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HOW CREDIT CYCLES ACROSS A FINANCIAL CRISIS

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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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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); Laeven and Valencia (2013); 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); Sufi and Taylor (2022); Müller and Verner (2023); Frydman and Xu (2023).

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.

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.

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 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 up to 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.

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 (Jordà *et al.*, 2011; Jorda *et al.*, 2013; Baron and Xiong, 2017; Mian *et al.*, 2017; Greenwood *et al.*, 2020). 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:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{crisis}] + \gamma_2 \text{Prob}^{\mathcal{Q}}(z_{i,t} \leq \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{no-crisis}]$$

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 45% "too low" pre-crisis 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 $\times$ losses and describing the runup to crises in terms of froth, are our main findings. They provide guidance for theories of financial crises. Models such as Gertler and Kiyotaki (2010), He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2012) are FZ models and are the types of models that can match the evolution and aftermath of a crisis. However, these models will not match the pre-crisis spread evidence. In the models, a prolonged period in which fragility and leverage rises will also be coupled with an increase in spreads and risk premia. That is, the logic of these models is that asset prices are forward looking and will reflect the increased risk of a crisis as fragility grows. The spread evidence is more consistent with models of belief formation in which agents discount the likelihood of a crisis. In Moreira and Savov (2014), severe crises are preceded by periods of low spreads where agents think a crisis is unlikely and hence increase leverage. 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 (see also Maxted (2019) for a behavioral model of crises). 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

Our data on credit spreads come from a variety of sources. Table 1 details the data coverage. Our early 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.

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	84	Y
Belgium	1960	2001	42	Y
Canada	1869	2001	113	Y
Denmark	1897	1929	24	Y
France	1869	2009	68	Y
Germany	1927	2021	58	Y
Greece	2003	2012	10	N
Italy	1869	2021	71	Y
Japan	1870	2001	32	Y
Korea	1995	2013	19	N
Netherlands	1880	1929	17	Y
Norway	1876	2003	67	Y
Spain	1871	2021	57	Y
Sweden	1869	2011	79	Y
Switzerland	2001	2022	22	Y
United Kingdom	1869	2014	112	Y
United States	1869	2014	131	Y

An alternative way to construct spreads is to use safe government debt as the benchmark. We find that our results are largely robust to using UK government debt as this alternative benchmark.[1] We form this spread for each country in each month and then average the spread over the last quarter of each year to obtain an annual spread measure.[2] This process helps to eliminate noise in our spread construction. Lastly, we deal with compositional changes in the sample by requiring at least 90% of the bonds in a given year to be the same bonds as the previous year. Our data appendix describes the construction of spreads during this period in more detail. This filter leads to gaps in the spread series, which we treat as missing data. For example, 1914 is a year when there are not enough bonds to construct spreads for many of the countries.

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 Switzerland. We use spreads on non-financial corporates from Gilchrist and Mojon (2018) for Germany, France, Italy, and Spain from 1999 onwards. We also collect data on Ireland, Portugal, 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 add additional 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. Table 1 gives the first and last year for each country as well as the total years of non-missing spread data for that country.

[1] One issue with UK government debt is that it does not appear to serve as an appropriate riskless benchmark during the period surrounding World War I as government yields rose substantially in this period. Because of this we follow Jordà *et al.* (2011) and drop the wars year 1913-1919 and 1939-1947 from our analysis

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

In order to describe patterns around financial crises, we need to know what is a financial crisis. We primarily use crisis dates from the macro-financial history database of Jordà *et al.* (2017), henceforth "JST dates". Our credit spread sample includes Korea and Greece, which are countries that JST do not study. For these countries we use crisis dates from Laeven and Valencia (2013). 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.

The chronologies in the literature date the financial crisis as the event of significant bank runs, bank closures, or government intervention in the banking sector. In many cases, this event occurs one or more years after the onset of a recession. For example, 2008 is the dated financial crisis in the U.S., while the NBER dates the peak of the business cycle prior to the crisis as December 2007. In our analysis, which is based on annual data, we are interested in studying the dynamics of the economy beginning with the downturn. We follow Jorda *et al.* (2013) and use the algorithm of Bry *et al.* (1971) to detect local peaks and troughs in real GDP per capita, which generally trends upwards over time. The algorithm usually provides dates that correspond to those provided by the NBER. In most cases, the turning point occurs in the year prior to the crisis, as in the example of the 2008 U.S. financial crisis. But there are cases where the turning point occurs up to three years before the crisis date, while in others it occurs in the year after the crisis date. In addition, there are some cases where there are multiple turning points in this window around the crisis date. In all of these cases, we pick the first turning point in the window of three years before the crisis to the year after the crisis.

We date a crisis as one year after the turning-point date, and refer to these dates as "JST crises." We have experimented with different lag procedures (i.e., tried zero or two years rather than one), and find that the one year lag generally lines up best with the credit spread rise as well as the decline in GDP. See Figure 1 below. Table 2 gives the crisis dates (JST or Laeven and Valencia (2013)) and the corresponding turning point dates from

Table 2: This table lists the crisis and the corresponding turning point dates from the Bry *et al.* (1971) algorithm for each of the 14 countries we study. Crisis dates are from JST except for those indicated with $*$, which are from Laeven and Valencia (2013).

Country	Turning Point Dates	Crisis Dates
France	1882,1929,2007	1882,1889,1930,2008
Japan	1887,1898,1907,1919,1925,1997	1871,1890,1901,1907,1920,1927,1997
Switzerland	1929,1990,2008	1870,1910,1931,1991,2008
United Kingdom	1889,1973,1990,2007	1890,1974,1991,2007
Denmark	1876,1883,1920,1987,2007	1877,1885,1908,1921,1987,2008
Australia	1891,1894,1989	1893,1989
Korea	1996	1997*
Italy	1874,1887,1891,1918,1929	1873,1887,1893,1907,1921,1930,1935
	1932,2007	1990, 2008
Netherlands	2008	1921,2008
Greece	2007	2008*
Belgium	1874,1883,1926,1930,1937,2007	1870,1876,1885,1925,1931,1934,1939
		2008
Sweden	1876,1879,1904,1920,1930,1990,2007	1878,1907,1922,1931,2008
Canada	1907	1907
Norway	1897,1920,1923,1930,1987	1899,1922,1931,1988
United States	1873,1892,1906,1929,1981,2007	1873,1893,1907,1930,1984,2007
Germany	1890,1898,1928,2008	1873,1891,1901,1931,2008
Spain	1884,1888,1911,1925,1929,1932,2007	1883,1890,1913,1924,1931,1977,2008

the Bry *et al.* (1971) algorithm.

The algorithm also detects peaks and troughs not associated with financial crises. We refer to these dates as non-financial recessions, and in some of our results we contrast the results involving financial crisis recessions and non-financial crisis recessions. This approach closely follows the analysis of Jorda *et al.* (2013).

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

The total number of observations in our credit spread sample ($N \times T$) is 1006. Most of our regressions use a sample that contains credit spreads, crisis dates and credit growth from the JST database, and GDP data from Barro-Ursua. This sample contains 840 observations. In some of our regressions, we use additional leads and lags of these variables which can change the number of observations further, particularly since there are gaps in the data series. In all cases, we report results based on regressions that use the maximum available data for that specification.

3. Normalizing Spreads

There is a large literature examining the forecasting power of credit spreads for economic activity (see Friedman and Kuttner (1992), Gertler and Lown (1999), Philippon (2009), and Gilchrist and Zakrajsek (2012)). 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 considerations that arise.

Table 3 examines the association of spreads and 1-year output growth in our sample. We run,

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

where $y_{i,t}$ is real per capita GDP in country i at time t. We include country (a_i) and time (a_t) fixed effects. Country fixed effects pick up different mean growth rates across countries. We also include a dummy ($Pre_{i,t}$) delineating the dates of the bond spread data from the London Stock Exchange (roughly pre-1930, but varying by country) from the spread data in the more recent sample. We discuss this further below.

In the regressions of Table 3, and most of the regressions of this paper, we also include time fixed effects. Time fixed effects will pick up common shocks to growth rates and spreads. For example, if there is a global shock to bond investors' risk bearing capacity,[3] or a global recession, the time fixed effects will pick up this shock. Our results thus reflect the association between the cross-country variation in spread changes and GDP outcomes. If we drop the time fixed effects, the global component of spread and output changes would also inform the regression results. In general, the signs and magnitude of the coefficients of interest are similar when including or excluding time fixed effects. However, the standard errors are larger when we exclude the time effects. The only regressions where we exclude time effects are the crisis prediction regressions, such as Table 10, where we are interested in predicting whether a crisis occurs at time t using data up to time $t-1$. In the majority of the analysis we are interested in documenting the association between credit, credit spreads, and output across the crisis cycle rather than in crisis-prediction. Finally, we follow Jorda *et al.* (2013) drop both war periods in all of our specifications. The bond prices during the war are affected by government actions, so that the information content in spreads is likely distorted.

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).

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

[3] In the IMM sample, the bonds are traded in London and thus plausibly face a common exposure to British banks' financial condition.

Table 3: 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. The last two columns split the sample into high spread (pre-1940) and low spread (post-1940) and examines whether our normalization choice produces similar coefficients across the split. Regressions include controls of two lags of GDP growth, a dummy for the early bond data years, and both country and year fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Raw	MeanNorm	OOSMean	Zscore	Prctile	High Spread	Low Spread
Spread	-0.07						
	(0.06)						
Lag Spread	0.08						
	(0.04)						
Spread/Mean		-0.76				-0.67	-0.96
		(0.19)				(0.21)	(0.39)
Lag Spread/Mean		0.56				0.54	0.55
		(0.22)				(0.26)	(0.36)
Spread/MeanOOS			-0.18				
			(0.08)				
Lag Spread/OOS			0.04				
			(0.03)				
Z-score Spread				-0.79			
				(0.25)			
Lag Z-score Spread				0.56			
				(0.18)			
Prctile Spread					-1.43		
					(0.84)		
Lag Prctile Spread					0.47		
					(0.75)		
Observations	969	968	953	897	897	489	479
R-squared	0.37	0.39	0.39	0.36	0.35	0.31	0.68
Number of groups	17	17	17	16	16	13	15

of credit risk. For example, in the 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.[4] 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 using data over 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. To operationalize this calculation, we need at least two data points for each country, which is why the sample drops. In column (4), we report results from converting the spread into a Z-score for a given country, while in column (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

[4] In the case where our spread series for a country comes from one set of bonds for a certain period and and another set of bonds for another period, we normalize by the mean within each sub-period.

regressions. But none of them does measurably better than the mean normalization. Finally, our approaches to normalization are implicitly making a homogeneity assumption that the information content in spreads for countries with on average higher spreads (or higher spread volatility) is no different than for 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 pre-war (pre-1940) and post-war. In the earlier sample the data is from bonds traded on the London Stock Exchange. The average spread in this data is 5.21%. In the later sample, the data sources are different as outlined above, and the sample contains higher grade bonds. The average spread in this sample is 1.13%. Note also that the mean normalization is within a country and data source for spreads, so that even within a country we are normalizing these series differently pre- and post-war. To check the homogeneity assumption, we run regressions within each subsample using the Spread/Mean normalization. These results are reported in columns (6) and (7). The coefficient estimates on Spread/Mean are economically and statistically similar across these samples, validating our homogeneity assumption. This cut of the data is also useful to show that our two types of spread series are comparable once we do the mean normalization. As discussed above, we still include the dummy $Pre_{i,t}$ in all of our regressions to control for any remaining systematic differences in the spreads from these two samples. 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 1 provides a first look at our data on credit, spreads, and output. Date 0 on the figure corresponds to the date we use for the start of the JST crisis. Table 2 lists these crises, of which there are 40 in our sample. The top-left panel plots the path of the mean across-country normalized spread, relative to the mean normalized spread for country-i, from 6-years before the crisis to 5-years after the crisis, along with one standard error bands. To produce the figure, we run a regression of the normalized spreads on crisis-time dummies, including country fixed effects, the dummy for the early bond data dates, and a control for spreads five years before the crisis. We plot the coefficients and standard errors on the crisis-time dummies. Table 9 presents the regression. We see that spreads are 30% below their average value in the years before the crisis. A one-sigma of the change in the normalized credit spread is 0.92, so that the spreads are equivalently 0.32σ below their mean value. Spreads rise in the crisis, going as high as 100% over their mean value in the year of the crisis, before returning over the next 5 years to the mean value. Additionally, note that the spread rises from $t = -2$ to $t = -1$ despite the crisis dated at $t = 0$. This illustrates the challenge in pinpointing the date at which a crisis starts. We use the turn-pointing algorithm to pick this date, but in general there will be measurement error in the crisis date which can downward bias our estimates of the relation between crisis-dated variables and subsequent outcomes.

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 and normalizing by the standard-deviation of credit growth for country-i. These coefficients are also from a regression with crisis-time dummies. 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 $t = 3$ 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 (but not normalizing by the standard-deviation of GDP growth for country-i). GDP grows in line with the average in the years preceding the crisis. GDP begins to fall at $t = -1$ and continues to fall below trend through the crisis date, remaining well below trend up to 5 years after the crisis.

These patterns in credit and output are consistent with prior evidence, in particular the work of Jorda *et al.* (2013). The magnitudes as reflected in Figure 1 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 1 reflect the average behavior across all JST crisis dates. There is considerable heterogeneity within these crises. Table 4 presents statistics. Across the 40 JST crisis dates in our sample, the mean decline in GDP over the 3 years subsequent to the date we use for the crisis is -2.4%. The mean decline in GDP from the business cycle peak preceding the crisis to the trough of the crisis recession is larger at -5.7%. We use the 3-year GDP growth metric in most of our regressions for the sake of consistency, but it should be noted that the macroeconomic downturn is larger than this statistic. The standard deviation of the the 3 year GDP decline is 8.7%. 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.

Figure 2a presents a histogram of spread changes (left figure) and 3 year GDP growth (right figure) around JST crises. Both GDP losses and spread spikes are skewed. Figure 2b presents a scatter plot of the spread changes against future 3 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 1: This figure plots the behavior of credit spreads, GDP, and the quantity of credit around crises, with date 0 as the beginning of recession associated with the 40 JST crises. GDP is expressed as the average across-country percentage change in the quantity from 6-years before the crisis to a given year, after demeaning by the sample growth rate in the quantity for country-i. Credit is defined similarly but also normalized by the standard-deviation of credit growth for country-i. That is, a value of 0.5 in the credit path implies that credit growth since time $t = -5$ has been 0.5σs faster than the country average. Spreads are normalized by dividing by the unconditional mean consistent with our normalization in the main text.

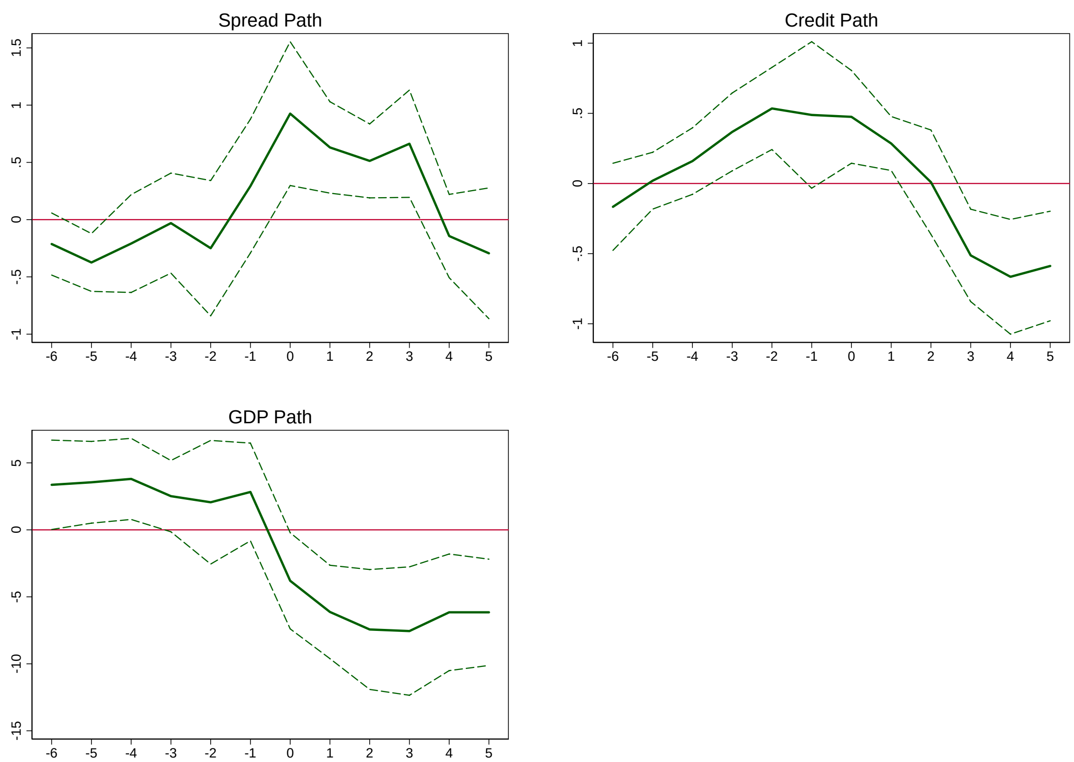
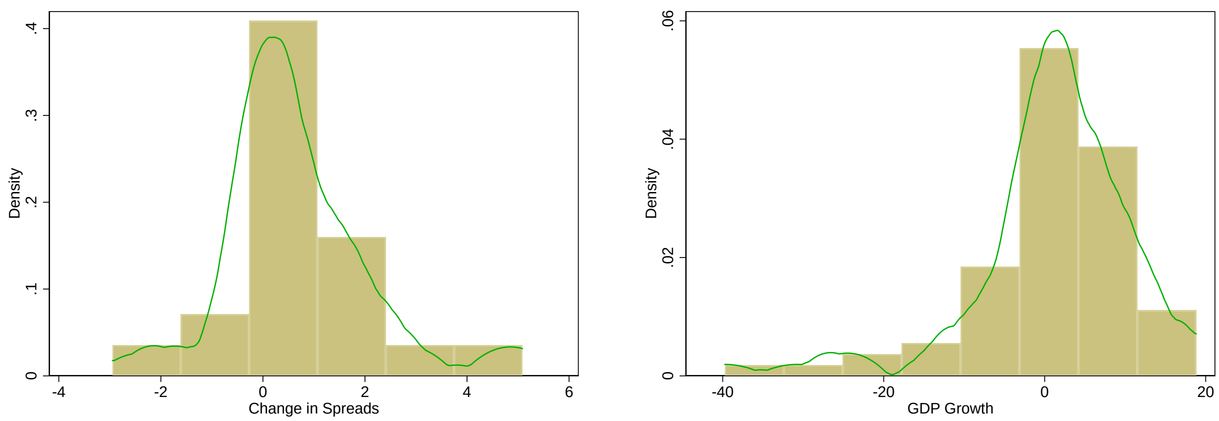


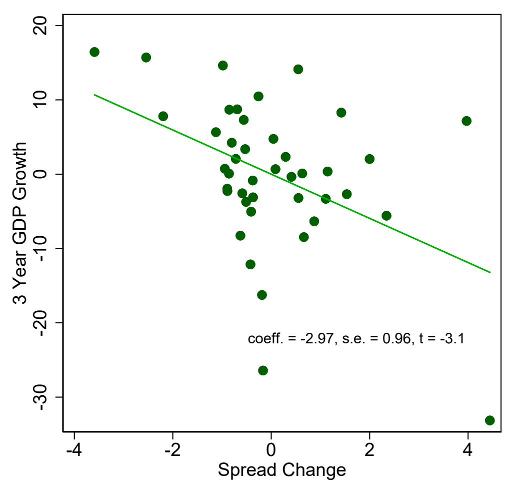
Table 4: This table provides summary statistics for peak to trough declines in GDP around the JST crisis episodes (Jorda *et al.* (2013)) as well as the 3 year growth rate in GDP.

Distribution of declines in GDP across JST episodes.

	Mean	Median	Std Dev	P 10th	P 90th	N
Trough	-5.7	-4.1	7.6	-12.7	0	40
3 year	-2.4	-1.2	8.7	-11.4	5.6	40



(a) Distribution of spread changes and future 3 year GDP growth around JST financial crises



(b) Spread changes against future 3 year GDP growth around JST financial crises

Figure 2: Spread changes and GDP declines around JST crises

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, a year fixed effect, and a dummy for the years of the early bond data. 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. Column (1) of Table 5 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. The independent variable is the change in the spread from $t-1$ to t interacted with the crisis dummy. We see that the change in the spread helps to explain subsequent GDP growth. 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 1. The result in column (2) indicates that if spreads spike by one (1.09σ) more than the average spike in spreads of around one, then output falls by an additional 2.2% relative to the mean path of Figure 1. This magnitude is roughly double the unconditional effect in column (1).

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

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 3 Year GDP Growth									
$\hat{s}_{i,t}$	-1.11								
	(0.39)								
$\hat{s}_{i,t-1}$	0.81								
	(0.33)								
$\Delta\hat{s}_{i,t} \times 1_{crisisST,i,t}$		-2.21	-2.11	-2.15					
		(0.74)	(0.51)	(0.56)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-2.06	-2.10					
			(0.95)	(0.84)					
$1_{crisisST,i,t}$				0.19					
				(1.27)					
$\hat{s}_{i,t} \times 1_{crisisST,i,t}$					-0.95				
					(0.51)				
$\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$						-0.52			
						(0.52)			
$\Delta\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$							-1.03		
							(0.54)		
$\hat{s}_{i,t} \times 1_{recess,i,t}$								-2.22	-1.70
								(0.65)	(0.72)
$\Delta\hat{s}_{i,t} \times 1_{recess,i,t}$									-1.17
									(0.88)
Observations	826	826	826	826	839	839	826	839	826
R-squared	0.53	0.53	0.54	0.54	0.52	0.52	0.53	0.54	0.55
Number of groups	15	15	15	15	15	15	15	15	15

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

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel B: 5 Year GDP Growth					
$\hat{s}_{i,t}$	-1.04								
	(0.43)								
$\hat{s}_{i,t-1}$	1.38								
	(0.31)								
$\Delta\hat{s}_{i,t} \times 1_{crisisST,i,t}$		-1.48	-1.35	-1.32					
		(0.60)	(0.28)	(0.42)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-2.65	-2.62					
			(1.10)	(0.92)					
$1_{crisisST,i,t}$				-0.13					
				(1.46)					
$\hat{s}_{i,t} \times 1_{crisisST,i,t}$					-0.38				
					(0.36)				
$\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$						-0.14			
						(0.56)			
$\Delta\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$							-0.86		
							(0.38)		
$\hat{s}_{i,t} \times 1_{recess,i,t}$								-1.69	-0.93
								(0.72)	(1.02)
$\Delta\hat{s}_{i,t} \times 1_{recess,i,t}$									-1.74
									(1.42)
Observations	816	816	816	816	829	829	816	829	816
R-squared	0.52	0.52	0.52	0.52	0.51	0.51	0.52	0.52	0.53
Number of groups	15	15	15	15	15	15	15	15	15

Next, we consider the importance of credit growth which is the variable that Jorda *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 -2.06 means that a one-sigma change in credit growth is associated with a lowering in post-crisis GDP growth of about 2.06%. Jorda *et al.* (2013) report that a one-sigma increase in credit growth leads to a lowering in post-crisis GDP growth of about 1%. 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.[5]

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 explanatory 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 40 JST dates. The standard deviation of 3-year GDP growth across these crisis episodes is about 9%. 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 4%. If we only consider the credit growth variable, the standard deviation is 1%. If we consider both of these variables, as well as their interaction, the standard deviation is 5%. That is, the two variables, credit spread changes

[5]See also Müller and Verner (2020).

and credit growth account for a significant fraction of the across-crisis variation in 3-year GDP growth. Similar statistics apply for the 5-year GDP growth case.

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 coefficients on the spread change and credit growth variables are minimally altered.

4.2 Credit spread spikes versus levels

In column (5) of Table 5, we report a regression where we only include the spread in the year of the JST crisis and not the spread change. Comparing the results from column (5) to those of columns (2)-(4), we see that changes in spreads rather than the level of spreads helps to explain GDP outcomes in crises.

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 JST crisis dates. We focus on the set of dates for which JST crises do not occur in any of the next 5 years. The coefficient estimates in (7) is larger than (6), but not statistically different, and the magnitudes are more similar than the same comparison for crisis dates. Columns (8) and (9) focus on recession dates not associated with a JST crisis. 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.

More formally, 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.[6] Our results in Table 5 confirm these predictions and the differential importance of spread changes in crises and recessions.

4.3 Crisis triggers and amplifiers without crisis dating

The start of a crisis is associated with a spike in spreads and larger spikes in spreads and higher pre-crisis credit growth are associated with worse crises. These results were de-

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

Table 6: Quantile Regressions. We run quantile regressions of future output growth over the next year on the change in credit spreads and the 3-year growth in credit/GDP for different quantiles. Controls include two lags of GDP growth, a dummy for the early bond data years, and country and time fixed effects. Our main result is that increases in spreads are particularly informative for lower quantiles of GDP growth. Standard errors in parenthesis cluster by year.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	90th	75th	50th	25th	10th
$\Delta s_{i,t}$	-0.39	-0.36	-0.59	-1.12	-0.55
	(0.29)	(0.46)	(0.19)	(0.57)	(0.83)
$\Delta Credit_{i,t}$	-1.25	-1.05	-1.00	-0.85	-0.77
	(0.25)	(0.23)	(0.37)	(0.45)	(0.56)
Observations	826	826	826	826	826
R-squared	0.30	0.41	0.50	0.47	0.42

rived from examining JST crises. In this section, we show that our main results relating credit growth, spreads, and subsequent GDP outcomes do not rely on a dating methodology such as our use of JST dates and the turning-point algorithm.

We first ask what information is contained in spread spikes without conditioning on the occurrence of a JST crisis. Table 7 presents quantile regressions of output growth over the next year on $\Delta\hat{s}_{i,t}$. Controls include country and time fixed effects, two lags of GDP growth, and a dummy for the years of the early bond data. 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 75th quantile, the coefficient on $\Delta\hat{s}_t$ is -0.36, while it is -1.12 at the 25th quantile. These results indicate that a spike in spreads shifts down the conditional distribution of output growth, fattening the left tail.

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.

To explore this possibility we construct a financial-sector fragility indicator. We create a variable ($\text{HighCredit}_{i,t}$) 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 $\text{HighCredit}_{i,t} = 1$ then credit growth has been above median in each of the last 5 years. The variable thus takes values in $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$. 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 the $\text{HighCredit}_{i,t}$ 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.

In Table 8 we regress GDP growth at horizons of $t+1$ to $t+5$ years on the HighCredit variable interacted with the change in spreads at time t. We also include $\text{HighCredit}_{i,t}$ as well as spreads separately. The inclusion of the term $(1 - \text{HighCredit}_{i,t})$ interacted with the spread at time t and the lagged spread at $t-1$ will pick up the direct effect of spread increases on output as we have shown in other regressions. Thus the new result here is that an increase in the spread at date t when $\text{HighCredit}_{i,t} = 1$ substantially reduces the path of output, above and beyond the direct effects of these variables.

The bottom panel of Table 8 presents these results in a different way, using a simple interaction of credit growth and changes in spreads.[7] Note that the regressions in the top panel implicitly condition on the entire sample since the $\text{HighCredit}_{i,t}$ variable is defined relative to the full-sample median of credit growth. The results in the bottom panel are

[7]The sample is smaller in the upper panel compared to the lower panel because in constructing the $\text{HighCredit}_{i,t}$ dummy we need to drop a number of the first observations.

Table 7: Which spread crises turn out badly? We run regressions where the left hand side is GDP growth at various horizons. In the top panel, the right hand side contains a 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 is negatively associated with subsequent output growth if lagged credit growth has also been high. Controls include two lags of GDP growth, a dummy for the early bond data years, and both time and country fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses.

When is an increase in spreads particularly bad for GDP?

VARIABLES	(1) 1yr	(2) 2yr	(3) 3yr	(4) 4yr	(5) 5yr
$(HighCredit_{i,t}) \times \Delta s_{i,t}$	-0.63	-1.07	-1.28	-0.75	-0.52
	(0.23)	(0.29)	(0.41)	(0.36)	(0.32)
$(HighCredit_{i,t}) \times s_{i,t-1}$	-0.18	-0.40	-0.19	0.29	0.85
	(0.15)	(0.27)	(0.43)	(0.67)	(0.85)
$(1 - HighCredit_{i,t}) \times s_{i,t}$	-0.93	-0.99	-0.75	-1.31	-1.54
	(0.43)	(0.64)	(0.71)	(1.04)	(1.26)
$(1 - HighCredit_{i,t}) \times s_{i,t-1}$	0.53	0.86	0.62	1.18	1.70
	(0.38)	(0.43)	(0.60)	(0.67)	(0.68)
$HighCredit_{i,t}$	-1.21	-1.36	-1.83	-1.92	-1.47
	(0.64)	(1.00)	(1.54)	(2.36)	(2.86)
Observations	812	807	802	797	792
R-squared	0.47	0.55	0.54	0.53	0.53
Number of groups	15	15	15	15	15

VARIABLES	(1) 1yr	(2) 2yr	(3) 3yr	(4) 4yr	(5) 5yr
$\Delta Credit_{i,t} \times \Delta s_{i,t}$	-0.20	-0.29	-0.38	-0.23	0.02
	(0.15)	(0.20)	(0.23)	(0.22)	(0.13)
$\Delta s_{i,t}$	-0.69	-0.97	-1.00	-0.97	-1.01
	(0.24)	(0.32)	(0.35)	(0.34)	(0.26)
$\Delta Credit_{i,t}$	-0.19	-0.66	-1.12	-1.37	-1.39
	(0.14)	(0.26)	(0.35)	(0.42)	(0.54)
Observations	836	831	826	821	816
R-squared	0.45	0.54	0.55	0.54	0.53
Number of groups	15	15	15	15	15

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 -0.38, meaning a one-sigma increase in the interaction term suggests an extra marginal effect of 0.38% 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), Gorton and Ordonez (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.

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:

$$s_{i,t-1} = \gamma_{i,0} + \gamma_1 \text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{crisis}] + \gamma_2 \text{Prob}^{\mathcal{Q}}(z_{i,t} \leq \underline{z}) \times E_t^{\mathcal{Q}}[\text{Loss}_{i,t}|\text{no-crisis}] \tag{4}$$

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 $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$ is low and moreover offsets the fragility-loss component of spreads. We investigate this further.

Table 9 present regressions where the left hand side is the spread at time t, and the right hand side includes dummies for the period from $t-6$ to $t+5$. The first column includes country fixed effects while the second column includes country and time fixed effects. The dummies trace out the path of spreads around a financial crises, where in column (1) the magnitudes are relative to the mean non-crisis period spread in the country, and in column (2) the magnitudes are relative to the mean non-crisis period spread in the country and the mean spread across countries at that time.[8] In column (1) we see that spreads are below mean in the years before the crisis and then rise at $t-1$ and again at time t before falling subsequently. The results in column (1) and column (2) are similar, albeit with larger magnitudes when include the time fixed effects. Note also that the inclusion of the post-crises dummies ensures that the low spreads pre-crisis is not

[8]The coefficients and standard errors presented in column (2) of Table 9 are plotted in Figure 1.

Table 8: Are spreads before a crisis too low? We run regressions of our normalized spreads on year dummies from $t-6$ to $t+5$ where t is the date of crisis. Columns (1) and (3) include country fixed effects but not time fixed effects, while the rest include both. We also consider dummies interacted with severe and mild crises, recessions, and credit growth. Controls include the dummy for the early bond data years and the 5-year lagged spreadnorm which controls for variation in the level of spreads. Driscoll-Kraay standard errors with 8 lags are in parentheses.

	Pre-Crisis Spreads							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	1	2	3	4	5	6	7	8
1_{t+5}	-0.29	-0.12	-0.31	-0.13	-0.10	-0.11	-0.13	0.03
	(0.28)	(0.23)	(0.29)	(0.23)	(0.22)	(0.24)	(0.23)	(0.18)
1_{t+4}	-0.14	-0.11	-0.15	-0.11	-0.05	-0.08	-0.08	0.02
	(0.18)	(0.22)	(0.18)	(0.21)	(0.22)	(0.24)	(0.25)	(0.20)
1_{t+3}	0.67	0.34	0.65	0.33	0.38	0.35	0.49	-0.00
	(0.24)	(0.29)	(0.24)	(0.28)	(0.30)	(0.29)	(0.35)	(0.16)
1_{t+2}	0.52	0.26	0.50	0.25	0.28	0.27	0.33	0.04
	(0.16)	(0.19)	(0.16)	(0.19)	(0.19)	(0.19)	(0.22)	(0.11)
1_{t+1}	0.63	0.39	0.63	0.38	0.40	0.40	0.44	0.18
	(0.20)	(0.24)	(0.20)	(0.24)	(0.25)	(0.24)	(0.26)	(0.11)
1_{t}	0.93	0.53	0.93	0.50	0.52	0.56	0.68	0.19
	(0.32)	(0.40)	(0.32)	(0.40)	(0.41)	(0.41)	(0.44)	(0.11)
1_{t-1}	0.30	0.09	0.29	0.08	0.06	0.09	0.17	0.16
	(0.30)	(0.41)	(0.30)	(0.42)	(0.44)	(0.42)	(0.46)	(0.12)
1_{t-2}	-0.25	-0.51	-0.25	-0.50	-0.52	-0.50	-0.40	0.03
	(0.30)	(0.59)	(0.30)	(0.58)	(0.60)	(0.58)	(0.65)	(0.09)
1_{t-3}	-0.04	-0.29	-0.04	-0.28	-0.25	-0.26	-0.18	0.00
	(0.21)	(0.27)	(0.21)	(0.27)	(0.27)	(0.26)	(0.27)	(0.14)
1_{t-4}	-0.21	-0.41						
	(0.21)	(0.22)						
1_{t-5}	-0.37	-0.55						
	(0.13)	(0.18)						
1_{t-6}	-0.21	-0.37						
	(0.13)	(0.15)						
$1_{t-6,t-4}$			-0.26	-0.44				
			(0.14)	(0.15)				
$1_{t-6,t-4} \times severe$					-0.42			
					(0.17)			
$1_{t-6,t-4} \times mild$						-0.38		
						(0.20)		
$1_{t-6,t-4} \times \Delta cred_t$							-0.34	
							(0.27)	
$recession_{t-6,t-4}$								-0.03
								(0.13)
Observations	799	799	802	802	791	791	715	791
R-squared	0.13	0.48	0.13	0.48	0.47	0.47	0.49	0.45
Number of groups	15	15	16	16	14	14	14	14
Year FE	N	Y	N	Y	Y	Y	Y	Y

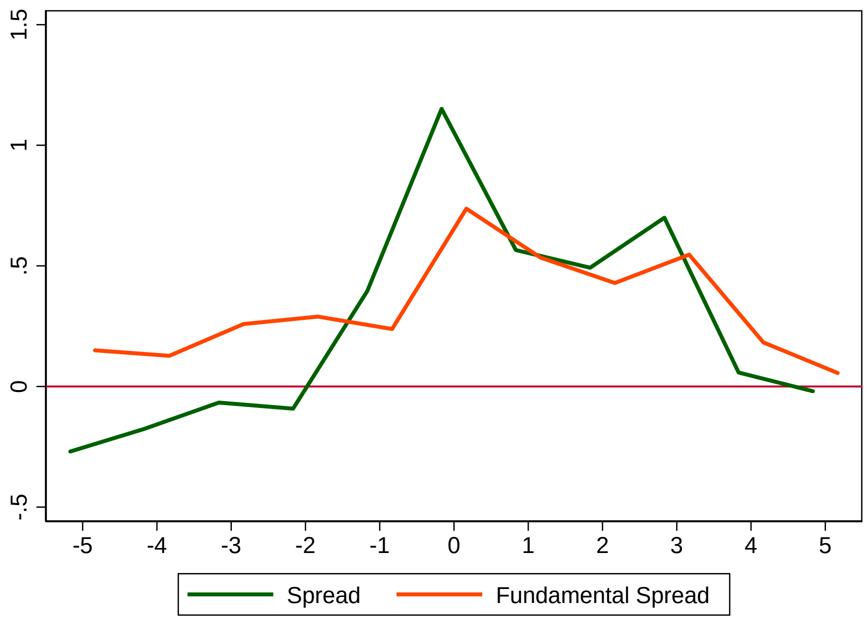
mechanically because we are judging spreads relative to an average that includes high crisis spreads. We also include a control for the level of spreadnorm 5 years before a crisis which controls for slow changes in the level of spreads.

In the rest of the columns we combine the dummies for years $t-4$ to $t-6$ which are years sufficiently before the start of the crisis and where the dummies indicate spreads that are statistically significantly below zero. In column (3), which excludes time fixed effects, the spread is -0.26, indicating that spreads are 0.28σ "too-low" pre-crisis. In column (4), which includes time fixed effects, the coefficient is -0.45, indicating that crises that happen in a given country are preceded by spreads that are not just low for that country but are especially low in the cross-section of countries. Column (5) considers the behavior of spreads before severe financial 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. However, the severe crisis dummy is similar to the dummy for all crises. In column (8), we examine the spread behavior leading up to a non-financial recession. We do not observe the low spread pattern, indicating that low spreads are a distinctive characteristic of the pre-crisis period.

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 (7) of the table makes this clear. We include an interaction of credit growth with the dummy for the 3 years ahead of the crisis. In the full sample credit growth and spreads are positively correlated. The feature that is unique to the pre-crisis period is that both spreads are low and credit growth is high (coefficient on pre-crisis credit growth of -0.33).

Figure 3 provides a visual representation of the behavior of spreads before and during crises. The green 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

Figure 3: This figure plots the path of spreads, fundamental spreads, and cumulative credit growth in the years surrounding a JST financial crisis. 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.



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.

In terms of equation (4), we can view these results as suggesting that investors' risk-neutral expectations of a large loss, $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$, 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) and

Krishnamurthy and Li (2020); or through a non-rational 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 9 do not allow one to distinguish between these possibilities.

5.2 Credit supply expansions predict crises

In Table 10 we construct a variable, labeled $\text{HighFroth}_{i,t}$, based on the difference between the fitted and actual lines in Figure 3. We first collect the residuals of a regression of credit spreads on fundamentals (two lags of GDP, credit growth, and country dummy). We set a dummy equal to one if the residual is below its full sample median. We define $\text{HighFroth}_{i,t}$ as the 5-year average of this dummy variable. The variable construction is analogous to the $\text{HighCredit}_{i,t}$ variable construction we have used earlier, and takes values from zero to one depending on how many of the past 5 years the variable is below its median. This variable thus captures an episode where spreads have been persistently low.[9]

Table 10 presents results using an OLS regression to forecast crises. Note that in these regressions we include country fixed effects but not time fixed effects since we are interested in forecasting crises using information prior to the crisis date. Column (1) uses only our $\text{HighFroth}_{i,t}$ measure. We see that $\text{HighFroth}_{i,t}$ meaningfully predicts a crisis. Column (2) is based on credit growth (the $\text{HighCredit}_{i,t}$ variable defined earlier). There is an association between high credit growth and crises, although our results are not as strong as those reported in Schularick and Taylor (2012).[10] Columns (3) and (4) forecasts

[9] We have also run regressions with the froth variable constructed in a simple manner: $\text{HighFroth}_{i,t} = 1$ 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.

[10] We define $\text{HighCredit}_{i,t}$ 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 $\text{HighCredit}_{i,t}$ variable with lagged 3-year growth in

Table 9: Credit market froth and fragility. We explore whether low spreads and high credit growth can forecast crises. $\text{HighFroth}_{i,t}$ measures if spreads have been abnormally low in the last 5 years. $\text{HighCredit}_{i,t}$ 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 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 $\text{HighFroth}_{i,t}$ with $\text{HighCredit}_{i,t}$, as this captures episodes where credit is booming and spreads are falling. Panel B repeats this exercise for recessions. We include country fixed effects and a dummy for the early bond data years. Driscoll-Kraay standard errors with 8 lags are in parentheses.

Panel A: Predicting Crises OLS

VARIABLES	(1)	(2)	(3)	(4)	(5) Rest. Sample
$(HighFroth)_{i,t}$	0.21			0.05	
	(0.06)			(0.11)	
$(HighCredit)_{i,t}$		0.18		0.01	
		(0.05)		(0.09)	
$(HighFroth) \times (HighCredit)_{i,t}$			0.26	0.22	0.28
			(0.09)	(0.20)	(0.09)
Observations	657	848	598	598	545
R-squared	0.09	0.10	0.12	0.12	0.12
Number of groups	14	15	14	14	12

Panel B: Predicting Recessions OLS

VARIABLES	(1)	(2)	(3)	(4)	(5) Rest. Sample
$(HighFroth)_{i,t}$	0.01			0.16	
	(0.08)			(0.11)	
$(HighCredit)_{i,t}$		-0.05		0.11	
		(0.08)		(0.14)	
$(HighFroth) \times (HighCredit)_{i,t}$			0.09	-0.14	0.05
			(0.08)	(0.22)	(0.08)
Observations	657	848	598	598	545
R-squared	0.21	0.15	0.22	0.23	0.24
Number of groups	14	15	14	14	12

credit and run the regression of Table 10, the t-statistic on credit growth is 3.8.

crises using the interaction of $\text{HighFroth}_{i,t}$ and $\text{HighCredit}_{i,t}$. We see that episodes of low spreads *and* high credit growth are the strongest signals of a future crisis.

In Panel B of Table 10 we repeat the forecasting exercise for non-financial recessions. There is a weak relation between the froth measures and the incidence of recessions in columns (1)-(3). In column (4), where we include both $\text{HighFroth}_{i,t}$ and $\text{HighCredit}_{i,t}$ and their interaction, we find a stronger relation between froth and subsequent recessions. In U.S. 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, while weaker are in line with their findings.

Figure 4 presents these results graphically. We run a Logit specification with the same explanatory variables as in Table 10 and report these results in Table 11. The Logit regression includes country fixed effects. For two of the countries, Belgium and Netherlands, the need for both the froth variables, which are based on a 5-year lag, and the crisis dates leads to not having a crisis observation in that country. Thus the sample size drops relative to the OLS regression.[11] We then plot the cumulative probability of a crisis from the Logit regression in Figure 4. In Panels B and C we condition on each of $\text{HighFroth}_{i,t} = 1$ and $\text{HighCredit}_{i,t} = 1$ separately. These plots show that the the cumulative probability of a crisis in the next 5 years are in the range of 20% to 30% when conditioning on the variables separately. In Panel A we report the results conditioning on both $\text{HighFroth}_{i,t}$ and $\text{HighCredit}_{i,t}$. It is apparent that prolonged periods of low spreads and high credit growth raise the probability of a financial crisis substantially. Greenwood *et al.* (2020) report a similar result when conditioning on credit growth and their measure of an "asset price bubble."

[11]For comparison, in the OLS regression of Table 10 we report in column (5) the $\text{HighFroth}_{i,t} \times \text{HighCredit}_{i,t}$ interaction for the smaller sample. The Logit specification implies a probability of crisis when the froth and credit variables are one to be about 20% more than when they are both zero. This compares to the OLS estimate of 28% increased crisis probability.

Figure 4: We plot the cumulative probability of a crisis at each horizon when we condition on credit market conditions. $\text{HighFroth}_{i,t}$ 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. $\text{HighCredit}_{i,t}$ 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" ($\text{HighFroth}_{i,t}$ and $\text{HighCredit}_{i,t}$ 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. See text for more details. Standard errors double clustered by country and year. Results are from Logit model with country fixed effects with standard errors double clustered by year and country.

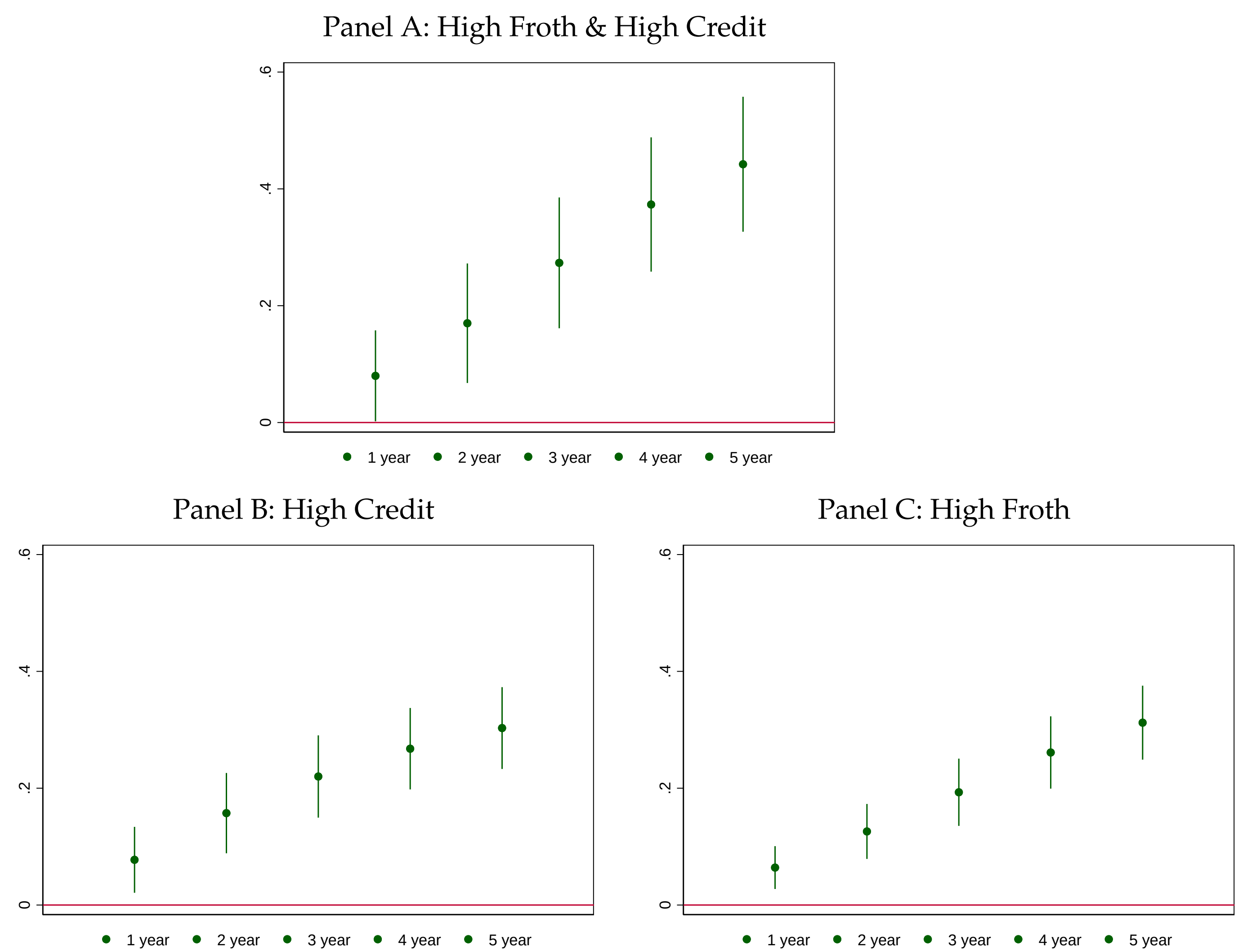


Table 10: Credit market froth and fragility: Logit. We explore whether low spreads and high credit growth can forecast GDP downturns and crises. $\text{HighFroth}_{i,t}$ measures if spreads have been abnormally low in the last 5 years. $\text{HighCredit}_{i,t}$ measures if credit growth has been abnormally 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 $\text{HighFroth}_{i,t}$ and $\text{HighCredit}_{i,t}$, as this captures episodes where credit is booming and spreads are falling. Panel B repeats this exercise for recessions. We include country fixed effects and a dummy for the early bond data years. Standard errors double clustered by country and year.

Panel A: Predicting Crises Logit

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	1.53			0.61
	(0.92)			(1.53)
$(HighCredit)_{i,t}$		1.28		0.39
		(0.46)		(1.50)
$(HighFroth) \times (HighCredit)_{i,t}$			1.93	1.14
			(0.86)	(2.02)
Observations	604	798	545	545
Pseudo R2	0.0867	0.0963	0.108	0.109

Panel B: Predicting Recessions Logit

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	0.06			0.88
	(0.44)			(0.71)
$(HighCredit)_{i,t}$		-0.20		0.67
		(0.47)		(0.83)
$(HighFroth) \times (HighCredit)_{i,t}$			0.53	-0.73
			(0.45)	(0.96)
Observations	657	848	595	595
Pseudo R2	0.169	0.120	0.176	0.180

The results in Table 10 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 12 presents the out-of-sample evidence.

Table 11: 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. See Table 10 for details. Standard errors double clustered by country and year.

Panel A: Predicting Crises OLS

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	0.05			0.00
	(0.08)			(0.09)
$(HighCredit)_{i,t}$		0.14		0.09
		(0.06)		(0.10)
$(HighFroth)_{i,t} \times (HighCredit)_{i,t}$			0.14	0.06
			(0.07)	(0.13)
Observations	624	699	620	620
R-squared	0.08	0.10	0.10	0.10
Number of groups	15	15	15	15

Panel B: Predicting Recessions OLS

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	-0.05			0.02
	(0.10)			(0.18)
$(HighCredit)_{i,t}$		-0.07		0.04
		(0.08)		(0.12)
$(HighFroth)_{i,t} \times (HighCredit)_{i,t}$			-0.08	-0.12
			(0.08)	(0.20)
Observations	624	699	620	620
R-squared	0.13	0.12	0.12	0.13
Number of groups	15	15	15	15

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 coefficient on the HighCredit$_{i,t}$ $\times$ HighFroth$_{i,t}$ interaction is 0.15 compared to that of 0.26 in Table 10, and the t-statistic is 1.875. The recession results of Panel B are also weakened, and the sign of the main coefficients of interest now have the opposite sign.

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 10 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 downturns outside of crises.

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 $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$ falls so that on net spreads fall before a crisis. The evidence is also consistent with non-rational models such as Gennaioli *et al.* (2013) and Bordalo *et al.* (2018) that the fall in $\text{Prob}^{\mathcal{Q}}(z_{i,t} > \underline{z})$ is more than under a rational benchmark.

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. Additionally, 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. 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 JST crises, drawn from the macro-financial history database of Jordà *et al.* (2017). 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

Table 13 shows that our results on crises, GDP outcomes and their interaction with spreads do not significantly change when considering only post-1950 data (although standard errors do increase). This table should be compared to Table 5. Table 14 relates the interaction between credit booms and spread spikes to subsequent GDP outcomes. Results are in line with the full-sample results of Table 8. Table 15 predicts crises using the post war sample and again finds high froth and high credit positively predicts crises. Finally, in Table 16 we investigate the stability of the coefficient estimates in the output prediction regressions of Table 8 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

Table 12: Post-War Data: Spreads and GDP. This table provides regressions of future cumulative GDP growth $\Delta ln\ y_{t+k,i}$ on credit spreads at the 3 year horizon. We include interactions with crisis or recession dummies. Controls include two lags of GDP growth, a dummy for the early bond data years. and both country and year fixed effects. Driscoll-Kraay standard errors with 8 lags are in parentheses.

VARIABLES	(1) 1	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9
$\hat{s}_{i,t}$	-0.80								
	(0.32)								
$\hat{s}_{i,t-1}$	0.63								
	(0.51)								
$\Delta\hat{s}_{i,t} \times 1_{crisisST,i,t}$		-1.43	-1.25	-2.02					
		(0.53)	(0.56)	(0.37)					
$\Delta cred_{i,t} \times 1_{crisisST,i,t}$			-0.58	-1.39					
			(0.55)	(0.35)					
$1_{crisisST,i,t}$				3.02					
				(0.70)					
$\hat{s}_{i,t} \times 1_{crisisST,i,t}$					-1.06				
					(0.57)				
$\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$						-0.03			
						(0.50)			
$\Delta\hat{s}_{i,t} \times 1_{nocrisis,i,t\to t+5}$							-0.54		
							(0.40)		
$\hat{s}_{i,t} \times 1_{recess,i,t}$								-0.82	-0.76
								(0.73)	(0.72)
$\Delta\hat{s}_{i,t} \times 1_{recess,i,t}$									0.51
									(0.64)
Observations	447	447	447	447	460	460	447	460	447
R-squared	0.71	0.71	0.71	0.71	0.68	0.68	0.70	0.68	0.71
Number of groups	13	13	13	13	13	13	13	13	13

the growth in credit as a continuous measure. These results indicate the relationships we document are stable pre- and post-war.

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). We use these crisis dates along with the turning point algorithm to pinpoint the start of the recession associated with a financial crisis.

There are three tables where crisis-dating affects the results: Tables 5, 9, and 10. In

Table 13: Post-War Data: Which spread crises turn out badly? We run regressions where the left hand side is GDP growth at various horizons. 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. We include interactions of this variable with spread changes and the level of spreads. The table shows that an increase in spreads is negatively associated with subsequent output growth if credit growth has also been high. Controls include two lags of GDP growth, country fixed effects, time fixed effects, and a dummy for the early bond data years. Driscoll-Kraay standard errors with 8 lags are in parentheses.

When is an increase in spreads particularly bad for GDP?

VARIABLES	(1) 1yr	(2) 2yr	(3) 3yr	(4) 4yr	(5) 5yr
$(HighCredit_{i,t}) \times \Delta s_{i,t}$	0.03	-0.18	-0.65	-0.32	-0.27
	(0.20)	(0.28)	(0.31)	(0.37)	(0.59)
$(HighCredit_{i,t}) \times s_{i,t-1}$	-0.34	-0.82	-0.88	-0.77	-0.69
	(0.19)	(0.35)	(0.53)	(0.80)	(1.14)
$(1 - HighCredit_{i,t}) \times s_{i,t}$	-1.21	-1.02	-0.73	-0.20	0.04
	(0.32)	(0.52)	(0.67)	(0.74)	(0.95)
$(1 - HighCredit_{i,t}) \times s_{i,t-1}$	1.14	1.43	1.71	1.85	1.91
	(0.19)	(0.45)	(0.60)	(0.72)	(0.69)
$HighCredit_{i,t}$	-0.25	-0.36	-0.57	-0.77	-0.84
	(0.45)	(0.72)	(1.09)	(1.54)	(2.16)
Observations	457	452	447	442	437
R-squared	0.72	0.71	0.73	0.75	0.76
Number of groups	13	13	13	13	13

Table 17 we investigate the relationship between spikes in spreads and subsequent GDP growth using the alternate dating, revisiting the main result of Table 5. The coefficient on the relationship is economically and statistically similar across these alternative chronologies.

Table 18 revisits the pre-crisis low spread regressions of Table 9 for the BVX and RR dates. Comparing the results between JST, RR and BVX, we consistently find a pattern of coefficients indicating low spreads ahead of crises, although the magnitudes differ across dating conventions. The RR dates give a lower magnitude. The BVX dates show low spreads particular in years $t-1$ to $t-3$, rather than the $t-3$ to $t-6$ of JST. These differ-

Table 14: Post-war Data: Credit market froth and fragility. We explore whether low spreads and high credit growth can forecast crises. $\text{HighFroth}_{i,t}$ measures if spreads have been abnormally low in the last 5 years. $\text{HighCredit}_{i,t}$ 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 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 $\text{HighFroth}_{i,t}$ with $\text{HighCredit}_{i,t}$, as this captures episodes where credit is booming and spreads are falling. Panel B repeats this exercise for recessions. We include country fixed effects and a dummy for the early bond data years. Driscoll-Kraay standard errors with 8 lags are in parentheses.

Panel A: Predicting Crises OLS

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	0.05			-0.04
	(0.06)			(0.13)
$(HighCredit)_{i,t}$		0.18		0.13
		(0.05)		(0.09)
$(HighFroth) \times (HighCredit)_{i,t}$			0.17	0.08
			(0.07)	(0.16)
Observations	310	470	310	310
R-squared	0.12	0.12	0.14	0.15
Number of groups	10	13	10	10

Panel B: Predicting Recessions OLS

VARIABLES	(1)	(2)	(3)	(4)
$(HighFroth)_{i,t}$	0.16			0.20
	(0.07)			(0.12)
$(HighCredit)_{i,t}$		-0.00		0.16
		(0.11)		(0.17)
$(HighFroth) \times (HighCredit)_{i,t}$			0.17	-0.13
			(0.12)	(0.24)
Observations	310	470	310	310
R-squared	0.11	0.13	0.11	0.11
Number of groups	10	13	10	10

ences likely arise because of the imprecision in pinpointing the date of a financial crisis.

Table 19 revisits the crisis forecasting regressions using the froth and credit variables.

Table 15: 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 a dummy for the early bond data years.. 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
5.68	4.21	6.13	4.34	4.82

Panel B: Continuous Change in Credit				
Baseline	Spread	Credit	Both	Interaction
5.74	4.21	3.42	2.40	2.24

Table 16: 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 5. Driscoll-Kraay standard errors with 8 lags are in parentheses.

VARIABLES	(1) ST	(2) BVX	(3) RR
$\Delta\hat{s}_{i,t} \times 1_{crisisST,i,t}$	-2.21		
	(0.74)		
$\Delta\hat{s}_{i,t} \times 1_{crisisBVX,i,t}$		-2.47	
		(0.71)	
$\Delta\hat{s}_{i,t} \times 1_{crisisRR,i,t}$			-2.36
			(0.48)
Observations	826	826	826
R-squared	0.53	0.54	0.53
Number of groups	15	15	15

Table 17: 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 9. Driscoll-Kraay standard errors with 8 lags are in parentheses.

VARIABLES	(1) JST	(2) RR	(3) BVX
1_{t+5}	-0.13	-0.02	0.01
	(0.23)	(0.10)	(0.18)
1_{t+4}	-0.11	-0.01	0.11
	(0.21)	(0.12)	(0.17)
1_{t+3}	0.33	0.23	0.51
	(0.28)	(0.31)	(0.30)
1_{t+2}	0.25	0.10	0.49
	(0.19)	(0.16)	(0.22)
1_{t+1}	0.38	0.17	0.53
	(0.24)	(0.18)	(0.15)
1_{t}	0.50	0.16	0.31
	(0.40)	(0.14)	(0.13)
1_{t-1}	0.08	0.10	-0.09
	(0.42)	(0.11)	(0.26)
1_{t-2}	-0.50	-0.05	-0.61
	(0.58)	(0.13)	(0.46)
1_{t-3}	-0.28	-0.15	-0.35
	(0.27)	(0.10)	(0.26)
$Crisis_{t-6,t-4}$	-0.44		
	(0.15)		
$RR_{t-6,t-4}$		-0.15	
		(0.08)	
$BVX_{t-6,t-4}$			-0.12
			(0.09)
Observations	802	814	814
R-squared	0.48	0.45	0.47
Number of groups	16	16	16
Year FE	Y	Y	Y

Table 18: Crisis Predictions using alternative crisis dates from Reinhart and Rogoff (2009) (Panel A "RR") and Baron *et al.* (2019) (Panel B "BVX"). Controls are the same as in Table 10. Driscoll-Kraay standard errors with 8 lags are in parentheses.

Panel A: RR				
	(1)	(2)	(3)	(4)
VARIABLES	1	1	1	1
$(HighFroth)_{i,t}$	0.08			-0.12
	(0.05)			(0.09)
$(HighCredit)_{i,t}$		0.20		0.04
		(0.05)		(0.08)
$(HighFroth) \times (HighCredit)_{i,t}$			0.29	0.35
			(0.07)	(0.15)
Observations	678	853	608	608
R-squared	0.08	0.09	0.11	0.12
Number of groups	16	15	14	14

Panel B: BVX				
	(1)	(2)	(3)	(4)
VARIABLES	1	1	1	1
$(HighFroth)_{i,t}$	0.09			0.05
	(0.05)			(0.08)
$(HighCredit)_{i,t}$		0.20		0.15
		(0.06)		(0.09)
$(HighFroth) \times (HighCredit)_{i,t}$			0.15	-0.03
			(0.07)	(0.18)
Observations	678	853	608	608
R-squared	0.07	0.13	0.09	0.10
Number of groups	16	15	14	14

Panel A reports result for the RR dates, and we see that the results are similar to our main JST results. Panel B presents the BVX dates, which also shows similar, albeit weaker, results. Recall that BVX date crises based on large reductions in bank equity values, while JST and RR date crises based on realized bank runs or bank closures. Thus, a note-worthy result from this table is that the froth variables are most informative in predicting banking panics.

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 than 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 FZ 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 model that only involves variation in beliefs cannot speak to the credit-interaction effects 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 (Germany, France, Italy, and Spain) from 1999-2022. Source: https://publications.banc
france.fr/en/economic-and-financial-publications-working-papers/credit-risk-euro-area. We take non-financial corporate spreads relative to German Bunds. The data construction is from Gilchrist and Mojon (2018).

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

Switzerland spreads from 2001 Source: https://data.snb.ch/en/topics/ziredev/chart/rendeidgkatch We take spreads as Manufacturing minus Confederation

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: Jordà *et al.* (2017) database (“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: Jordà *et al.* (2017) database.

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