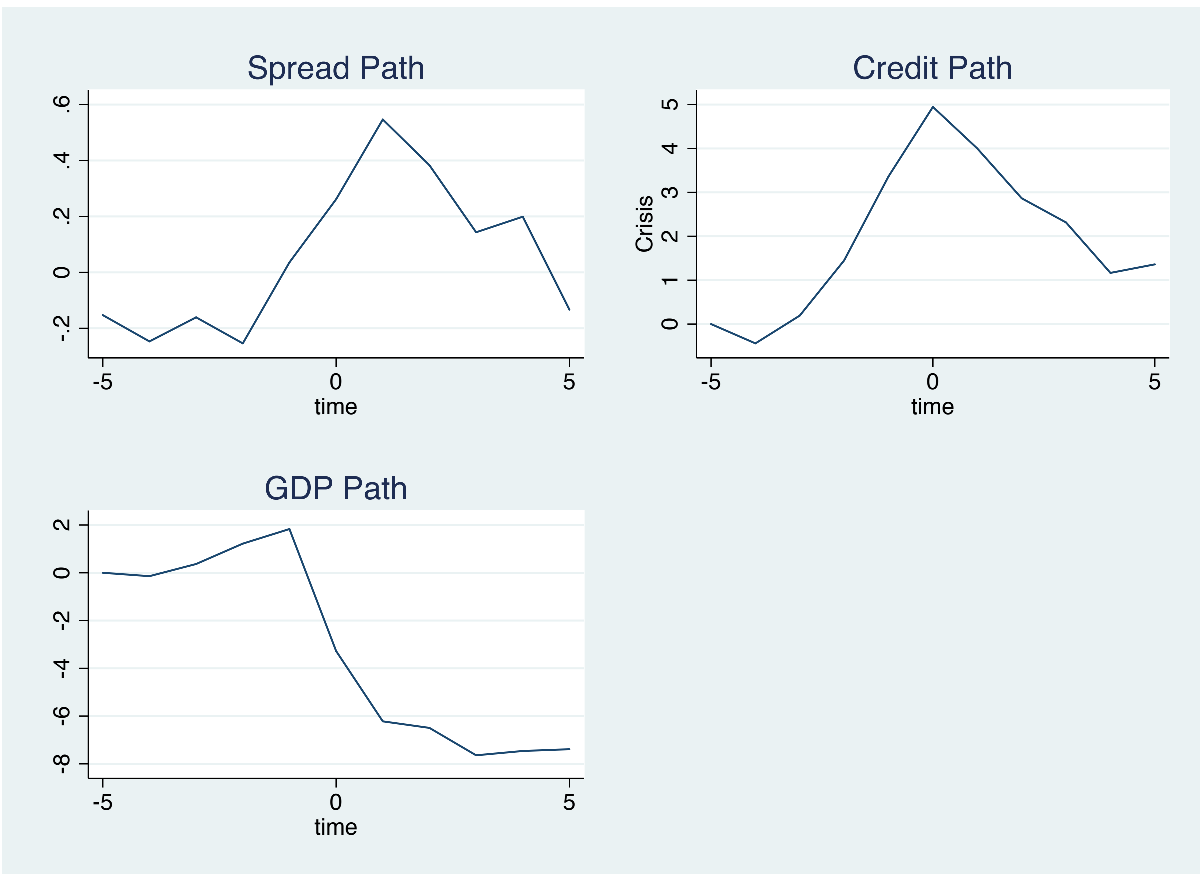
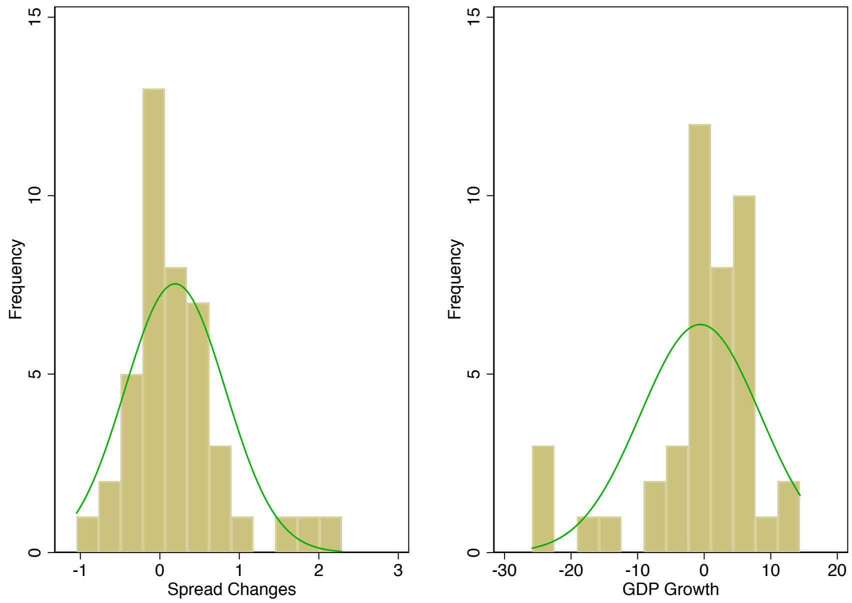
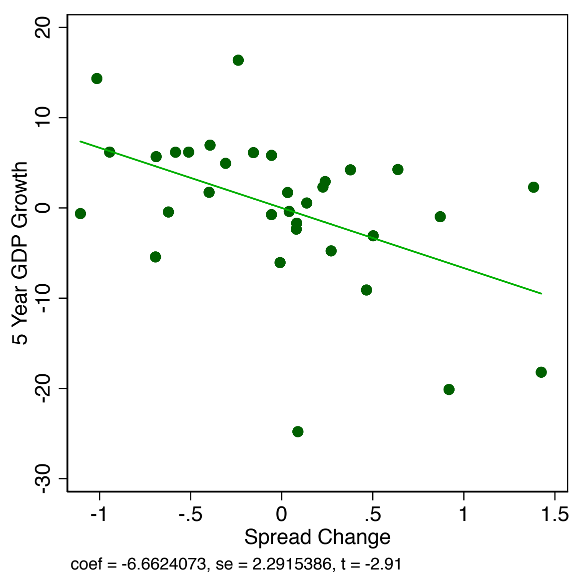


Figure 2: This figure plots the behavior of credit spreads, GDP, and the quantity of credit around a financial crisis with the crisis beginning at date 0. GDP and credit growth are expressed as the average across-country percentage change in the quantity from 5-years before the crisis to a given year, after demeaning by the sample growth rate in the quantity for country-i. That is, positive values in the credit path imply that credit growth since time -5 has been faster than average. Spreads are normalized by dividing by the unconditional mean consistent with our normalization in the main text. We use crisis dates from Jordà *et al.* (2013).





(a) This figure plots the distribution of spread changes and future 5 year GDP growth around JST financial crises



(b) This figure plots spread changes against future 5 year GDP growth around JST financial crises

Figure 3: Spreads and GDP declines around JST crisis episodes (Jordà *et al.* (2013))

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

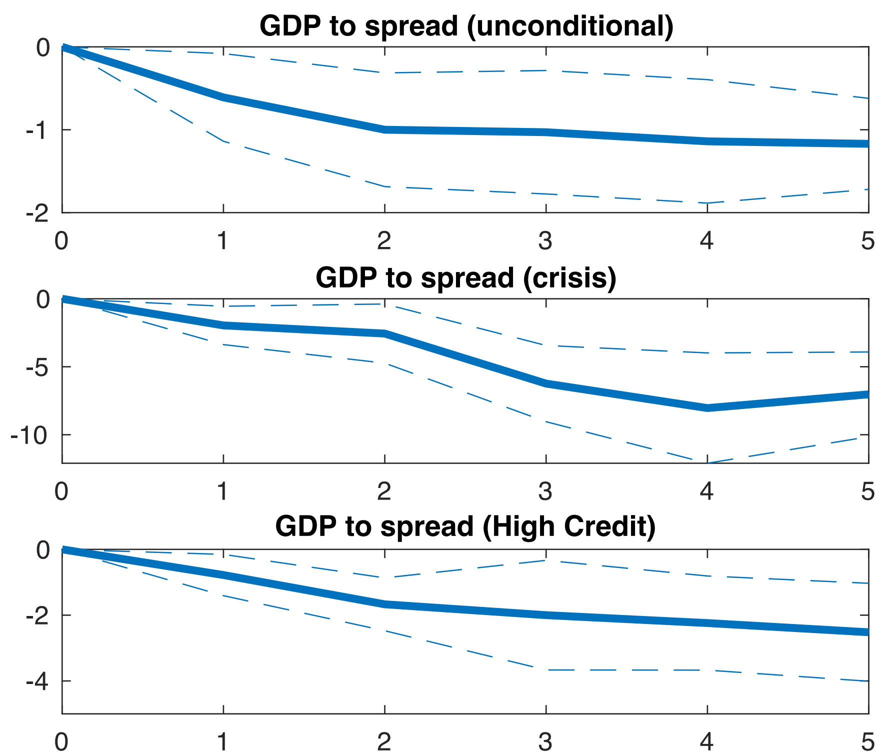


Figure 5: This figure plots the path of spreads, fundamental spreads, and cumulative credit growth in the years surrounding a financial crisis (using JST dates). The paths are formed by running regressions with dummies at various dates. "Fundamental spreads" are computed as the predicted value from a regression of spreads on fundamentals including two lags of GDP growth and the change in credit.

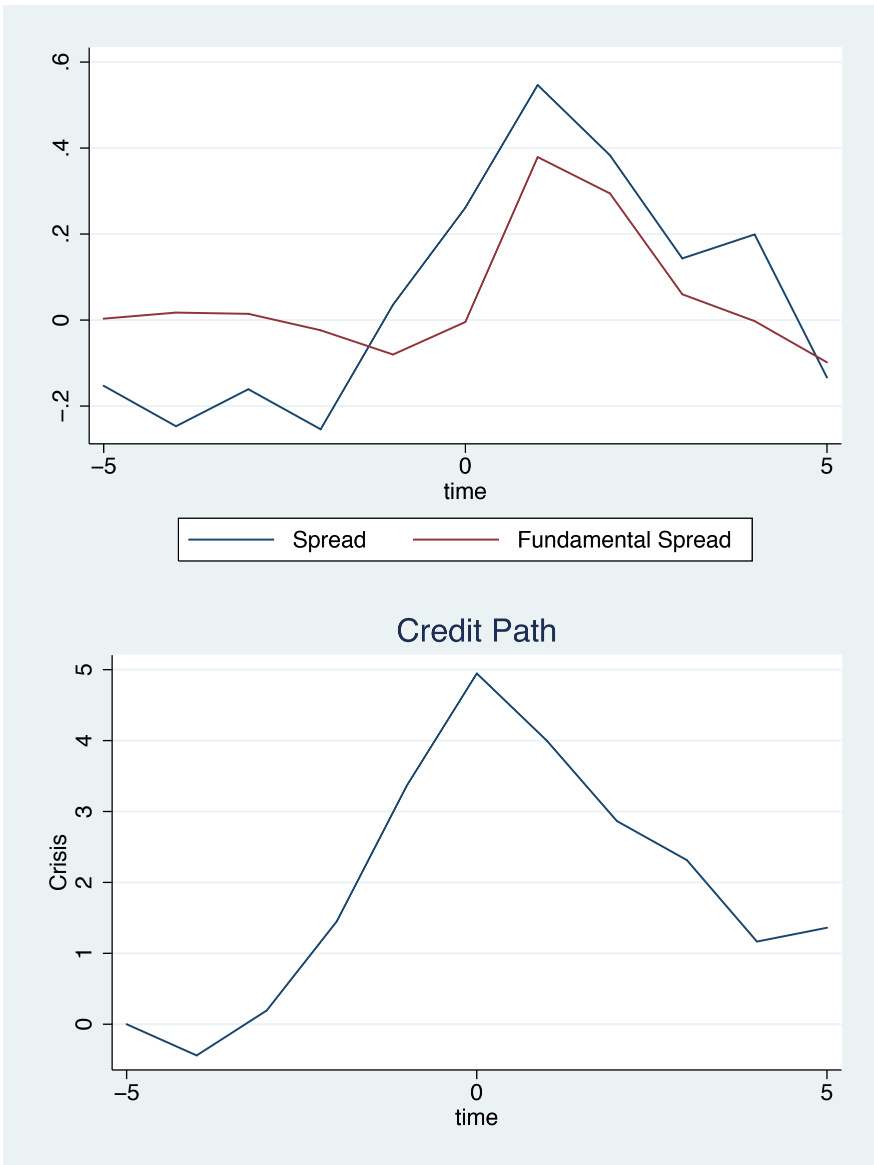
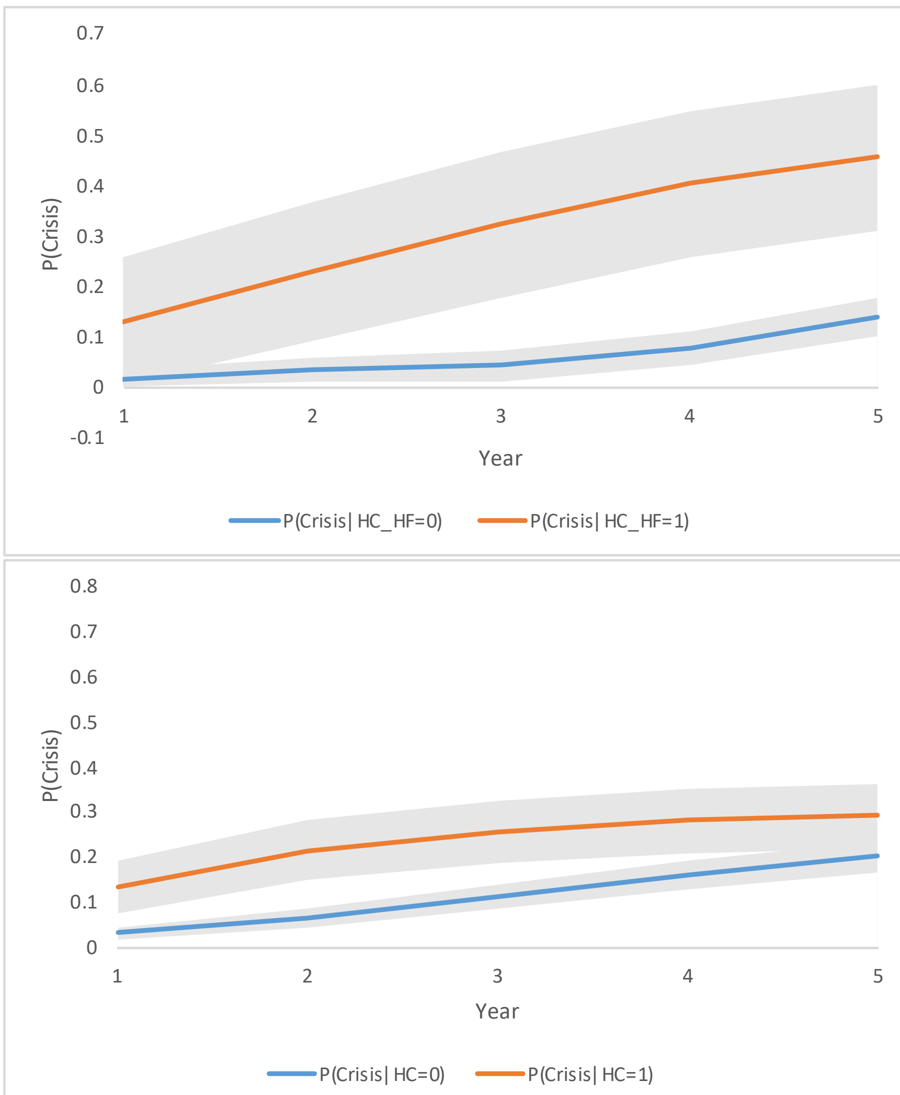


Figure 6: We plot the cumulative probability of a crisis at each horizon when we condition on credit market conditions. HF (high froth) is a dummy equal to 1 if abnormal credit spreads (the residual of spreads regressed on two lags of GDP and credit growth) over the last 5 years have been below their median. HC is a dummy equal to 1 if credit growth over the past 5 years has been high. We compare the future probability of a crisis when credit markets appear "frothy" (HC and HF both equal 1) to when they are not (both equal to zero). In the bottom panel we compare this to only cases where credit is high (HC=1). See text for more details. Standard errors double clustered by country and year.



List of Tables

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

Table 2: This table provides regressions of future 1 year GDP growth on credit spreads where we consider different normalizations of spreads. The first column uses raw spreads, the second normalizes spreads by dividing by the unconditional mean of the spread in each country, the third also divides by the mean but does so using only information until time t-1 so does not include any look ahead bias. We refer to this as the out of sample (OOS) normalization. The fourth and fifth columns compute a z-score of spreads and percentile of spreads by country. Each of these normalizations captures relative percentage movements in spreads in each country. Controls include two lags of GDP growth and both country and year fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses. The last two columns split the sample into high spread and low spread countries (based on the unconditional mean raw spread over all countries) and examine whether our normalization choice produces similar coefficients across these countries.

	(1) Raw	(2) MeanNorm	(3) OOSMean	(4) Zscore	(5) Prctile	(6) High Spread	(7) Low Spread
Spread	-0.08						
	(0.06)						
Lag Spread	0.07						
	(0.04)						
Spread/Mean		-0.73				-0.78	-0.72
		(0.18)				(0.39)	(0.22)
Lag Spread/Mean		0.52				0.25	0.49
		(0.22)				(0.36)	(0.29)
Spread/MeanOOS			-0.18				
			(0.08)				
Lag Spread/OOS			0.01				
			(0.05)				
Z-score Spread				-0.79			
				(0.25)			
Lag Z-score Spread				0.47			
				(0.18)			
Prctile Spread					-1.33		
					(0.83)		
Lag Prctile Spread					0.31		
					(0.65)		
Observations	900	900	882	900	900	545	355
R-squared	0.35	0.36	0.36	0.36	0.35	0.62	0.30
Country FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

Table 3: This table provides summary statistics for peak to trough declines in GDP around the JST crisis episodes (Jordà *et al.* (2013)) as well as the 3 year growth rate in GDP.

Distribution of declines in GDP across JST episodes

	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

Table 4: This table provides regressions of future cumulative GDP growth $\Delta lny_{t+k,i}$ on credit spreads at the 3 and 5 year horizon. We include interactions with crisis or recession dummies. Controls include two lags of GDP growth and both country and year fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses.

Panel A: 3 year GDP growth									
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{s}_{i,t}$	-1.06								
	(0.42)								
$\widehat{s}_{i,t-1}$	0.97								
	(0.47)								
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-0.30	-0.18	0.89	-1.48				
		(0.44)	(0.43)	(0.52)	(0.67)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-7.46	-6.88	-6.26					
		(1.46)	(1.19)	(0.64)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-0.60	-0.67					
			(0.14)	(0.74)					
$1_{crisisST,i,t}$				-4.72					
				(1.00)					
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$						-0.49			
						(0.23)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$							-0.52		
							(0.35)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$								-1.50	-1.58
								(0.80)	(0.58)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$									0.43
									(2.15)
Observations	641	641	641	641	641	641	641	641	641
R-squared	0.54	0.55	0.55	0.55	0.55	0.55	0.54	0.54	0.55

Panel B: 5 year GDP growth									
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{s}_{i,t}$	-0.93								
	(0.37)								
$\widehat{s}_{i,t-1}$	1.74								
	(0.41)								
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-0.06	1.14	1.14	-1.39				
		(0.42)	(0.56)	(0.55)	(0.81)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-8.48	-7.52	-7.58					
		(1.62)	(1.37)	(1.34)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-0.61	-0.46					
			(0.16)	(0.57)					
$1_{crisisST,i,t}$				-1.31					
				(4.25)					
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$						-0.47			
						(0.28)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$							-0.13		
							(0.40)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$								-1.94	-1.63
								(1.47)	(1.11)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$									-1.90
									(3.22)
Observations	634	634	634	634	634	634	634	634	634
R-squared	0.53	0.54	0.55	0.55	0.52	0.52	0.52	0.52	0.55

Table 5: Quantile Regressions. We run quantile regressions of future output growth over the next year on the change in credit 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 cluster by year.

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

Table 6: 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 variable HighCredit which counts the number of times that credit growth has been above median in each of the past 5 years. The lower panel instead directly interacts changes in credit spreads with credit growth over the previous 3 years. The table shows that an increase in spreads negatively forecast output on average. A given increase in spreads predicts more negative output growth if lagged credit growth has also been high. Controls include two lags of GDP growth. Driscoll-Kraay standard errors with 8 lags are in parentheses.

When is an increase in spreads particularly bad for GDP?

	(1)	(2)	(3)	(4)	(5)
	1yr	2yr	3yr	4yr	5yr
$(\text{HighCredit}_{i,t}) \times \Delta\widehat{s}_{i,t}$	-0.78	-1.67	-2.00	-2.24	-2.52
	(0.32)	(0.41)	(0.85)	(0.73)	(0.76)
Observations	667	664	661	658	651
R-squared	0.43	0.52	0.53	0.53	0.53
Controls	Y	Y	Y	Y	Y

	(1)	(2)	(3)	(4)	(5)
	1yr	2yr	3yr	4yr	5yr
$\Delta Credit_{i,t} \times \Delta\widehat{s}_{i,t}$	-0.37	-0.61	-0.64	-0.35	-0.02
	(0.16)	(0.17)	(0.25)	(0.18)	(0.10)
$\widehat{s}_{i,t}$	-0.75	-1.17	-1.19	-1.17	-1.10
	(0.27)	(0.34)	(0.43)	(0.40)	(0.26)
$\Delta Credit_{i,t}$	-0.00	-0.16	-0.38	-0.44	-0.50
	(0.15)	(0.23)	(0.32)	(0.36)	(0.44)
Observations	667	664	661	658	651
R-squared	0.44	0.54	0.54	0.53	0.52
Controls	Y	Y	Y	Y	Y

Table 7: 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. Importantly, we control for a post crisis dummy as well which is equal to 1 in the 5 years after a crisis, the means the pre-crisis dummy should be judged relative to other "normal times" and is not mechanically low because spreads during crises are high. 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 then split 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. Driscoll-Kraay standard errors with 8 lags are in parentheses. Column 4 repeats the analysis instead for recessions.

	Spreads before a crisis			Recessions
	(1)	(2)	(3)	(4)
$1_{t-5,t-1}$	-0.34			-0.13
	(0.15)			(0.11)
$1_{t-5,t-1}$ × Severe		-0.45		
		(0.18)		
$1_{t-5,t-1}$ × Mild		-0.27		
		(0.15)		
$1_{t-5,t-1} \times \Delta Credit_{t-1}$			-1.42	
			(0.78)	
$\Delta Credit_{t-1}$	0.98	0.92	1.18	0.20
	(0.58)	(0.52)	(0.70)	(0.58)
ΔGDP_{t-1}	-0.16	-0.18	-0.22	-0.64
	(1.68)	(1.68)	(1.54)	(1.98)
Observations	621	621	621	601
R-squared	0.40	0.40	0.40	0.50
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 8: Credit market froth and fragility. We explore whether low spreads and high credit growth can forecast crises. HighFroth measures if spreads have been abnormally low in the last 5 years. HighCredit measures if credit growth has been abnormally high in the last 5 years. See text for details. Panel A uses these variables to forecast a financial crisis (using JST dates). We run probit regressions on the cumulative crisis indicator at the five year horizon (e.g., we predict whether a crisis occurs in any of the next 5 years). We also interact HighFroth with HighCredit, as this captures episodes where credit is booming and spreads are falling. Panel B repeats this exercise for recessions. In Panel C, we test whether HighFroth/HighCredit periods negatively forecast future GDP growth. Standard errors double clustered by country and year.

Panel A: Probit Predictions of a Crisis					
	(1)	(2)	(3)	(4)	
HighFroth	1.76			0.74	
	(0.91)			(1.20)	
HighCredit		0.55		-0.77	
		(0.46)		(0.40)	
(HighFroth)×(HighCredit)			1.95	2.00	
			(0.66)	(0.40)	
Observations	528	549	456	456	
Country FE	Y	Y	Y	Y	
Year FE	N	N	N	N	
Panel B: Probit Predictions of a Recession					
	(1)	(2)	(3)	(4)	
HighFroth	-0.69			-0.97	
	(0.50)			(1.36)	
HighCredit		-0.45		-0.34	
		(0.87)		(2.09)	
(HighFroth)×(HighCredit)			-0.39	0.66	
			(0.64)	(2.28)	
Observations	504	550	440	440	
Country FE	Y	Y	Y	Y	
Year FE	N	N	N	N	
Panel C: Predicting GDP Growth by Horizon					
	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
(HighFroth)×(HighCredit)	-0.89	-1.76	-3.02	-3.64	-3.69
	(0.76)	(1.30)	(1.84)	(2.16)	(2.46)
Observations	508	505	502	499	495
R-squared	0.40	0.53	0.55	0.57	0.56
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table 9: Credit market froth and fragility: Logit. We explore whether low spreads and high credit growth can forecast GDP downturns and crises. HighFroth measures if spreads have been abnormally low in the last 5 years. HighCredit measures if credit growth has been abnormally high in the last 5 years. See text for further details. Panel A uses these variables to forecast a financial crisis (using JST dates). We run logit regressions on the cumulative crisis indicator at the five year horizon (e.g., we predict whether a crisis occurs in any of the next 5 years). We also interact HighFroth with HighCredit, as this captures episodes where credit is booming and spreads are falling. Panel B repeats this exercise for recessions. Standard errors double clustered by country and year.

Panel A: Logit Predictions of a Crisis				
	(1)	(2)	(3)	(4)
HighFroth	1.83			0.84
	(0.88)			(1.22)
HighCredit		0.23		-1.05
		(0.42)		(0.50)
(HighFroth)×(HighCredit)			1.74	2.00
			(0.67)	(0.75)
Observations	528	549	456	456
Country FE	Y	Y	Y	Y
Year FE	N	N	N	N
Panel B: Logit Predictions of a Recession				
	(1)	(2)	(3)	(4)
HighFroth	-0.40			0.86
	(0.54)			(0.84)
HighCredit		-0.75		-0.43
		(0.56)		(0.72)
(HighFroth)×(HighCredit)			0.00	-0.29
			(0.51)	(0.95)
Observations	504	550	440	440
Country FE	Y	Y	Y	Y
Year FE	N	N	N	N

Table 10: Out-of-sample Results: Credit market froth and fragility. Our previous regressions use the full sample to determine cutoffs for high froth in credit spreads and high credit growth. We repeat our results where we use out of sample measures of froth and high credit growth episodes using only the information up to time t to construct each variable. Standard errors double clustered by country and year.

Panel A: Probit Predictions of a Crisis (Real Time)

	(1)	(2)	(3)	(4)
HighFroth	1.07			-0.26
	(0.69)			(1.12)
HighCredit		1.11		-0.65
		(0.81)		(2.60)
(HighFroth)×(HighCredit)			1.04	1.67
			(0.93)	(3.37)
Observations	404	507	372	372
Country FE	Y	Y	Y	Y
Year FE	N	N	N	N

Panel B: Probit Predictions of a Recession (Real Time)

	(1)	(2)	(3)	(4)
HighFroth	-0.68			-0.45
	(0.50)			(1.11)
HighCredit		-0.48		-0.07
		(0.58)		(1.57)
(HighFroth)×(HighCredit)			-0.68	-0.34
			(0.48)	(1.74)
Observations	404	507	372	372
Country FE	Y	Y	Y	Y
Year FE	N	N	N	N

Panel C: Predicting GDP Growth by Horizon (Real Time)

	(1)	(2)	(3)	(4)	(5)
	1 yr	2 yr	3 yr	4 yr	5 yr
(HighFroth)×(HighCredit)	0.25	0.01	0.92	1.40	1.96
	(0.54)	(0.93)	(1.14)	(1.32)	(1.44)
Observations	455	452	449	446	442
R-squared	0.44	0.55	0.57	0.57	0.56
Country FE	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N

Table 11: Post-War Data: Spreads and GDP. This table provides regressions of future cumulative GDP growth $\Delta lny_{t+k,i}$ on credit spreads at the 3 year horizon. We include interactions with crisis or recession dummies. Controls include two lags of GDP growth and both country and year fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses.

Panel A: 3 year GDP growth

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{s}_{i,t}$	-1.14								
	(0.35)								
$\widehat{s}_{i,t-1}$	0.53								
	(0.58)								
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-6.84	-5.05	-6.13	-5.44				
		(0.59)	(1.07)	(1.03)	(1.06)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-9.64	-9.62	-8.30					
		(2.41)	(1.57)	(1.74)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-1.53	-5.45					
			(1.18)	(4.08)					
$1_{crisisST,i,t}$				6.61					
				(6.24)					
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$						-0.25			
						(0.60)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$							-0.53		
							(0.35)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$								-1.45	-0.62
								(0.50)	(0.92)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$									-2.48
									(1.89)
Observations	288	288	288	288	288	285	285	288	288
R-squared	0.70	0.72	0.72	0.72	0.72	0.69	0.70	0.70	0.70

Panel B: 5 year GDP growth

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{s}_{i,t}$	-0.93								
	(0.41)								
$\widehat{s}_{i,t-1}$	0.58								
	(0.85)								
$\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-5.09	-0.71	-2.49	-3.52				
		(0.95)	(1.14)	(1.89)	(1.39)				
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$		-10.80	-10.75	-8.57					
		(3.85)	(1.86)	(2.08)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-3.74	-10.23					
			(1.41)	(3.22)					
$1_{crisisST,i,t}$				10.93					
				(5.54)					
$\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$						0.31			
						(0.99)			
$\Delta\widehat{s}_{i,t} \times 1_{nocrisis,i,t\to t-5}$							-0.56		
							(0.45)		
$\widehat{s}_{i,t} \times 1_{recess,i,t}$								-1.36	-0.04
								(0.75)	(1.16)
$\Delta\widehat{s}_{i,t} \times 1_{recess,i,t}$									-3.96
									(2.09)
Observations	281	281	281	281	281	279	279	281	281
R-squared	0.72	0.73	0.73	0.73	0.73	0.73	0.73	0.72	0.73

Table 12: Post-War Data: 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 variable HighCredit which counts the number of times that credit growth has been above median in each of the past 5 years. The lower panel instead directly interacts changes in credit spreads with credit growth over the previous 3 years. The table shows that an increase in spreads negatively forecast output on average. A given increase in spreads predicts more negative output growth if lagged credit growth has also been high. Controls include two lags of GDP growth. Driscoll-Kraay standard errors with 8 lags are in parentheses.

When is an increase in spreads particularly bad for GDP?

	(1)	(2)	(3)	(4)	(5)
	1yr	2yr	3yr	4yr	5yr
$(\text{HighCredit}_{i,t}) \times \Delta\widehat{s}_{i,t}$	-0.42	-1.47	-1.13	-1.13	-1.01
	(0.20)	(0.54)	(0.43)	(0.38)	(0.40)
Observations	276	273	270	267	263
R-squared	0.71	0.70	0.72	0.74	0.74
Controls	Y	Y	Y	Y	Y

	(1)	(2)	(3)	(4)	(5)
	1yr	2yr	3yr	4yr	5yr
$\Delta Credit_{i,t} \times \Delta\widehat{s}_{i,t}$	-0.41	-2.04	-2.19	-2.19	-1.47
	(0.59)	(1.51)	(1.11)	(1.54)	(1.74)
$\widehat{s}_{i,t}$	-1.37	-1.22	-0.84	-0.77	-0.76
	(0.27)	(0.30)	(0.43)	(0.63)	(0.75)
$\Delta Credit_{i,t}$	-0.99	-3.62	-7.10	-8.68	-9.63
	(0.75)	(1.75)	(3.12)	(3.76)	(4.30)
Observations	294	291	288	285	281
R-squared	0.31	0.24	0.24	0.25	0.26
Controls	Y	Y	Y	Y	Y

Table 13: Predicting Output Out-of-sample. We use prewar data to fit our regressions, then compare the mean squared forecast errors out of sample using post-war data keeping the coefficients fixed from the earlier exercise. Numbers given in percent. There are 288 postwar observations across the countries in our sample. Baseline uses two lags of GDP growth, country fixed effects, and the change in interest rates. Spread uses only data from spreads in the regression, Credit uses only credit growth. Both uses spreads and credit individually, and Interaction uses the interaction term between credit and spreads. In panel A, credit is a dummy for being above its mean, while in panel B we take the growth in credit as a continuous measure.

Panel A: High Credit Dummy				
Baseline	Spread	Credit	Both	Interaction
5.91	4.66	5.20	4.64	4.26

Panel B: Continuous Change in Credit				
Baseline	Spread	Credit	Both	Interaction
5.91	4.48	5.42	4.30	3.52

Table 14: Crisis and Spread Interaction using Baron *et al.* (2019) (BVX) and Reinhart and Rogoff (2009) (RR) dates. The left-hand side variable is future 3 year GDP growth. Controls are the same as in Table 4. Driscoll-Kraay standard errors with 8 lags are in parentheses.

	(1) JST	(2) BVX	(3) RR
$\Delta\widehat{s}_{i,t} \times 1_{crisisST,i,t}$	-6.24		
	(1.43)		
$\Delta\widehat{s}_{i,t} \times 1_{crisisBVX,i,t}$		-2.66	
		(0.51)	
$\Delta\widehat{s}_{i,t} \times 1_{crisisRR,i,t}$			-1.09
			(0.81)
Observations	641	853	853
R-squared	0.55	0.49	0.48
Time FE	Y	Y	Y

Table 15: Spreads too low using alternative crisis dates from Reinhart and Rogoff (2009) and Baron *et al.* (2019). We include country and time fixed effects, along with GDP growth and lagged GDP growth as controls as discussed in Table 7. Driscoll-Kraay standard errors with 8 lags are in parentheses.

	(1) JST	(2) BVX	(3) RR
$1_{t-5,t-1}$	-0.34	-0.32	-0.17
	(0.14)	(0.23)	(0.08)
Controls	Y	Y	Y
Time FE	Y	Y	Y
Observations	601	825	794
R-squared	0.52	0.46	0.47

Table 16: Crisis Predictions using alternative crisis dates from Reinhart and Rogoff (2009) (Panel A "RR") and Baron *et al.* (2019) (Panel B "BVX"). Panel C again uses the BVX dates but drops dates which BVX date a crisis and no crisis is recorded according to Jordà *et al.* (2013) in a 5 year window around that date. Controls are the same as in Table 8. Standard errors double clustered by country and year.

Panel A: RR

	(1)	(2)	(3)	(4)
HighFroth	0.21			-1.66
	(0.90)			(0.97)
HighCredit		0.72		-0.71
		(0.67)		(0.91)
(HighFroth)×(HighCredit)			0.63	2.60
			(1.01)	(1.53)
Observations	537	585	475	475

Panel B: BVX

	(1)	(2)	(3)	(4)
HighFroth	0.20			-0.53
	(1.00)			(1.52)
HighCredit		0.36		0.15
		(0.45)		(1.15)
(HighFroth)×(HighCredit)			0.02	0.35
			(0.86)	(1.64)
Observations	591	615	493	493

Panel C: BVX $\cap$ JST

	(1)	(2)	(3)	(4)
HighFroth	1.68			0.68
	(1.21)			(1.84)
HighCredit		0.70		-0.36
		(0.52)		(0.42)
(HighFroth)×(HighCredit)			1.80	1.48
			(0.97)	(1.11)
Observations	536	552	458	458